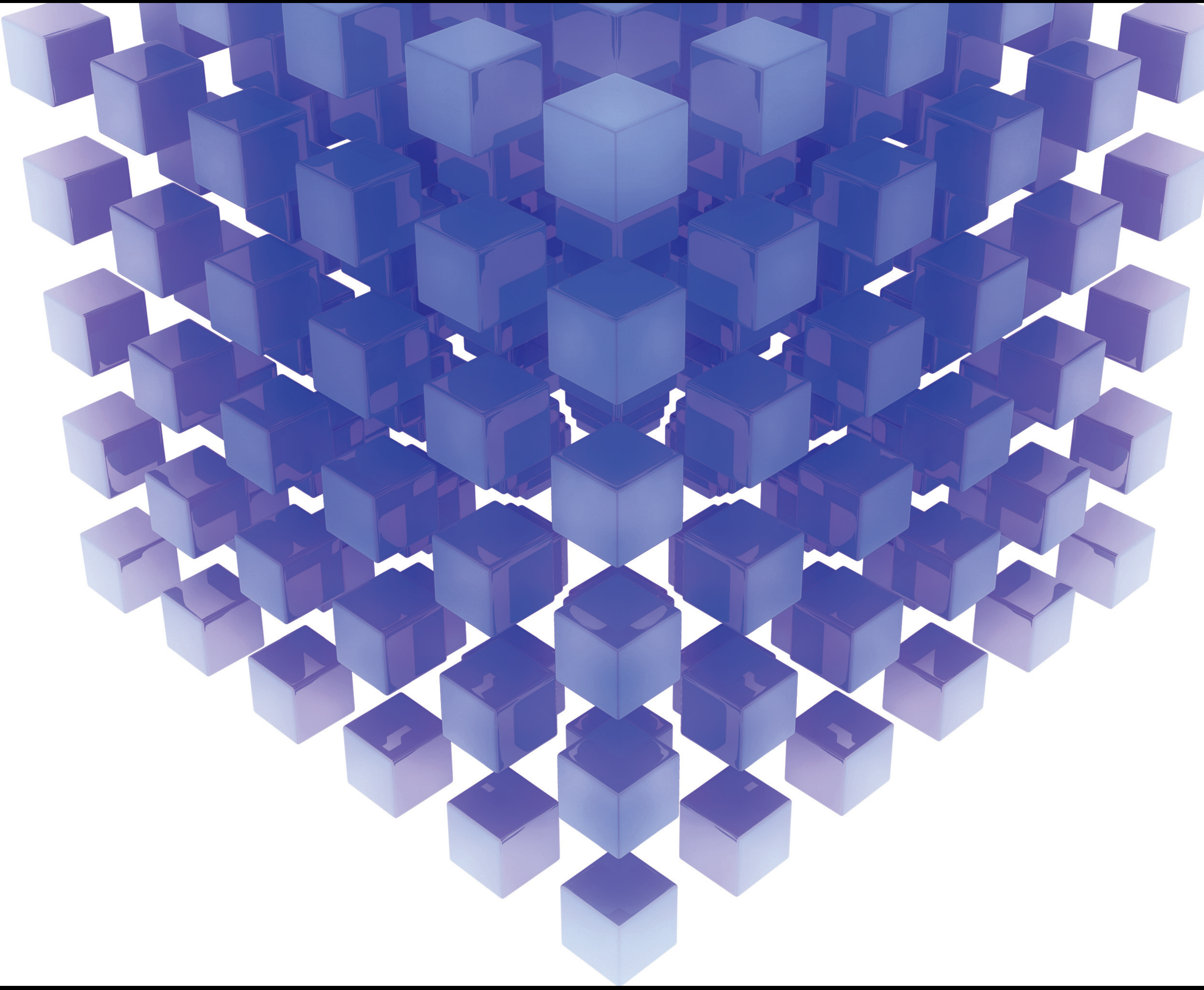
Mathematical Problems in Engineering

Machine Learning in Sustainable Industrial Development

Lead Guest Editor: Alireza Goli
Guest Editors: Erfan Babaee Tirkolaee and Ernesto D. R. Santibanez Gonzalez



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Research Article

A Multiobjective Multiproduct Mathematical Modeling for Green Supply Chain considering Location-Routing Decisions

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Global warming and environmental pollution are concepts that are more or less encountered in the news and newspapers today. Protecting the environment is crucial to the survival of humanity and the many plant and animal species that inhabit the planet. Lack of control of greenhouse gases can increase the average surface temperature and lead to floods and serious damage in the near future. On the other hand, overproduction of plastics by factories can lead to environmental pollution and the destruction of many food cycles on Earth. In this study, in order to sustainability integrate issues in supply chain network design decisions, a multiobjective optimization model is presented, which is a two-level routing location problem and optimizes economic and environmental goals. The first level is decisions related to the selection of operating facilities from a set of potential facilities (manufacturers and distribution centers), and the second level is related to determining the number of products from distribution centers to retailers and from manufacturers to distribution centers. The objective function is also of the minimization type, which is related to minimizing fixed and variable costs, and minimizing the environmental effects of the whole chain, which includes reducing the costs of greenhouse gas and carbon emissions.

1. Introduction

Global structure, increasing regulation of governmental and nongovernmental organizations, and pressure and demands for environmental issues have been created, which organizations have considered the necessary measures to apply supply chain management to improve the performance of the environment and the economy [1]. The world today is facing issues such as global warming, various types of pollution, increasing greenhouse gas emissions, and so on [2]. These issues could potentially lead to the extinction of humanity. Therefore, environmental protection and related strategies soon became a priority of programs as an organizational innovation. The organizations, on the one hand, had to pay attention to profitability and competitive advantage, on the other hand, to eliminate or minimize waste. Green supply chain management integrates supply chain management with environmental requirements at all stages of product design, selection, and supply of raw materials [3]. The green supply chain also includes all stages of production and manufacturing, distribution and transfer processes, delivery to the customer, and finally after consumption, recycling, and reuse management [4, 5]. One of the possible logistics strategies is to reduce latency, prelocate, and store inventory near the location used. This formal logistics strategy is adapted from military operations used in

World War II. Therefore, in general, it can be said that in order to achieve goals, logistics is an area that can improve a lot and location is one of the specific logistics strategies to move toward faster and better response. Many studies have been carried out in relation to supply chain network and location-routing issues, some of which are examined in this part of the research according to their classification [6]. Konstantaras et al. [7] have presented a multiobjective optimization model for green supply chain network design. In their study, the issue of supply chain network design with environmental concerns is studied. Sensitivity analysis for the case study shows that improving network capacity and increasing supply to facilities will reduce total carbon dioxide emissions and total cost. The model has several objectives, which include minimizing total costs and environmental impact.

Yuan et al. [8] examined the effect of green activities. The purpose of their study is to analyze the effects of environmental programs on each of the goals (economic and environmental). Their study includes considering the environmental and social effects together and comparing the effect of internal and external programs and analyzing green operational projects at the company level.

Tavana et al. [9] designed a green closed-loop supply chain network. Their study simultaneously covers the gap between considering environmental issues with economic issues. The objective function is to minimize total costs and environmental impacts. In their study, a complex integer programming model for a closed-loop supply chain network is considered. To solve this problem, a new method has been considered.

Khalili Nasr et al. [10] have proposed a multiobjective fuzzy model to minimize costs in the closed-loop supply chain. The proposed two-stage model selects suppliers and assigns them to manufacturers. The main purpose of this study is to minimize environmental costs, operating costs, and lost demand and maximize employment. Intended innovation involves considering supply chain sustainability. Finally, the proposed model is solved by goal programming.

Green logistics networks were designed and evaluated by Lin and Zhang [11]. The goal of logistics networks has gone from minimizing costs to minimizing costs and reducing environmental impact. The purpose of their study is to develop a framework for designing and evaluating green logistics networks that balances profitability and environmental impact. Their study examines the main activities that affect the environment and costs in the logistics network, which include transportation, production, product use, etc., and a framework for optimizing the effective design of logistics networks.

Chen et al. [12] designed an integrated closed-loop supply chain network model. In the proposed supply chain, strategic and tactical decisions are simultaneously made. Strategic-level decisions relate to the quantities of products flowing in the forward and reverse chain, and tactical-level decisions relate to the balance of dismantling lines in the reverse supply chain.

Wu et al. [13] have proposed a closed-loop logistic model with a spanning tree based on the genetic algorithm. In their study, a model for logistics planning is formulated by formulating the periodic logistics network problem in the form of an integer linear programming model. In addition, the decision to select the location of manufacturers, distribution centers, and recycling centers with activities related to the lowest cost is considered. The revised envelope tree on the enamel of the exact algorithm is used by the specified encryption to solve the model.

Sadeghi Rad and Nahavandi [14] proposed a green mathematical model to minimize supply chain costs. In their research, in addition to the cost, it deals with the amount of pollution in the supply chain. The proposed model creates an exchange between location and models of transportation, and between costs and emissions in the supply chain. The optimization of the models is based on carbon monitoring policies for the design of the closed-loop supply chain network and logistics operations.

Nurjanni et al. [15] presented a green multiobjective mathematical model for managing environmental issues. The proposed model is a nonlinear programming problem of two-objective integer, and to solve it, an effective multiobjective programming approach algorithm is proposed. This model determines the optimal flow of components and products in the supply chain network and optimizes the number of vehicles available in the forward supply chain.

In this study, in order to integrate sustainability issues in supply chain network design decisions, a multiobjective optimization model is presented, which is a two-level routing location problem and optimizes economic and environmental goals. The problem under study is NP-hard, which is optimized by a two-level programming. The first level is decisions related to the selection of operating facilities from a set of potential facilities (manufacturers and distribution centers), and the second level is related to determining the number of products from distribution centers to retailers and from manufacturers to distribution centers. The objective function is also of the minimization type, which is related to minimizing fixed and variable costs, and minimizing the environmental effects of the whole chain, which includes reducing the costs of greenhouse gas and carbon emissions.

2. Mathematical Programming

As mentioned in the previous section, the problem model discussed in this study has multiobjective functions, the first objective function seeks to minimize supply chain costs, and the second objective function seeks to minimize greenhouse gas emissions. Before dealing with the mathematical model of the problem, sets, parameters, and variables used are presented.

2.1. Model Assumptions

(i) The number of retailers and recycling centers is known.

(ii) The demand for retailers is known and somewhat independent.

(iii) Each retailer or active distribution center is visited by a specific vehicle at most once.

(iv) Each route is traversed by one vehicle (except recycling and collection routes).

(v) Recycled materials are used by production centers to produce all products.

(vi) Environmental variables are the type of greenhouse gas emissions such as CO2, and their unit is cubic meters.

2.1.1. Indices

K_h set of vehicle in level h

D set of distribution centers

R set of recycle centers

N_1 set of manufacturer and distribution centers

N_2 set of retailers and distribution centers

N_3 set of retailers and recycle centers

M set of manufacturer

L set of retailers

P set of products

2.1.2. Parameters

VE_m emission rate of greenhouse gases from one product unit in the production center m

VE_d emission rate of greenhouse gases from a product unit in the distribution center d

OC_m cost of establishing manufacturer m

EO_d emission of greenhouse gases due to the opening of the distribution center d

C_{ij} transportation cost from node i to j

EO_m emission of greenhouse gases due to the opening of the production center m

FVF_k fixed cost of level 1 vehicle

β percentage of recycled products received by the retail center

Q_m capacity of manufacturer m

α percentage of recyclability that can be used in the recycling center r

$M_{\max}$ maximum number of manufacturer

FC_1 the fixed cost of retailing in retailer l

OC_d cost of establishing distribution center d

VCR_r variable cost of recycling in recycle center r

FVS_k fixed cost of level k vehicle

VC_{dp} variable transportation cost of product p in distribution center d

Q_d capacity of distribution center d

VCR_{mp} variable cost of produce product from recycle material in manufacturer m for product p

Q_k capacity of vehicle k

VC_{mp} variable cost of produce in manufacturer m for product p

$D_{\max}$ maximum number of distribution centers

d_{lp} demand of customer l for product p

ET_{ij} average greenhouse gas emissions from node i to j

2.1.3. Variables

$y\ dl_{dl}^k$ 1 if the vehicle k follows the path d to l; otherwise 0.

$ymd_{m\ d}^k$ 1 if the vehicle k follows the path m to d, and otherwise, 0.

ylr_{lr}^k 1 if the vehicle k follows the path l to r, and otherwise, 0.

$y\ dr_{dr}^k$ 1 if the device k follows the path d to r, and otherwise, 0.

h_{mp} the amount of product p produced by the production center m from raw materials.

$x_{m\ dp}^k$ the amount of product p transported by vehicle k from the production center m to the distribution center d.

xr_{lr}^k the amount of product used by the k device from the retailer l for recycling to the recycling center r.

y_m 1 if the production center m is open, and otherwise, 0.

$y\ dd_{d_1d_2}^k$ 1 if vehicle k goes from d1 to d2.

$yll_{l_1l_2}^k$ 1 if vehicle k goes from retailer L1 to L2.

$ymm_{m_1m_2}^k$ 1 if the vehicle k goes from the production center m1 to m2.

yrm_{rm}^k 1 if the vehicle k follows the path r to m, and otherwise, 0.

$yrd_{r\ d}^k$ 1 if the vehicle k follows the path r to d, and otherwise, 0.

hr_{mp} The amount of product p produced by the production center m from recycled materials.

$x_{dl\ p}^k$ The amount of product p given by vehicle k from the distribution center d to the retailer l.

xr_{rm}^k The amount of product given by vehicle k from the recycling center r to the production center m.

y_d 1 if center d is open, and otherwise, 0.

2.2. Mathematical Modeling. The problem consists of two objective functions, the first objective function minimizing the sum of fixed and variable costs of the entire supply chain, and the second objective function minimizing greenhouse gas emissions.

$$
\begin{aligned}
\operatorname{Min} OBJ1 = {} & \sum_{m\in M} OC_m y_m + \sum_{d\in D} OC_d y_d + \sum_{l\in L} FC_1 \\
& + \sum_{k\in k_1} FVF_k \left(\sum_{m\in M} \sum_{d\in D} \sum_{p\in P} ymd_{m\ dp}^{k} \right) + \sum_{k\in k_2} FVS_k \left(\sum_{d\in D} \sum_{l\in L} \sum_{p\in P} y\ dl_{dl\ p}^{k} \right) \\
& + \sum_{m\in M} \sum_{p\in P} VC_{mp} h_{mp} + \sum_{m\in M} \sum_{p\in P} VCR_{mp} hr_{mp} \\
& + \sum_{d\in D} \sum_{p\in P} VC_{dp} \left(\sum_{m\in M} \sum_{k\in k_1} x_{m\ dp}^{k} \right) \\
& + \sum_{r\in R} VCR_R \left(\sum_{k\in k_2} \sum_{l\in L} xr_{lr}^{k} \right) + \sum_{k\in k_1} \sum_{a,b\in M} C_{ab} ymm^{k}{}_{ab} \\
& + \sum_{k\in k_1} \sum_{i,j\in N_1} C_{ij} ymd_{ij}^{k} + \sum_{k\in k_2} \sum_{i,j\in N_2} C_{ij} y\ dl_{ij}^{k} + \sum_{k\in k_2} \sum_{i,j\in N_3} C_{ij} ylr_{ij}^{k} \\
& \cdot \sum_{k\in k_1} \sum_{j\in R,M} C_{ij} yrm_{ij}^{k} + \sum_{k\in k_1} \sum_{a,b\in D} C_{ab} y\ dd_{ab}^{k} + \sum_{k\in k_2} \sum_{a,b\in L} C_{AB} yll_{ab}^{k} + \sum_{k\in k_1} \sum_{i,j\in D,R} C_{ij} y\ dr_{ij}^{k} + \sum_{k\in k_2} \sum_{i,j\in D,R} C_{ij} yrd_{ij}^{k}.
\end{aligned} \tag{1}
$$

$$
\begin{aligned}
\operatorname{Min} OBJ2 = {} & \sum_{m\in M} EO_m y_m + \sum_{d\in D} EO_d y_d + \sum_{k\in k_1} \sum_{i,j\in N_1} ET_{ij} ymd_{ij}^{k} + \sum_{k\in k_2} \sum_{i,j\in N_2} ET_{ij} y\ dl_{ij}^{k} \\
& \cdot \sum_{k\in k_2} \sum_{i,j\in N_3} ET_{ij} ylr_{ij}^{k} + \sum_{k\in k_1} \sum_{i,j\in R,M} ET_{ij} yrm_{ij}^{k} + \sum_{m\in M} VE_m \left(\sum_{p\in P} \left[h_{mp} + hr_{mp} \right] \right) \\
& + \sum_{d\in D} VE_d \left(\sum_{m\in M} \sum_{k\in k_1} \sum_{p\in P} x_{m\ dp}^{k} \right).
\end{aligned} \tag{2}
$$

Subject to the following:

$$\sum_{i,j\in N_1} ymd_{ij}^{k} \le 1, \quad \forall k \in k_1, \tag{3}$$

$$\sum_{i,j\in N_2} ydl_{ij}^{k} \le 1, \quad \forall k \in k_2, \tag{4}$$

$$\sum_{i,j\in D} ydd_{ij}^{k} \le 1, \quad \forall k \in k_1, \tag{5}$$

$$\sum_{i,j\in L} yll_{ij}^{k} \le 1, \quad \forall k \in k_2, \tag{6}$$

$$\sum_{p\in P} \sum_{m\in M} \sum_{d\in D} x_{mdp}^{k} \le Q_K, \quad \forall k \in k_1, \tag{7}$$

$$\sum_{p\in P} \sum_{d\in D} \sum_{l\in L} x_{dlp}^{k} \le Q_K, \quad \forall k\, k_2, \tag{8}$$

$$\sum_{l\in L} \sum_{r\in R} xr_{lr}^{k} \le Q_K, \quad \forall k \in k_2, \tag{9}$$

$$\sum_{r\in R} \sum_{m\in M} xr_{rm}^{k} \le Q_K, \quad \forall k \in k_1, \tag{10}$$

$$\sum_{p\in P} \left(h_{mp} + hr_{mp} \right) \le Q_m y_m, \quad \forall m \in M, \tag{11}$$

$$\sum_{k\in K_1} \sum_{p\in P} \sum_{m\in M} x_{mdp}^{k} \le Q_d y_d, \quad \forall d \in D, \tag{12}$$

$$\sum_{d\in D} \sum_{k\in K_2} xr_{dl\ p}^{k} = d_{lp}, \quad \forall l \in L, \forall p \in P, \tag{13}$$

$$\sum_{k\in K_2} \sum_{r\in R} xr_{lr}^{k} = \beta \sum_{p\in P} d_{lp}, \quad \forall l \in L, \tag{14}$$

$$\sum_{m\in M} \sum_{k\in K_1} xr_{rm}^{k} = \alpha \left(\sum_{k\in K_2} \sum_{l\in L} xr_{lr}^{k} \right), \tag{15}$$

$$\sum_{p\in P} hr_{mp} = \sum_{r\in R} \sum_{k\in K_1} xr_{rm}^{k}, \quad \forall m \in M, \tag{16}$$

$$\sum_{k\in K_1} \sum_{m\in M} ymd_{md}^{k} \le y_d, \quad \forall d \in D, \tag{17}$$

$$\sum_{k\in K_2} \sum_{l\in L} y\ dL_{dl}^{k} \le y_d, \quad \forall d \in D, \tag{18}$$

$$\sum_{k\in K_1}\sum_{d\in D} ymd_{md}^{k} \le y_m, \quad \forall m \in M, \tag{19}$$

$$\sum_{k\in K_1}\sum_{r\in R} yrm_{rm}^{k} \le R \times y_m, \quad \forall m \in M, \tag{20}$$

$$\sum_{d\in D} y_d \le D_{\max}, \tag{21}$$

$$\sum_{m\in M} y_m \le M_{\max}, \tag{22}$$

$$Y = (0, 1), \tag{23}$$

$$x, h \ge 0. \tag{24}$$

Objective function (1) minimizes total fixed costs (including fixed costs of production centers, distributors and retailers, and fixed costs of vehicles) and variable costs (including variable costs of product production in production centers, variable cost of relocation in distribution centers, variable cost of recycling products in recycling centers, and the variable costs of moving and traveling between centers throughout the supply chain).

The objective function (2) also minimizes the amount of greenhouse gas emissions due to the establishment of production and distribution centers, travel between centers, and product production in the production center.

Constraint (3) guarantees that each level 1 device travels from the production center to the distribution center at most once. Constraint (4) guarantees that each level 2 device will be retailed to the retailer at most once. Constraints (5) and (6) indicate that each vehicle can travel between distribution centers or retailers for up to one time. Constraints (7)–(10) show the capacity of the vehicle in the first, second, and third levels and transportation from recycling centers to production centers. Constraint (11) indicates production capacity in production centers. Constraint (12) indicates the capacity of distribution centers for storage. Constraint (13) ensures that retailers' demand for all products is met. Constraint (14) states that the β percentage of products sold is returned as recycled. Constraint (15) states that the α percentage of products is recycled by the center and can be used in production centers. Constraint (16) ensures that products based on recycled materials in production centers do not exceed the recycled materials received in this center. Constraint (17) ensures that if the distribution center has not been established then has no any input. Constraint (18) ensures that if the distribution center has not been established then has no any output. Constraint (19) ensures that if production center has not been established then has no any output. Constraint (20) ensures that if production center has not been established then has no any input. Constraints (21) and (22) ensure that the number of distribution and production centers does not exceed the maximum. Constraints (23) and (24) indicate decision variables.

```
Procedure NSGA-II
Input: N, g, f_k (X) >N members evolved g generations to solve f_k (X)
Initialize Population P;
Generate random population - size N;'
Evaluate Objectives Values;
Assign Rank (level) based on Pareto - sort;
Generate Child Population:
  Binary Tournament Selection;
  Recombination and Mutation;
  for i=1 to g do
 for each Parent and Child in Population do
   Assign Rank (level) based on Pareto - sort;
   Generate sets of nondominated solutions;
   Determine Crowding distance;
   Loop (inside) by adding solutions to next generation starting from
   the first front until N 'individuals;
  end
Select points on the lower front with high crowding distance;
Create next generation;
Binary Tournament Selection;
Recombination and Mutation;
end
```

Figure 1: Pseudocode of NGSA-II algorithm.

3. Solution Methods

In this section, two solution approaches are developed.

3.1. Development of a NSGA-II Algorithm. In this algorithm, the initial population with twice the member is considered. Also, in order to speed up the convergence and elitism, suitable unfavorable points are selected and the distances of the points from each other are considered as a criterion. The pseudocode of NGSA-II algorithm is shown in Figure 1.

The two-objective genetic algorithm is as follows:

1- Production of primary population (*Pt*) with *N* chromosomes.

2- Sorting based on nondominated points.

2-1- Starting from the largest *E*, which indicates the amount of CO_2 emissions.

2-2- Find the lowest cost for the E.

2-3- Subtract one unit from *E* until you reach the lowest E.

2-4- If the mentioned *E* is not in the chromosomes, go to step 2-3. Otherwise, go to step 2-2.

3- For each nondominated answer, assign a rank corresponding to the fitness point so that the first rank has the lowest *E* and cost.

$$\text{fitness} = \frac{E}{E_{\max}} + \frac{C}{C_{\max}}. \tag{25}$$

4- Production of secondary population (Q_t) with *N* chromosome by selecting, mutating, and mating on *N* primary chromosome (primary population).

5- Sorting points based on nonpost point algorithm.

6- Select *N* nonpost members (Pt + 1) from the set of nonpost points with 2*N* members from Pareto front.

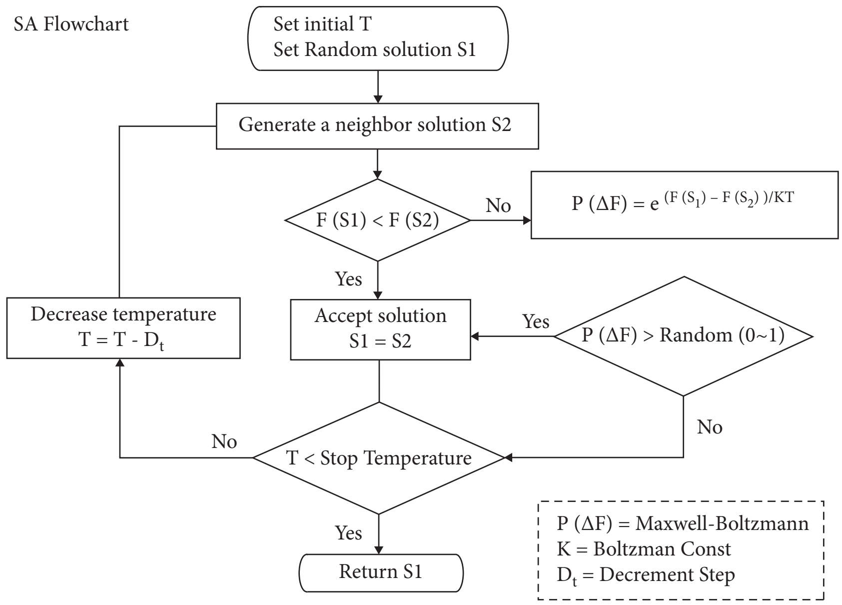

Figure 2: Proposed MOSA algorithm.

6-1- If the number of nonpost points reaches N, the set N will be selected from among them; otherwise, if the number of selected points is from N to more, the answers with the least congestion will be added to the set.

6-2- Crowd algorithm.

6-2-1- Assigning the number 0 to the point with the highest cost and the highest E.

6-2-2- Assigning the number 1 to the point with the lowest E and the lowest cost.

6-2-3- For $0 < i < 1$, Cd is calculated as follows:

$$Cd_E = \frac{(E_{i+1} - E_{i-1})}{(E_{\max} - E_{\min})},$$
$$Cd_{\text{cost}} = \frac{(\text{cost}_{i+1} - \text{cost}_{i-1})}{(\text{cost}_{\max} - \text{cost}_{\min})}. \quad (26)$$

3.2. Multiobjective Simulation Annealing Algorithm. The multiobjective simulation annealing algorithm serves multiobjectives in this research. The behavior of the annealing simulation algorithm is like a process of exploiting to achieve a solution by a search-based method based on a goal that is to reduce costs. This step works almost like the NSGA algorithm. In later stages, when the search begins to converge, the simulation annealing algorithm acts as an exploration to diversify the process of reaching a solution. To achieve the two objectives mentioned, the behavior of the multiobjective refrigeration simulation algorithm is consistent based on evolution-based observations (see Figure 2).

The multiobjective simulation annealing algorithm produces a solution to this problem. Therefore, this algorithm can provide a number of solutions (for example, how to deploy and the amount of products to transport) with a

Table 1: Samples.

No.	Manufacturers	Distribution centers	Retailers	Recycling center
1	2	2	3	2
2	3	4	3	3
3	4	5	4	4
4	7	7	6	4
5	9	8	7	5
6	11	12	10	8

Table 2: Comparison of algorithms.

No	MOSA			NSGA-II			Error (%)	
	f_1	f_2	Time (s)	f_1	f_2	Time (s)	f_1	$\mathbf{f}_2$
1	509	289.4	1	509	289.4	1	0	0
2	541	300.2	37	542	300.2	5	0.001	0
3	649	302.1	49	650	303.3	6	0.001	0.003
4	691	320.3	99	693	321.9	14	0.008	0.005
5	1454	629	1021	1457	631.6	27	0.002	0.004
6	1568	737.5	3975	1572	740.4	37	0.002	0.003
AVE	902	429.75	863.66	903.83	431.133	15	0.002	0.002

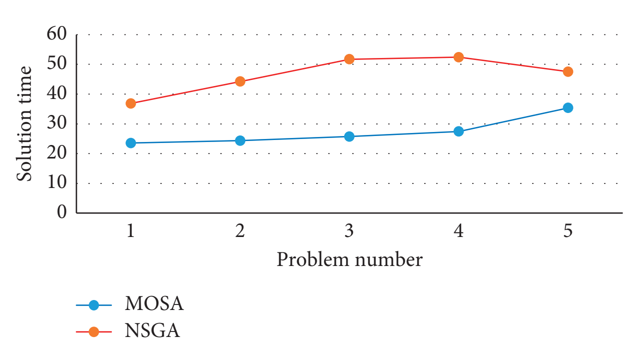

Figure 3: Comparison of computation time in proposed algorithms.

Table 3: The generated problems.

	No	Manufacturer	Distribution center	Retailer	Recycling center	Level 1 vehicle	Level 2 vehicle
Small	S1	14	11	13	6	12	15
	S2	19	22	21	9	19	18
	S3	17	32	34	16	33	39
	S4	10	21	23	11	23	27
	S5	13	24	23	14	29	27
	S6	19	25	29	16	33	31
Medium	M7	23	30	32	14	29	30
	M8	31	25	24	12	26	27
	M9	26	10OSA algorithm	9	4	9	7
	M10	30	17	20	12	28	19
	M11	23	28	29	14	30	30
	M12	32	35	37	19	40	37
Large	L13	18	41	46	22	45	52
	L14	41	44	45	23	48	47
	L15	28	30	36	20	41	38
	L16	31	28	27	13	27	27
	L17	44	39	37	17	36	37
	L18	35	35	35	16	34	39

balance between different objectives [16, 17]. We run this algorithm in such a way that we give the answer generated by the genetic algorithm as the initial answer to this algorithm.

When we use the answer generated by the genetic algorithm as the initial answer of the MOSA algorithm, we consider the value of α to be close to zero, i.e., (0.1). This is because the solutions generated by the genetic algorithm are in fact optimal values, so in the MOSA algorithm we consider the value of α to be low so that the function is in the local optimization instead of looking for the optimal solution again in the same range of the answer. The optimization generated by the genetic algorithm seeks the most optimal solution in the shortest possible time $\alpha = 0.1$.

Also, considering that the values of the new solutions produced by the chromosome are close to the previous solutions, we consider the value of T0 to be about 0.8 so that the generated solutions are not too far from the optimal one. We consider the stop condition as the number of iterations with the number: MaxIt: 20 and MaxSubIt: 50.

3.3. Epsilon Constraint Method. The epsilon constraint method is one of the most accurate methods for solving multiobjective programming, which overcomes some of the convexity problems of the total weight method, which is the most basic method for solving such problems. This method involves optimizing one main objective function (f_p) and expressing other objectives in the form of unequal constraints.

The basic form of epsilon constraint is as follows:

$$\begin{aligned} &\min_{x \in \Omega} F_p(x), \\ &\text{subject to } F_i(x) \le \varepsilon_i \quad i = 1, \ldots, m \, i \ne p. \end{aligned} \tag{27}$$

The steps of the Epsilon constraint method are as follows:

(1) One of the objective functions should be selected as the main objective function.

(2) The problems should be solved each time by considering one of the objective functions, and find the optimal values of each objective function.

(3) The interval should be divided between the two optimal values of the auxiliary objective functions into a predetermined number, and find a table of values for $\varepsilon 2 \ldots, \varepsilon n$.

(4) Each time, the problem with the main objective function with each of the values $\varepsilon 2, \ldots, \varepsilon n$ should be solved.

(5) The discovered Pareto solutions should be reported.

(6) By applying changes on the right-side values of the constraints (εi), efficient solutions to the problem should be found.

4. Computational Results

In this section, first the computational results for small size problems that can be solved with the GAMS software are given and the exact results are compared with the results obtained from the proposed algorithms. Then, in order to test the efficiency of the proposed algorithm, we examine the randomly generated problems and observe the results.

Here, we solve six problems of small size by the proposed algorithms and compare the obtained solutions with the exact answer to evaluate the performance of the proposed algorithms in finding the near-optimal solution. The structure of the sample problems is shown in Table 1.

The results of the calculations are summarized in Table 2 and Figure 3 According to the results obtained, only in problems 1 to 5 where the exact solution is available, the answer obtained by the algorithm deviates from the exact answer by 1–6 units, and problems with larger dimensions such as problem number 6 due to increasing number of

Table 4: Computational results of proposed algorithms to solve randomly generated problems.

No	NSGA-II				MOSA				Solution time	
	First obj ($)	Second obj	MID	SM	First obj ($)	Second obj	MID	SM	NSGA-II	Sa
S1	137	382	4.45	0.08	136	378	4.44	0.08	62.74	65.51
S2	240	516	4.48	0.08	240	521	4.46	0.08	100.59	108.94
S3	395	663	4.56	0.09	401	663	4.54	0.09	119.51	129.66
S4	264	474	4.65	0.11	260	475	4.65	0.10	77.03	92.14
S5	257	495	4.68	0.13	255	486	4.65	0.12	91.12	105.03
S6	335	591	4.73	0.13	331	589	4.71	0.13	107.69	111.84
M7	376	549	4.98	0.19	378	545	4.95	0.17	129.07	132.04
M8	290	463	5.01	0.19	283	465	5.00	0.18	136.16	139.25
M9	102	436	5.05	0.23	99	437	5.05	0.22	89.77	97.78
M10	197	482	5.09	0.25	197	487	5.06	0.24	114.77	114.09
M11	360	641	5.14	0.26	362	642	5.13	0.25	124.24	130.73
M12	414	720	5.19	0.29	418	718	5.15	0.27	162.17	167.70
L13	433	652	5.77	0.33	441	641	5.74	0.31	143.25	134.05
L14	431	704	5.78	0.36	427	700	5.73	0.34	204.75	204.86
L15	380	701	5.85	0.41	378	700	5.82	0.40	140.90	146.70
L16	296	549	5.88	0.41	296	548	5.85	0.40	144.26	143.09
L17	431	703	5.89	0.43	423	705	5.84	0.42	200.02	195.55
L18	360	528	5.94	0.44	364	531	5.90	0.43	169.34	174.92
AVE	316.55	569.38	5.17	0.24	316.05	568.38	5.95	0.23	128.74	132.99

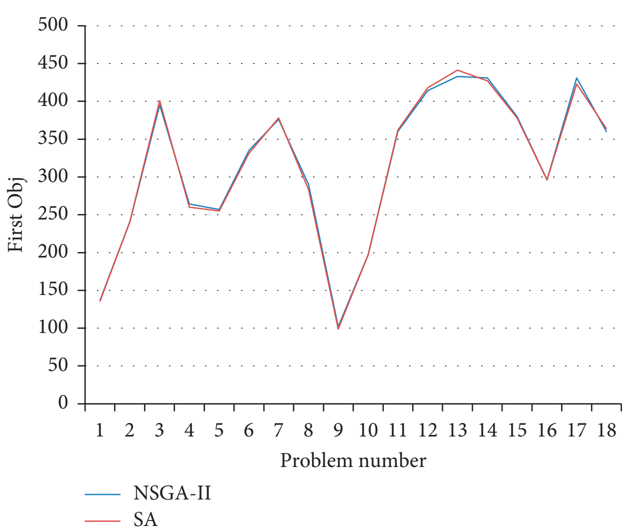

Figure 4: Comparison of the first objective based on problem number.

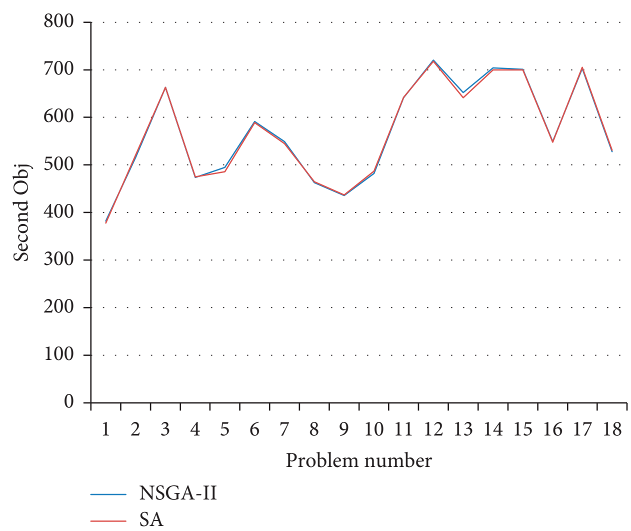

Figure 5: Comparison of the second objective based on problem number.

constraints and long solution time cannot be solved by the GAMS software. As can be seen, the optimal distance deviates by a maximum of 1.35% from the exact solution, which is an acceptable value and indicates that the answers of the algorithm are close to the exact answer. We consider the maximum allowable deviation to be 2%, with which a confidence level of 98% can be claimed that the answers are close to the exact answer, and as can be seen in the solved problems, the optimal distance is below 2%.

4.1. Test the Performance of the Proposed Algorithms. After designing an algorithm, it is time to test its efficiency in the field. In order to test the performance of the proposed algorithms using the function written in MATLAB software, problems in different sizes for production, distribution, retail, and recycling centers as well as level 1 and 2 equipment with random sizes have been determined. We produce between 10 centers and 50 centers. Capacities are also randomly assigned between 20 and 80 units. To test the proposed algorithms, 18 sample problems are randomly generated. The structure of the sample problems is given in Table 3. The calculation results are summarized in Table 4 and shown in Figures 4–6. As can be seen, the proposed algorithm has obtained acceptable answers in all cases. For example, the value of objective function 1 in the NSGA-II and MOSA methods is 137 and 136, the value of the second objective function in the NSGA-II and MOSA methods is 382 and 378, and the solution time is 62.74 and 65.51, respectively. Also, the mean ideal distance

Figure 6: Comparison of solution time based on problem number.

(MID) and spacing metric (SM) show the superiority of the MOSA algorithm (see Table 4).

5. Conclusions

In this study, the main purpose of the model development and optimization of the green supply chain network was to consider the location of multilevel multivehicle routing. Therefore, we set the subobjectives of the research to develop a green closed-loop supply chain model by adding collection, recycling, and disposal centers, and optimizing the routing location problem using new hybrid heuristic algorithms. In order to model the problem, we defined two objective functions, the first objective function minimizing the cost, and the second objective function minimizing greenhouse gas emissions. In the first objective function, we calculated the fixed costs of production centers, distributors and retailers, fixed costs of equipment, and variable production costs in production centers, and warehouse costs, recycling costs, and transportation costs on all routes. In the second objective function, we calculated the amount of greenhouse gas emissions for the construction and operation of the centers and the amount of gas emissions in transportation along the routes and greenhouse gases resulting from production and storage in production and distribution centers. Among the applications of this research, we can mention distribution and location in the automotive industry, home appliances, etc. Also, organizations such as municipalities and environmental organizations are among the beneficiaries of this research.

The proposed algorithms for solving this model are the NSGA-II and multiobjective simulation annealing. Initially, 6 small problems were solved by the GAMS software and the exact answer was obtained. According to the results obtained, only in problems 1 to 5 where the exact solution is available, the obtained answer of the algorithm deviates from the exact answer by 1 to 6 units. Also, problems with larger dimensions such as problem number 6 could not be solved by the GAMS software. As it was observed, the optimal distance deviated by a maximum of 1.35% from the exact answer, which is an acceptable value and shows that the answers of the algorithm are close to the exact answer. We considered the maximum allowable deviation to be 2%, with which a confidence level of 98% can be claimed that the answers are close to the exact answer, and as it was observed in the solved problems, the optimal distance was below 2%. Then, we tested the efficiency of the proposed algorithms. To investigate the proposed NSGA-II algorithm, 18 sample problems were generated with a random answer generation algorithm. As observed, the proposed algorithms have obtained acceptable answers in all cases. The main bounds and limitations of the presented algorithm are summarized as follows: the presented metaheuristic algorithm is not able to calculate the global optimum and calculate the local optimum. The presented metaheuristic algorithm also requires access to a computer system equipped with features such as high RAM and CPU.

In this research, a green closed-loop supply chain model for location-routing problems was presented; hence, the following suggestions for future studies are as follows:

(i) The proposed model is developed in conditions of uncertainty of a number of parameters.

(ii) Using other metaheuristic algorithms such as ant colony and neural network, the proposed model is solved and its results are compared with the results of this research.

(iii) Other decisions such as scheduling in the presented network are considered.

Data Availability

The data are in the article file.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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Review Article

Application of Data Mining Methods in Grouping Agricultural Product Customers

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The sheer complexity of the factors influencing decision-making has required organizations to use a tool to understand the relationships between data and make various appropriate decisions based on the information obtained. On the other hand, agricultural products need proper planning and decision-making, like any country's economic pillars. This is while the segmentation of customers and the analysis of their behavior in the manufacturing and distribution industries are of particular importance due to the targeted marketing activities and effective communication with customers. Customer segmentation is done using data mining techniques based on the variables of purchase volume, repeat purchase, and purchase value. This article deals with the grouping of agricultural product customers. Based on this, the K-means clustering method is used based on the Davies–Bouldin index. The results show that grouping customers into three clusters can increase their purchase value and customer lifespan.

1. Introduction

Nowadays, an essential part of doing business is identifying the variety of customers that purchase the offered products/services and establishing a relationship with them such that they remain a source of revenue for the business in the future. Indeed, retaining valuable old customers is as important as attracting new customers [1–3]. One way to gain a deeper understanding of customers is to segment them into several groups and examine the characteristics of each group. In fiercely competitive markets where customers have many options to choose from, analyzing customer behavior and selecting the appropriate marketing method may determine whether a company can survive the competition [4].

A true understanding of customer behaviors is one of the most important aspects of customer relationship management (CRM) [5]. With the rapidly increasing use of information technology in many fields of business, which has resulted in the collection of large volumes of customer data, businesses now need more sophisticated data analyses to gain accurate knowledge and a deep understanding of customer behaviors and purchase patterns in order to adopt marketing strategies and respond to customer needs [6, 7]. As a result, the need for customer data mining and analysis tools as a prerequisite for adopting appropriate marketing and CRM approaches to satisfy and retain customers is felt more than ever. One of such data mining techniques is customer segmentation, which involves dividing heterogeneous customers into homogeneous groups with similar purchasing behaviors and patterns in order to make it easier to understand how they behave and develop the appropriate marketing and CRM strategy accordingly [8]. The success or failure in this effort can play a major role in the survival of a business [9]. In today's highly complex and competitive business environment, which demands constant business growth, customer segmentation can help improve long-term customer loyalty and customer relationships, ultimately affecting businesses' profitability [10]. Data mining can help a company identify and track customer behaviors and behavioral patterns over the course of their interaction with the company, which will ultimately lead to better customer service, higher sales, more effective distribution, and marketing strategies [11]. In this regard, it is necessary to use novel artificial intelligence to help the decision-makers in the agriculture industry [12–15].

Previous studies show that in order to determine appropriate strategies in the production and sale of agricultural products, it is necessary to perform appropriate grouping for them and their customers. This issue has many challenges. First, much information is generated in this field and which data are used has a significant impact on the research method. Second, customer lifespan has a significant impact on determining strategies. These challenges have not been seriously addressed in previous research. In this regard, the main question of this research is how to provide a framework for customer grouping by considering the lifespan and using big data analysis.

Accordingly, the machine learning approach is used to group agricultural customers in this research. Moreover, a fuzzy formulation for calculating customer lifespan is provided. In summary, the main contribution of this research and its innovation can be stated in presenting a method based on big data analysis in order to group customers by considering the impact of customer lifespan and finally presenting appropriate strategies for each group. Moreover, in this article, business-to-business (B2B) customers of a business are examined and segmented using the RFM (recency, frequency, and monetary) value model.

The rest of the article is organized as follows. The theoretical foundation of the research area and literature review are explained in Section 2. The problem statement is provided in Section 3. In Section 4, the numerical results are presented; in Section 5, the discussion is provided; and finally, in Section 6, the article is concluded.

2. Theoretical Background

CRM begins with customer identification, which involves identifying and targeting the groups of people who may be profitable for the business. In this regard, it is important to analyze the behavior of past and present customers in order to understand their common characteristics Goli et al. [16, 17]. Businesses often analyze the data they collect from their customers and sales records through the customer segmentation process, which involves dividing customers into multiple groups and categories with similar needs, characteristics, and functional variables in order to develop appropriate customer retention and customer acquisition strategies for each group in the next stages of CRM. Customer segmentation is one of the most effective tools for customer-centric marketing (Butel). Segmentation is a data mining technique that attempts to find how data items should be clustered in order to have the greatest similarity within each cluster and the greatest differentiation between clusters [18].

The customer segmentation process has three main components: segmentation variables, method, and validation. The relationship between product decision-making information systems and big data-driven is inspired by [19–22]. Moreover, the following items are a brief description of each component and how they are chosen or performed in this study.

2.1. Segmentation Variables. Customer segmentation should be done based on variables that are measurable for every customer, such as purchase time, customer type, purchase frequency, and purchase value. In the RFM model, customers are segmented based on three variables: 1—recency (R), which indicates the time elapsed since the customer's last purchase; 2—frequency (F), which indicates the number of times the customer has made a purchase over a certain period, and 3—monetary value (M), which indicates the amount of money the customer has paid the business. The FRM model can be used to segment customers for the purpose of determining preferable marketing policies. The results of this model are also a common input for the development of marketing strategies. This model is also commonly used in customer lifetime value (CLV) calculations.

2.2. Segmentation Method. RFM is a descriptive model and cannot predict customer behavior. Thus, it initially segments customers in terms of each segmentation variable alone without considering the impacts of other variables. Clustering methods and algorithms can be divided into two categories: hierarchical methods and partitioning methods. Among clustering algorithms of the latter category, the k-means algorithm has received a lot of attention because of its sophistication, high speed, and accuracy. This algorithm tries to assign the data items to k clusters iteratively with the goal of minimizing the distance of each item from the center of the cluster to which it is assigned. The iterations of this algorithm continue until cluster centers remain the same over a number of successive iterations. This algorithm aims at achieving maximum similarity in the data items assigned to each cluster and maximum difference between the data items assigned to different clusters.

2.3. Segmentation Validation. One input of the clustering method is the number of clusters (k), which needs to be specified and will have a notable impact on the clustering performance. One way to determine the best number of clusters is to execute the algorithm with different numbers of clusters and compare the outcomes in terms of an indicator like the Davies–Bouldin index. This index calculates the average similarity of data in each cluster and can be used to assess the lack of similarity between clusters. Lower values for this index indicate higher clustering quality.

2.4. Literature Review. In a study by Anitha et al., these researchers used the RFM model and the k-means algorithm to analyze customer behavior. In this study, the optimal number of clusters was determined with the Silhouette method [23]. Wu et al. used the RFM model and the k-means clustering method to analyze the value of customers of industrial equipment manufacturing companies. After preparing the data, customers were clustered into six segments by k-means based on RFM indicators, and customer characteristics in the segments were studied through a CLV analysis. In the end, this article also offered some suggestions for using appropriate promotion programs for different segments of customers [24]. Monalisa et al. [25] used the RFM model with the fuzzy C-means algorithm to segment the customers of a company called LWC. These researchers also calculated the CLV of the obtained segment. A research paper by Miguies [26] stated that customer segmentation is a key step for developing and maintaining customer relationships, which tend to lead to increased sales. This article proposed a method of market segmentation for retailers based on customer lifespan as indicated by exchange volume and a method of customer segmentation based on purchase history.

Rabiei et al. [27] combined the RFM model with a classification method to develop a model for estimating CLV. For this purpose, these researchers constructed an RFM model and computed the CLV of customer clusters by incorporating the CLV calculations into the C5 algorithm. In a study by Mohammadi et al. [28], a combination of three methods, namely, RFM, FAHP, and k-means, was used for customer segmentation. In this study, FAHP was used to weight the segmentation variables, and the resulting variables were used to cluster the customers into five segments. In a study by Christy et al. [29], customer segmentation with the RFM model was performed by using both k-means and fuzzy C-means algorithms for clustering. Taghi Livari and Zarrin Ghalam [30] segmented the customers of an insurance company with the RFM model using self-made SOM and k-means algorithms. Nguyen et al. [31] reviewed the previous studies on the relationship between customer behavior and order fulfillment in the context of marketing in online retail companies and introduced various marketing tools for improving the level of service offered to customers. In a study by Arunachalam and Kumar [32], customer segmentation was conducted with fuzzy methods and SOM. Shokouhyar et al. [33] segmented the customers of the after-sales services of an automobile manufacturer using the RFM model. These researchers used KANO and SERVQUAL models as tools to measure customer satisfaction.

In one of the new and most related research items, Ernawati et al. [34] assessed the decision-making (DM) methods that collaborated with the RFM model and synthesized them to propose a customer segmentation framework. This study uses a comprehensive literature review published in 2015–2020. The most widely used methods are clustering and visualization from seven DM methods analyzed.

Purwanto et al. [35] proposed a clustering method for potential customer grouping in digital trade environments. They applied data mining that was collected from potential customers by online questionnaires. The authors do the data collection by distributing questionnaires online through Google form. Ciccullo et al. [36] assessed the agri-food supply chain as well as the role of food waste prevention technology in the food industry. This study reveals that adopting different technological options can represent the engine to establish vertical collaborations between the adopter of the technology and another stage in the agri-food supply chain to fight food waste. Donnet et al. [37] proposed a conceptual framework to find the effect of each critical risk index in the production and sale the agricultural products. Insights from this study can help farmers and agribusiness managers by defining and adapting their strategies within their local contexts.

Previous studies show that calculating the CLV is always fraught with complexity. Because when measuring the value of indicators, the value of its inputs must be known definitively. On the other hand, CLV depends on several factors, including customer preferences. Therefore, this study proposes using the fuzzy analytical hierarchy process method (FAHPM) approach to calculate the CLV.

3. Problem Statement

Many manufacturing and distribution companies have a large database of customer information and purchase history, including customer profile, purchase dates and frequency, and the amount of money exchanged. The owners of these large businesses are perfectly aware that they can use these data to achieve improvement in all aspects of CRM, including customer identification, acquisition, retention, and promotion. One of the most important processes of customer identification in businesses that deal with a large number of customers with massive amounts of data is customer segmentation. This process can help a business interact properly with its customers and ensure that provided products and services meet the standards demanded by customers to their satisfaction [38]. In this context, the primary measures of segmentation quality are the similarity of customers placed in the same segment and the dissimilarity of customers placed in different segments in terms of functional variables. One of the models that are commonly used in customer segmentation and analysis is the RFM model proposed by Hughes in 1994. In this model, the functional variables for the segmentation of customers are the recency of purchases (R), their frequency (F), and their monetary value (M) [39, 40]. This study used the RFM model to segment the customers through clustering with the k-means algorithm. The Davies–Bouldin index was used to evaluate the quality of clusters (segments), and in the end, the CLV of each cluster was also estimated.

4. Methodology

In this study, the RFM model and the k-means algorithm were used to segment 12 major B2B customer groups of a food company, each group representing similar consumer markets (e.g., hospitals, universities, municipalities). The data mining and analysis process for knowledge extraction was carried out using the standard CRISP-DM methodology. This methodology comprises a number of major steps, which include understanding the business environment, data selection, data preparation, modeling, model evaluation, and evaluation of the results (Figure 1). The steps of this method are described in Figure 1.

As mentioned earlier, the PVC model is applied to manage the CRIS-DM process. The proposed PVC model is inspired by [41–43].

Step 1: understanding the business environment

Considering the importance of customer identification and retention for all businesses, in this study, we tried to identify and group the customers of the studied business in order to improve its performance in this area. Customer segmentation into similar categories is one of the major topics of CRM, which is based on the idea that not all customers should be viewed and treated the same way. In this context, the definition of a customer may differ depending on the situation. In business-to-business (B2B) enterprises, most or all customers are either a business or an organization (Butel). Given the importance of B2B customers for the studied business, this study was focused on this type of customer.

Step 2: dataset selection

In this step, the data required for conducting the research as described in the previous step were collected. The required dataset is collected in the Cambodia agriculture affair institute. The list of products with the most important customers is gathered and put in the dataset. For each customer, the purchase recently and purchase frequently is considered.

The following customer data needs to be collected to build the RFM model.

Purchase recency indicates the number of days passes since the customer's last purchase. Lower recency is more desirable.

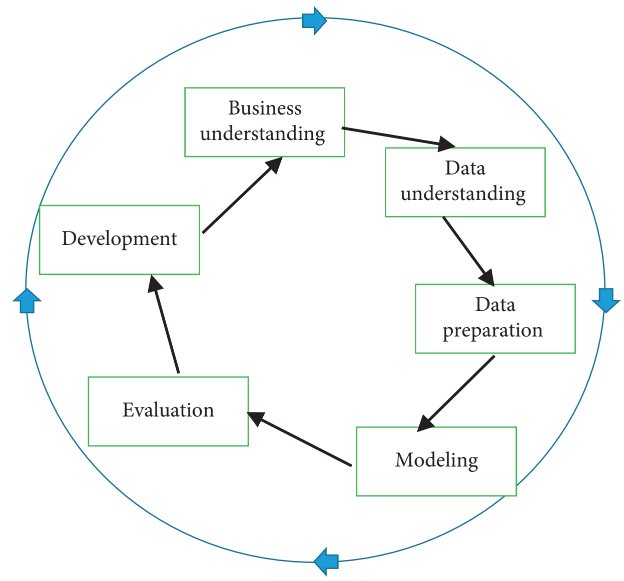

Figure 1: CRISP-DM process.

Purchase frequency: this indicates the number of times the customer had made a purchase. Higher purchase frequency rates are generally more desirable.

The monetary value of purchases: this indicates the total amount of money exchanged between the customer and the business. The higher values of this index are more desirable.

Step 3: data preparation

This step involves preparing and preprocessing data to facilitate the extraction of the knowledge it contains. For this purpose, incomplete, invalid, and inaccurate data must be discarded, and all of the remaining data must be converted into the format that suits the software (in this study, the software was RapidMiner).

Step 4: measurement of segmentation variables

As mentioned earlier, the common RFM model uses the three variables of recency, frequency, and monetary value to segment customers. In this study, these variables for each customer group were determined from the data collected over a one-year period. Table 1 shows the description and type of these variables.

Step 5: customer clustering with k-means

The results of a clustering algorithm for a dataset can strongly depend on the choice of algorithm parameters. The purpose of cluster validation is to determine how well clusters fit the data. The two basic criteria for evaluating clusters in this respect are compactness and separation.

Compactness
The data items assigned to the same cluster should be as similar to each other as possible. The most widely used criterion for measuring the compactness of clusters is variance.
Separation

Table 1: Type of RFM variables.

No.	Variable name	Description	Variable type	
1	ID	Customer code	Integer	Numeric
2	Monetary	Total monetary value of all purchases made by the customer	Numeric	Continuous numeric
3	Date	Purchase dates	Date	Date
4	Recency	Time passed since the last purchase	Date	Date
5	Frequency	Number of times the customer made a purchase	Integer	Numeric

The obtained clusters must be sufficiently separated (differentiable) from each other. There are three criteria for measuring the separation of clusters: the distance between the closest data in two clusters, the distance between the farthest data in two clusters, and the distance between the centers of two clusters.
In this study, the comparisons needed to determine the optimal number of clusters were performed based on the Davies–Bouldin index. Since these assessments showed that using three clusters results in the best (lowest) value for this index, it was decided to perform the customer segmentation with the parameter k in the k-means algorithm set to 3.

Step 6: determining the optimal number of clusters based on the Davies–Bouldin index

To determine the optimal number of clusters, the Davies–Bouldin index was calculated using the following formula:

$$DB = \frac{1}{n}\sum_{\substack{i-1 \\ i\neq j}}^{n} max\left\{\frac{S_n(Q_i) + S(Q_j)}{S(Q_i, Q_j)}\right\}, \quad (1)$$

where n is the number of clusters, S_n is the average distance of each record from the cluster center, and $S(Q_i, Q_j)$ is the distance between cluster centers. The best number of clusters is the one giving the lowest DB value.

The results of this step are presented in Table 2.

Since the lowest DB value was obtained with three clusters, it was determined that the optimal number of clusters according to this index is 3. Therefore, customers were clustered into three segments.

Step 7: comparison and evaluation of the results

The results of customer segmentation are shown in Table 3.

It can be seen, customers were classified into three clusters: customers in Cluster 0 are highly valuable for the business, customers in Cluster 1 are low-value, and customers in Cluster 2 have moderate value for the business. Table 4 shows the type of customers placed in each cluster.

Next, we labeled the clusters based on their value for the business. Customers with higher value creation were labeled golden, those with medium value were labeled silver, and those with lower value creation were labeled bronze customers (Table 5).

Table 2: Davis–Boldin index values calculated for different numbers of clusters.

Index	2	3	4	5	6
DB	0.621	0.495	0.586	0.595	0.501

Table 3: Customer segmentation results.

No of records	2	5	5
Cluster	Cluster 0	Cluster 1	Cluster 2
Monetary value	1889969500	328290299	887774385
Frequency	18	10	14
Regency	27	104	46

Table 4: Placement of customers in clusters.

cluster_2	Hospitals
cluster_2	Universities
cluster_1	Automobile manufacturers
cluster_1	Ministry of energy
cluster_2	Municipality

Step 8CLV calculations

n marketing, the CLV of a customer is the estimated profitability of future interactions with that customer. The higher the CLV of a customer is, the more valuable the customer is for the business. After clustering customers, the CLV of each customer was calculated by weighting the RFM variables (recency, frequency, and monetary value) as formulated in the following formula [25, 27]:

$$clv = w_m * nm + w_r * nr + w_f * nf, \quad (2)$$

where w_r, w_f, and w_m are the weights of recency, frequency, and monetary value, respectively. Based on an analysis of expert opinions with the help of ExpertChoice software, these weights were set to $w_m = 0.497$, $w_r = 0.225$, and $w_f = 0.278$. In (2), Nr, Nf, and Nm are the normalized values of model variables, which were obtained by fuzzy nondimensionalization as shown in Table 6. Having these values, CLV values of customers were determined as shown in Table 7.

Table 5: Cluster labeling.

Cluster	Label
Cluster 0	Gold customers
Cluster 1	Bronze customers
Cluster 2	Silver customers

Table 6: Normalization results.

Cluster	Normalized R	Normalized F	Normalized M
Cluster 0	0.95	0.91	0.91
Cluster 1	0.218	0.21	0.1
Cluster 2	0.64	0.55	0.515

Table 7: CLV calculations for clusters.

Label	w_m * nm	w_r* nr	w_f * nf	CLV	Rank
Gold	0.4522	0.2137	0.2529	0.919	1
Bronze	0.0497	0.0490	0.0583	0.1571	3
Silver	0.2559	0.144	0.1529	0.5528	2

$$N = \frac{x-\mu}{\sqrt{\sigma^2}}. \quad (3)$$

The higher the CLV value of a cluster is, the more valuable its customers are for the business. As expected, the CLV value of customers in the Golden Cluster was higher than that in other clusters.

5. Discussion

The numerical results showed that the customers with the highest value creation for the studied business are the Cambodian agriculture industry and "Prisons and Security and Corrective Measures Organization," which belonged to Cluster 0 (golden customers). These customers have an average CLV of 0.919 and constitute only 17% of all customers. To retain this group of customers and maintain their loyalty, it is recommended to adopt expansion strategies.

The businesses and organizations allocated to Cluster 1 or the low-value cluster (bronze customers) had an average CLV of 0.15, which indicates limited room for improvement in cooperation and limited potential for further profitable interactions. The recommended strategy for this group of customers is negative retention. The customers placed in Cluster 2 (silver customers) include hospitals, law enforcement, the Cambodian agriculture industry, and municipalities. The average CLV of these customers is 0.55, and they make up 41% of all customers of the studied business. With an appropriate strategy, the businesses and organizations placed in this cluster can potentially be added to the list of golden customers. Using the variety of strategies listed in Francis Butel's book "Customer Relationship Management" as the reference, in the following, we offer a number of marketing and customer loyalty strategies that can be expected to fit the studied company and its customers.

One viable strategy for customer retention is to create commitment. There are multiple verities of this strategy, each of which can be tailored to the characteristics of customers in each segment. In particular, this strategy can be utilized to retain the silver and gold customers of the studied business.

5.1. Instrumental Commitment. The loyalty of university customers can be increased through the instrumental commitment strategy. For example, this can be done by holding at the university campus a cooking competition with the company's products to create instrumental commitment among customers and encourage them to buy more of the products.

5.2. Relational Commitment. An improvement in work relationships can help improve customer loyalty and retention. This strategy can be applied to hospital customers. For example, the quality control agents of the production can visit these customers to ensure them of the quality and safety of offered products. Granting customers support cards can also help improve their relationship commitment.

5.3. Value-Based Commitment. Making the customers feel that the company's values are aligned with their own values will increase their loyalty. This strategy is more suitable for hospital customers that were placed in the silver cluster. This can be done by offering customers organic products that improve their health and accelerate their recovery.

Another group of viable strategies for customer retention is bonding strategies [Butel], which involves creating a variety of structural bonds to make it more difficult for the customer to cut its relationship with the business.

5.4. Financial Bonds. This strategy could be very effective on B2B customers because most public and private organizations have periodic purchase budgets, and this makes the strategy function as both a negative and positive customer retention strategy. For example, this strategy can be implemented by giving valuable customers a credit line for their purchases.

5.5. Process Bonds. This strategy can be applied to school vendor customers. For example, the sales share of these customers can be increased by offering single-person and student-specific products.

5.6. Multiproduct Bonds. When multiple products that a customer uses are produced by a single company, their bond becomes more challenging to break. Therefore, this strategy can be very effective for maintaining and improving the loyalty of "Cambodia universities" and "Prisons and Security and Corrective Measures Organization," as they are among the company's loyal customers with substantial orders.

5.7. Customer Termination Strategy. The business may need to break its relationship with those customers that are not profitable and cannot be made profitable by any strategy.

Table 8: Summary of adaptable strategies for each cluster of customers.

Description	Customer	Strategy type
Dispatching quality control agents to check the quality of products	Hospitals	Relational commitment
Offering organic products	Hospitals	Values-based commitment
Offering single-person and student-specific products	School vendors	Process bonds
Building stronger bonds by offering more products	Prisons	Multiproduct bonds
Offering credit arrangements	Loyal customers	Financial bonds
Holding conferences and competitions	Universities	Instrumental commitment
Setting a minimum purchase volume	Customers in cluster 2	Negative retention

Bronze customers are good candidates for this strategy. For these customers, it is best to adopt a negative customer retention strategy based on setting a minimum order size to see whether there will be an increase in their purchase volume. After identifying the customers that are loyal to the company through this process, customers that do not meet the minimum purchase criteria need to be terminated.

(i) Future studies are recommended to try using other models such as LRFM for customer segmentation

(ii) It is recommended to use association rules to discover the relationships between the products purchased by customers

(iii) It is recommended to implement customer loyalty-building strategies and assess the outcome by using customer satisfaction measurement tools like the Kano model and gathering feedback from customers

Table 8 provides a summary of the strategies that can be adopted for the customers in each cluster.

A deep comparison of the provided results with some important previous works like [33, 40] indicates that the implemented machine learning method to conduct the strategies for the customers in the agriculture industry can lead to an appropriate plan for this industry and enhance the profitability and efficiency.

6. Conclusions and Future Directions

The agricultural sector in developing countries, as well as industrial-based countries, is the main engine of economic growth and development. In order to overcome the crisis of underdevelopment, they should go to their agricultural sector, and while trying to expand agricultural production, they should think of combining this sector with advanced technologies in order to make their products efficient [44]. Due to its extensive connections with other economic sectors, it can provide market creation, currency generation, and industry growth [45]. Therefore, in order to overcome the economic crisis, all countries should consider the agricultural sector as one of the main pillars of economic development because of its important role in the food supply, social welfare, GDP, and ultimately economic growth.

On the other hand, considering that this sector includes a large number of people who are directly or indirectly involved in the various stages of production to supply agricultural products and work, it can be said that the development of agriculture and related industries can increase GDP, job creation, and currency exchange as well as the self-sufficiency of the country in importing agricultural products. Therefore, increasing attention to the agricultural industry should become one of the main goals of any country for economic and social development [46].

In developing countries, the agricultural sector is usually large and of special importance, because agriculture plays an important role in the economy of such countries and can be used in various ways such as labor supply and capital, supply of raw materials, and cheap food, creating a market for manufactured goods in the industrial sector, and foreign exchange to economic development [47].

Industrialization can have a positive effect on agricultural growth in various ways. During industrialization, incomes increase rapidly, which in turn increases the demand for agricultural products, especially food. Moreover, it will increase employment in rural areas [30].

Industrialization increases the volume of capital in the agricultural industry. This also helps to modernize agriculture and thus increase production. Regarding the relationship between the agricultural sector and services, it can be mentioned that the two subsectors of transportation and communications have a direct relationship with the agricultural industry; The relationship between the amount of transportation and total costs is increasing. The ability to maintain agricultural products in the face of technological changes in the world is rapidly moving towards the growth of trade and globalization.

One of the most important managerial applications of this research is the issue of improvement strategies in the agricultural industry. Implementing a machine learning approach was able to identify several effective strategies. This approach can be applied to other challenges of the agricultural industry as well. For example, this approach can be used to supply industrial equipment and agricultural growth and development to determine the best relevant strategies.

The most important limitation of this research is its high dependence on input data. Lack of all necessary data availability causes the lack of achieving the desired outputs. Moreover, in order to improve this research, it is suggested to focus on optimizing customer grouping and using the novel meta-heuristic algorithms like Gray Wolf Optimizer and Ant Lion Optimization algorithms.

Data Availability

No data were used to support this study.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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Research Article

Performance Measurment and Lead-Time Reduction in EPC Project-Based Organizations: A Mathematical Modeling Approach

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To characterize the process of lead-time reduction in EPC project-based organizations, including the engineering, procurement, and construction activities, various elements such as organizational issues, firm resources, used methods and techniques, and performance measuring tools are important. In this study, the four mentioned elements are evaluated through a survey in different EPC project-based organizations. The survey is sent to only experts and managers who are involved in EPC projects, and the obtained data is used to test the relationship between the mentioned variables and the lead time of developing new products. This evaluation is followed by a set of generalized lessons learned and courses of action to improve the development process. Additionally, the attributes of performance measurement in such projects are scrutinized. Therefore, to analyze the impacts of the mentioned variables and their variations on the performance measurement, a mathematical model based on the fuzzy approach is developed. The results show that all of the four considered variables are correlated to the lead time and affect the quality perceived by the main client and the cost of the project. Moreover, data obtained from the proposed mathematical formulations illustrated that the fuzzy modeling approach is an effective method to predict the performance measurement level when the levels of the input variables are given.

1. Introduction

In today's economic world, most organizations are looking to find the factors that create competitive advantages regarding the new product development (NPD) [1]. The development of new products helps organizations to maintain their competitive and monopoly position in the market. Introducing the development of new products' strategies, models, and processes plays a crucial role for all types of organizations and their long-term survival [2–4]. Competitive markets force small- and medium-sized enterprises (SMEs) to move and improve themselves from the designing process to the engineering one. Therefore, SMEs that can fulfill the customer needs regarding features and quality of products can successfully enter the global market. The phrase "Customer is the king" indicates how much customer needs are important and how much their needs change over the time. This shows that only companies that offer the right products, at the right time and with the right price, can expect success in the market. Naturally, any product that does not meet the needs of customers, or since it is expensive or is produced and delivered after the deadline and so forth, cannot be successful [5–7]. The only way to reduce production's lead time is to coordinate all stages of development. By analyzing the stages of the NPD process, the volume and content of product development activities may be controlled, considering the quantity and production objectives. Consequently, such considerations make significant differences between NPD activities on the scale of individual or mass production [8–10].

Competitions for faster launching new products in the market have forced companies to discover effective ways to minimize the lead time of new products. Several methods have already been suggested in the literature to decrease the lead time of NPDs [11–13]. One of the strategic approaches which are used to boost the variety of products and to speed up the NPD process is product modularity. This approach standardizes product components that can be shared and reused in a range of products and is launched frequently and easily by modifying and combining different qualified modules from the existing designs. Therefore, different teams can design and test modules and reduce the time of product design simultaneously. Despite convincing evidence of potential benefits in reducing NPD lead time, very few empirical studies confirm its effect on NPD performance. Studies show that there is a positive relationship between the modularity of products and their strategic flexibility [14–16]. Product modularity affects several dimensions of competitive performance, such as product costs, quality, flexibility, and manufacturing cycle time [17–21].

The motivation for rapid product development is different according to the aims of companies. It is important to identify why a company wants to accelerate the process, as the reason verifies which rules and tools should be used and how they should be implemented. This research focuses on the elements that may have the biggest effect in attaining speed and flexibility in NPD. Moreover, the four main perspectives, which we believe could lead to a reduction in NPD time, are discussed in detail. Given the framework defined above, there are two major objectives [22–24]. The first one is to characterize the process of reducing the lead time in NPD, and the second one is to identify and evaluate the issues that facilitate the process for performance measurement in EPC organizations [25].

The current study, by considering four main indicators in new product development, organizational issues, firm resources, used methods and techniques, and performance measuring tools and their main subfactors, aims to find the correlation among each of the factors and the time reduction. Moreover, a mathematical model based on fuzzy logic modeling is introduced to predict the performance measurement level, based on its subfactor impacts.

This study is continued by revising the related literature in the next chapter. Chapter 3 contains the research methodology including data collection and the proposed mathematical model. The results of both data analysis and fuzzy logic results are provided in Chapter 4. Chapter 5 contains the discussions, and, finally, the study is concluded in Chapter 6.

2. Literature Review

Success in launching a new product is an important issue for business owners and managers. Additionally, this issue has a special complexity, as determining the factors affecting the successful development of a new product in different studies has different results. One of the reasons is related to characteristics of the company such as technology, structure, and size [3, 26].

From a broader perspective, a new product development strategy is an important factor in a country's economic wealth. Unfortunately, the importance level of new product development is not commensurate with the level of success, while the risk of failure in the new product development strategy is very high [27, 28]. Although the failure rate of new product developments is known in various studies, scientists have warned that the percentage of failure of new products is still worrying. Therefore, researchers try to provide a prescriptive theory to guide the best practical context of a new product development strategy to achieve success. The successes are categorized as empirical and theoretical perspectives, which ultimately lead to the identification and study of various factors of success in the new product development strategy [29, 30]. Hence, the following concepts should be considered in new product development strategies.

2.1. Nonstop Need for New Products. Intense global competition, rapid shifting of customers' needs, and increasing the rate of their sophistication, besides the technological improvements, force firms to develop new products endlessly. The business press constantly addresses the failure of NPD processes within the firms in responding to market changes, while it seems that their new products have the potential to be successful [31]. So, what are the problems that look common in many well-established firms?

2.2. New Product Strategy. Product development faces big challenges and intense competition in today's fast environmental changes. In other words, attention has turned toward rapid NPD, in which cost and quality are among the main prerequisites. So far, taking all the arguments into account, there is no doubt that speed and flexibility in product developments are the main indicators that determine which companies could meet this sustainable competitive advantage [32].

2.3. Cycle Time Reduction. The lead-time reduction can be another goal, besides the profit and market share. However, the lead-time reduction cannot be attained without organizational change. According to Goldt [33], there are some managerial issues related to the lead-time reduction debate:

(1) Concentration on the process rather than personal level: This detachment of the personal level permits individuals to look for the root cause of the problems within the process.

(2) Evaluation of tasks based on the created value for external customers: this means that when the staff of a company is expected to meet the needs of internal customers, such as top managers, they tend to focus on partial optimization of a department instead of creating value for the whole system. This causes a general lack of quality, which contradicts the philosophy of reducing lead time.

(3) Integration and management of required information: a particular group keeps information within the organization and it causes a delay in the decision-making process. Organizations should provide an open integrated information flow while considering recently raised values of knowledge management and security issues. In other words, the required information should be received at the right time, in right place, and in the right format [34].

(4) To create a shared goal and a common sense within the different functional areas: according to the initial principles of concurrent engineering, individuals within a team view the same problem from different perspectives. Therefore, the trade-offs must be resolved based on the merits of the ideas, not the individuals. Consequently, few spaces within different functions remain unviewed by the personnel [35].

(5) Knowledge and nonmanufacturing resources should be added: to improve the process, besides design, tools, and techniques, the knowledge, information, and other nonmanufacturing resources should be considered, which need continuous attention and commitment of the individuals [36, 37].

(6) Cost of delay should be included in trade-off analysis: to have more sophisticated decision-making, the cost of delay should be considered as well. Every particular product has an ending point considering its market demand. The later introduction of products is, the less market share could be achieved by the firm and vice versa [38].

(7) Bottleneck management should be applied for NPD: Surplus capabilities and facilities in terms of human resources, engineering techniques, and so forth should be presented to avoid bottlenecks in NPDs. Especially in a learning organization, dependency on bottlenecks should be reduced in favor of process improvement and lead-time reduction. Moreover, such tools should provide a transparent image of the bottleneck, which provides better utilization of nonconstrained resources [39]. To have high efficiency in this field, it is required to make a balance between resource utilization and bottlenecks. Although various factors help to achieve this harmony, planning tools as well as MES is needed for achieving the goal.

(8) Sometimes a common misunderstanding according to the lead-time reduction is realized by concerns about working faster and harder in longer hours. Likewise, utilizing the latest technologies and automation systems is not the principal objective of lead-time reduction [40]. The lead-time reduction is a nonstop journey with the objective of continuous learning and commitment, dedicated to the improvement of the process and knowledge of the workers.

(9) A conflicting set of management demands on the NPD lead-time reduction should be met: time, cost, and quality are internally interconnected, and just optimizing all of them can create a market value. The NPD should fulfill three distinctive inputs: right quality product, right time, and acceptable cost [14, 41].

The lead-time reduction may be considered as an umbrella that is integrated with cost and quality. In other terms, the lead-time reduction acts as a cover, where cost and quality could be progressed underneath. Regarding the main indicators of time reduction in EPC organizations, after conducting interviews with some directing managers of the companies in this study, the four levels are investigated as organizational issues, process attributes for design methods and techniques, company resources issues, and performance measuring tools. Each of the mentioned levels is explained in the following.

2.3.1. Organizational Issues. According to the literature, many researchers have studied organizational issues in NPD and considered various attributes in this area [42–44]. Considering the studies in the literature and the interviews with the managers, thirteen attributes and their related measurements are considered in this study to deal with the organizational issues. These attributes are projectization, team empowerment, cross-functionality, rewards and incentives, top management support, hierarchical levels, individuals experience, rapid decision-making, team common sense, number of parallel projects, number of projects per person, project objectives definitions, and change flexibility.

2.3.2. Process Attributes for Design and Manufacturing Methods and Techniques. Similar to the organizational issues, there are various studies related to the process attributes for design and manufacturing methods and techniques in NPD [45–47]. Based on the literature and interviews with the managers, the following attributes and their measurements are considered for this purpose:

(i) CAD/CAM: Computer-aided design (CAD), computer-aided manufacturing (CAM), and computer-aided engineering (CAE).

(ii) DFM/DFA: reducing time for entering market while maintaining product quality and functionality results in the introduction of design for manufacturing (DFM), which is the concurrent development of process and product design. Design for assembly (DFA) also plays a major role in the design for manufacturing and assembly (DFMA). It is said that DFM and DFA are two sides of the same coin in practice.

(iii) Robust design: according to Thornton et al. [48], robust design is a set of engineering design methods used to create robust products and processes. Likewise, a robust design (or process) performs properly in the presence of noise effects. Noises are due to many kinds of uncontrolled variables that can influence final performance such as temperature and humidity.

(iv) QFD: Quality Function Deployment (QFD) is a procedure-based approach for identifying and formulating the customer needs and converting them into exact criteria and plans to meet the needs. This is called the customer input or the voice of the customer, which is attempted to be captured in various ways such as deep interviews, focus groups, participant observation, field reports, and questionnaires.

2.3.3. Company Resources Issues. For examining the company recourses issues, various elements such as key suppliers, reliance on suppliers, access to reliable suppliers, integration among suppliers, outsourcing, and lead user involvement should be considered.

2.3.4. Performance Measuring Tools. Regarding the performance measuring tools in the NPD, six attributes and their measurements are considered, based on the outcomes of the interviews. These attributes are PERT/CPM, rework, credible schedule, time as a measurement tool, visibility of delay factors, and communication; the latter is related to the management information system (MIS). Note that the critical path method (CPM) and program evaluation and review techniques (PERT) are the two powerful tools that help to schedule and manage complex projects.

3. Research Methodology

To find the starting and ending points of the development time and the characteristics of the activities in this research, some Iranian EPC organizations that are involved in national strategic projects are requested to participate. As it has been clarified that the influencing variables, stages, and factors are interconnected to form a development process, considering the four main mentioned perspectives and their related elements, a survey in the form of a questionnaire is designed. The considered respondents must have degrees/diplomas in engineering, management, or business field and be aged from 30 to 55 years, with at least 5 years of work experience in the EPC organizations. The managers are asked if their organizations evaluate their organizational performance, new product design, development strategies, supplier assessment practices, methods and techniques used in NPD, and performance monitoring and measurement tools. They are asked to reply to the questions using a 6-point Likert scale, where the importance of the various attributes is 1 for extremely low up to 6 for extremely high. A couple of experts and managers are considered for a pretest of the survey to examine the validity of the questionnaire. Then, in case of any clarification, the questions are reworded to improve validity and precision. For those who are enlightened and familiar with the survey structure, just the questionnaire is sent. It is assumed that the repliers are familiar with their organizations' new product design and development practices. An incentive for sending the survey results is provided to encourage them to participate in filling out the surveys precisely. Managers are also asked about the company's abilities related to competitors to minimize the time of the NPD.

3.1. Data Collection. Among the 14 considered companies, 10 could be able to answer the questions free of inaccuracy. An average of four EPC projects per company, during the past three years, have been considered to comply with the survey's objectives, which includes a total number of 40 projects. The mean number of employees in these companies was 46, including both part-time and full-time staff. The development programs during the past three years have been carried out within the companies. For each attribute that is mentioned in Tables 1, 2, 3, and 4, an appropriate measure is defined to study the level of importance of the attributes in the company and subsequently their effects on the lead time of the development programs. Table 1 shows the attributes and measurements of the organizational issues. Followingly, Tables 2 to 4 contain the attributes and measurements of the process, techniques, and methods, company resources issues, and performance measuring tools, respectively.

3.2. Fuzzy Modeling. In this study, to model the performance measuring (PM), a fuzzy logic model is proposed considering the parameters, that is, PERT/CPM (PE), rework (RE), credible schedule (CS), time as a measuring tool (TM), delay factors visibility (DV), doing things right first (DR), and management information (MI) system. Fuzzy logic which was proposed by Zadeh is used to model uncertain or linguistic variables [49]. Figure 1 shows the developed fuzzy model.

To show a degree for the variables, fuzzy membership functions are used. One of the most important fuzzy membership functions is the triangular, which in this study is used to model the performance measuring parameter. Equation (1) shows the general format of the triangular fuzzy membership function, where l, m, and u denote the lowest, the most promising, and largest possible values, respectively.

$$\mu_A(x) = \begin{cases} \dfrac{(x-l)}{(m-l)}, & l \leq x < m, \\ \dfrac{(u-x)}{(u-m)}, & m < x \leq u, \\ 0, & \text{otherwise}. \end{cases} \tag{1}$$

Table 1: Organizational issues.

Attribute	Measure (importance of the attribute based on a 6-point Likert scale)
Projectization	1 = pure functional, 6 = pure projectization
Team empowerment	1 = extremely low, 6 = extremely high
Cross-functionality	1 = extremely low, 6 = extremely high
Rewards and incentives	1 = extremely low, 6 = extremely high
Top management support	1 = extremely low, 6 = extremely high
Hierarchical level	1 = extremely high hierarchical, 6 = low hierarchical
Individuals experience	1 = extremely low, 6 = extremely high
Rapid decision-making	1 = extremely low, 6 = extremely high
Team common sense	1 = extremely low, 6 = extremely high
Number of parallel projects	1 = too many projects, 6 = just one project
Number of projects per person	1 = too many projects, 6 = just one project
Project objectives definition	1 = extremely low, 6 = extremely high
Change flexibility	1 = extremely low, 6 = extremely high

Table 2: Process attributes, techniques, and methods.

Attribute	Measure (importance of the attribute based on a 6-point Likert scale)
Simplicity and number of documents	1 = extremely low, 6 = extremely high
Standardization	1 = extremely low, 6 = extremely high
Project complexity	1 = extremely low, 6 = extremely high
Project newness	1 = extremely low, 6 = extremely high
Concurrent development	1 = extremely low, 6 = extremely high
Easy testability	1 = extremely low, 6 = extremely high
CAD/CAM	1 = extremely low, 6 = extremely high
DFM/DFA	1 = extremely low, 6 = extremely high
Robust design	1 = extremely low, 6 = extremely high
QFD	1 = extremely low, 6 = extremely high

Table 3: Company resources issues.

Attribute	Measure (importance of the attribute based on a 6-point Likert scale)
Number of key suppliers	1 = too many, 6 = low number
Reliance on suppliers	1 = extremely low, 6 = extremely high
Access to reliable suppliers	1 = extremely low, 6 = extremely high
Integration among suppliers	1 = extremely low, 6 = extremely high
Outsourcing	1 = extremely low, 6 = extremely high
Lead user involvement	1 = extremely low, 6 = extremely high

Table 4: Performance measuring tools.

Attribute	Measure (importance of the attribute based on a 6-point Likert scale)
PERT/CPM	1 = extremely low, 6 = extremely high
Rework	1 = extremely low, 6 = extremely high
Credible schedule	1 = extremely low, 6 = extremely high
Time as a measurement tool	1 = extremely low, 6 = extremely high
Visibility of delay factors	1 = extremely low, 6 = extremely high
Communication (MIS)	1 = extremely low, 6 = extremely high

A six-degree function is considered for all the mentioned inputs and the output as shown in Table 5.

For providing the fuzzy model, a fuzzy inference system is used, which is capable of inferring the performance of complex systems from data, without the need for any preceding description of a functional structure. Equation (2) contains the membership functions of all the inputs and the output variables.

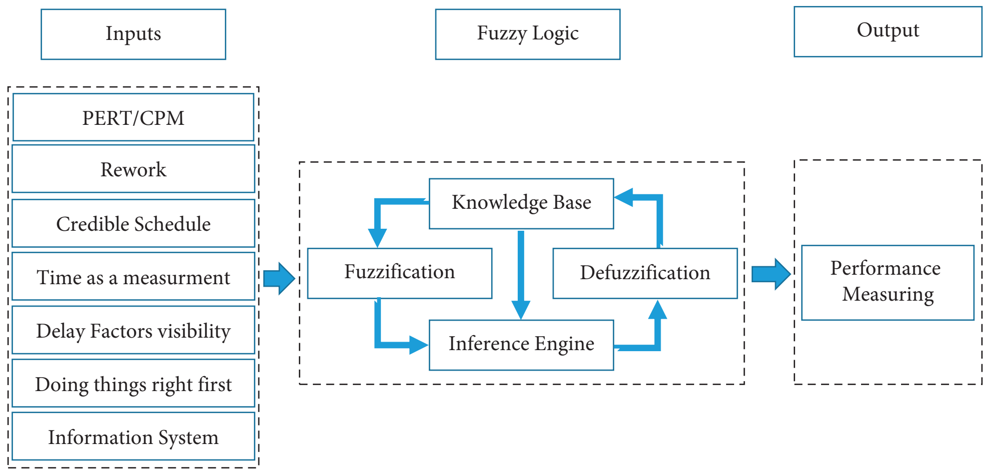

FIGURE 1: Input and output variables of the fuzzy model.

$$\mu_{EL}(x) = \begin{cases} 1, & x \le 1 \\ \dfrac{(2-x)}{(2-1)}, & 1 < x \le 2, \\ 0, & \text{otherwise} \end{cases}$$

$$\mu_{VL}(x) = \begin{cases} \dfrac{(2-x)}{(2-1)}, & 1 < x \le 2 \\ \dfrac{(3-x)}{(3-2)}, & 2 < x \le 3 \\ 0, & \text{otherwise} \end{cases},$$

$$\mu_{SL}(x) = \begin{cases} \dfrac{(3-x)}{(3-2)}, & 2 < x \le 3 \\ \dfrac{(4-x)}{(4-3)}, & 3 < x \le 4 \\ 0, & \text{otherwise} \end{cases}, \quad (2)$$

$$\mu_{VH}(x) = \begin{cases} \dfrac{(5-x)}{(5-4)}, & 4 < x \le 5 \\ \dfrac{(6-x)}{(6-5)}, & 5 < x \le 6 \\ 0, & \text{otherwise} \end{cases},$$

$$\mu_{EH}(x) = \begin{cases} \dfrac{(6-x)}{(6-5)}, & 5 < x \le 6 \\ 1, & x \ge 6. \\ 0, & \text{otherwise} \end{cases}$$

The variations of the inputs and the output parameters and the linguistic values of the experimental design matrix are listed in Tables 6 and 7, respectively.

The considered If-Then rules based on the outcomes from the companies are shown in Table 8.

4. Results

4.1. Data Analysis. After collecting the data from the 10 companies that answered the questionnaires without any error, appropriate analysis was performed on the obtained data. Figure 2 shows the correlation between the time and lead user content among the 10 considered firms. Moreover, the regression analysis is illustrated in this figure.

As shown in Figure 2, the more companies tend to develop products on time, the more lead user's content is achieved. Figure 3 illustrates the correlation between the time and cost among the 10 firms. Additionally, the regression analysis is visible in this figure.

As illustrated in Figure 3, the more companies tend to develop the products on time, the more projects will be on a budget. On the other hand, it should be mentioned that emphasizing on only being on a budget could not lead the companies to be on time as well. Figure 4 depicts the correlation and the regression analysis between the time and organizational issues among the companies.

From Figure 4, it is concluded that organizational issues have their effects on shortening development lead time. In other words, the more companies involve elements of the organizational issue in development programs effectively, the more projects tend to be finished sooner or on time. Figure 5 contains the correlation and the regression analysis between the time and progress measure among the companies.

As shown in Figure 5, the progress measuring tools have a direct effect on shortening development lead time. In other words, the more companies make use of measuring tools effectively, the more projects could be developed on time. The correlation and the regression analysis between the time and supplier assessment among the companies are shown in Figure 6.

Table 5: Likert scales of the answers to the questionnaires.

Extremely low	Very low	Somewhat low	Somewhat high	Very high	Extremely high
EL	VL	SL	SH	VH	EH
1	2	3	4	5	6

Table 6: The input and output parameter levels and their values.

Company no.	Inputs							Output
	PE	RE	CS	TM	DV	DR	MI	PM
1	4	3	4	4	4	5	4	4
2	3	2	3	3	2	3	4	3
3	2	3	2	2	1	1	2	2
4	4	3	2	3	3	5	4	3
5	2	3	2	4	2	3	2	3
6	3	2	4	3	2	1	2	2
7	4	5	4	4	4	3	5	4
8	2	2	1	3	1	1	1	1
9	3	2	1	2	2	1	1	2
10	5	6	4	5	4	5	3	5

Table 7: Experimental design matrix.

Company no.	Inputs							Output
	PE	RE	CS	TM	DV	DR	MI	PM
1	SH	SL	SH	SH	SH	VH	SH	**SH**
2	SL	VL	SL	SL	VL	SL	SH	**SL**
3	VL	SL	VL	VL	EL	EL	VL	**VL**
4	SH	SL	VL	SL	SL	VH	SH	**SL**
5	VL	SL	VL	SH	VL	SL	VL	**SL**
6	SL	VL	SH	SL	VL	EL	VL	**VL**
7	SH	VH	SH	SH	SH	SL	VH	**SH**
8	VL	VL	EL	SL	EL	EL	EL	**EL**
9	SL	VL	EL	VL	VL	EL	EL	**VL**
10	VH	EH	SH	VH	SH	VH	SL	**VH**

From Figure 6, it is concluded that the supplier assessment affects the lead time of the development programs. In other terms, the more companies emphasize suppliers' evaluation, the more projects could have the chance to be finished on time. Similarly, Figure 7 illustrates the correlation and the regression analysis between the time and used techniques.

As may be concluded from Figure 7, the used techniques on the development programs have a direct effect on shortening the lead time of the projects. In other words, the more companies exploit the tools and rules that match their system, the more they can achieve lead-time reduction in their projects.

4.2. Fuzzy Logic Results. The model whose rules are mentioned in Table 8 was solved by MATLAB application according to Figure 8.

Equation (3) is used for defuzzification of the fuzzy number obtained by the proposed model. In this equation, the output, x^* is a fixed and real number, x_i gives the central value of every zone, $\mu(x_i)$ is the ith level, and n is the number of rules [50].

$$x^* = \frac{\sum_{i=1}^{n} x_i \cdot \mu(x_i)}{\sum_{i=1}^{n} \mu(x_i)}. \quad (3)$$

The experimental results and the predicted values obtained by the fuzzy model are reported in Table 9.

In Table 9, it is seen that all the fuzzy predicted values are exactly equal to the obtained data except for company 8 which is found as 1.32 instead of 1. The results show that fuzzy modeling is an appropriate method to anticipate the data that are not given previously. Figures 9(a) to 9(h) illustrate the effects of every two mentioned variables on the output which is performance measuring.

Figure 9(a) shows the impact of PERT/CPM (PE) and doing things right first (DR) variables on the performance measuring (PM). It is seen that when the PE variable gets the values in the range of 3 to 5 and DR gets its high values in the range of 4 to 6, the output variable get the value of 4, and for other values of these mentioned inputs, the output gets 3.5, which is an average grade. Figure 9(b) illustrates the impact of delay factors visibility (DV) and rework (RE) variables on the performance measuring. The figure shows that when both mentioned inputs are in their lower values, the output variable gets the value of 3 which is less than the average. For the other values of the mentioned inputs, the output value is an average of 3.5.

Figure 9(c) is related to the impact of rework (RE) and doing things right first (DR) variables on the output variable, which is performance measuring (PE). When the DR is in its high values in the range of 4 to 6 and RE is between 2 and 4, the output will be more than average (4). On the other hand, as shown in Figure 9(d), when both input variables of RE and management information (MI) system get high values, the output, PM, is higher than the average. Figure 9(e) shows the impact of the DR and credible schedule (CS) on the PM. This

Table 8: Rules of the proposed fuzzy model.

Rules	Rule definition
1	If PE is SH and RE is SL and CS is SH and TM is SH and DV is SH and DR is VH and MI is SH then PM is SH.
2	If PE is SL and RE is VL and CS is SL and TM is SL and DV is VL and DR is SL and MI is SH then PM is SL.
3	If PE is VL and RE is SL and CS is VL and TM is VL and DV is EL and DR is EL and MI is VL then PM is VL.
4	If PE is SH and RE is SL and CS is VL and TM is SL and DV is SL and DR is VH and MI is SH then PM is SL.
5	If PE is VL and RE is SL and CS is VL and TM is SH and DV is VL and DR is SL and MI is VL then PM is SL.
6	If PE is SL and RE is VL and CS is SH and TM is SL and DV is VL and DR is EL and MI is VL then PM is VL.
7	If PE is SH and RE is VH and CS is SH and TM is SH and DV is SH and DR is SL and MI is VH then PM is SH.
8	If PE is VL and RE is VL and CS is EL and TM is SL and DV is EL and DR is EL and MI is EL then PM is EL.
9	If PE is SL and RE is VL and CS is EL and TM is VL and DV is VL and DR is EL and MI is EL then PM is VL.
10	If PE is VH and RE is EH and CS is SH and TM is VH and DV is SH and DR is VH and MI is SL then PM is VH.

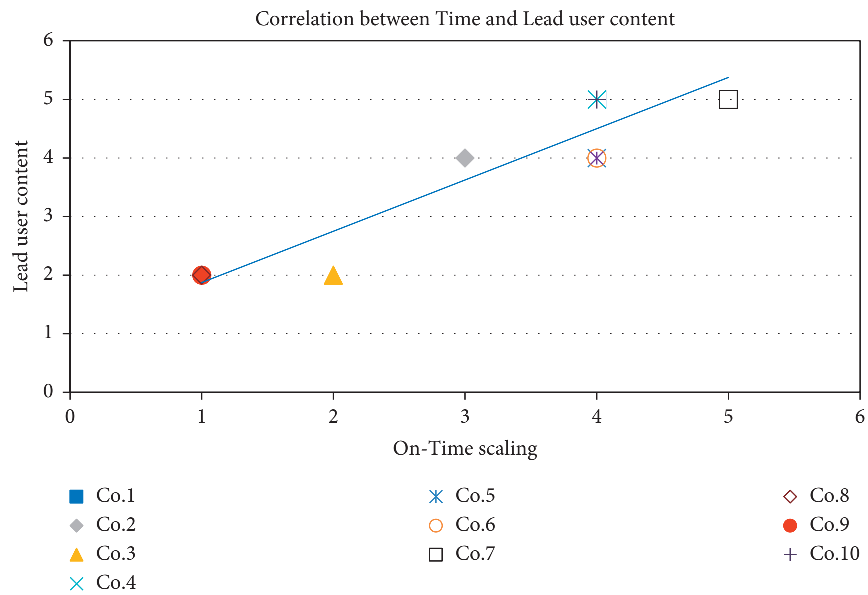

Figure 2: Correlation between the time and lead user content among the firms.

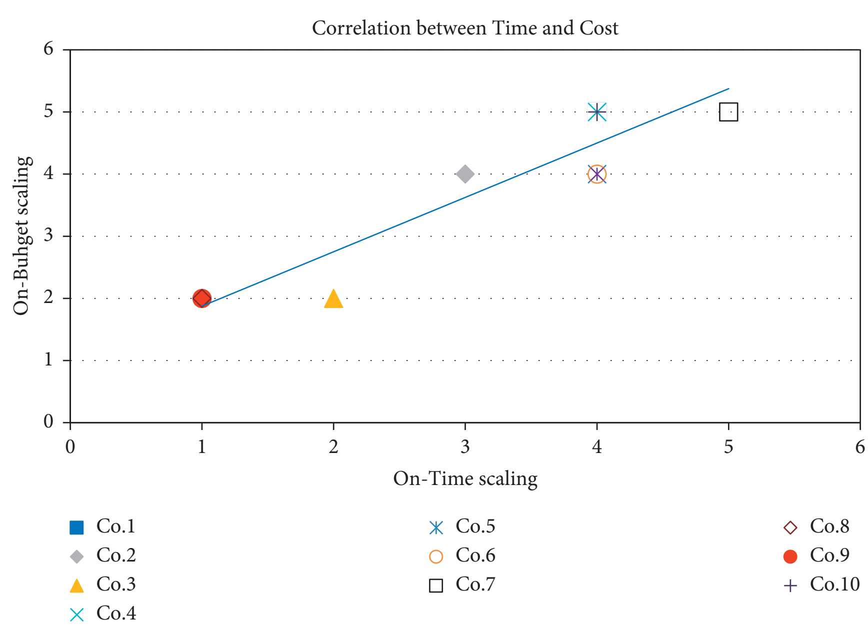

Figure 3: Correlation between the time and cost among the firms.

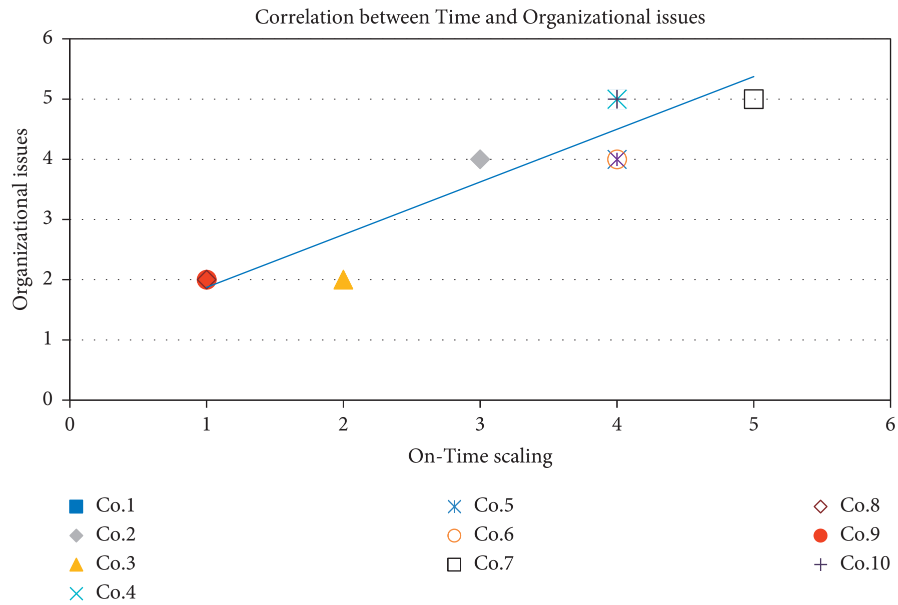

Figure 4: Correlation between the time and organizational issues among the firms.

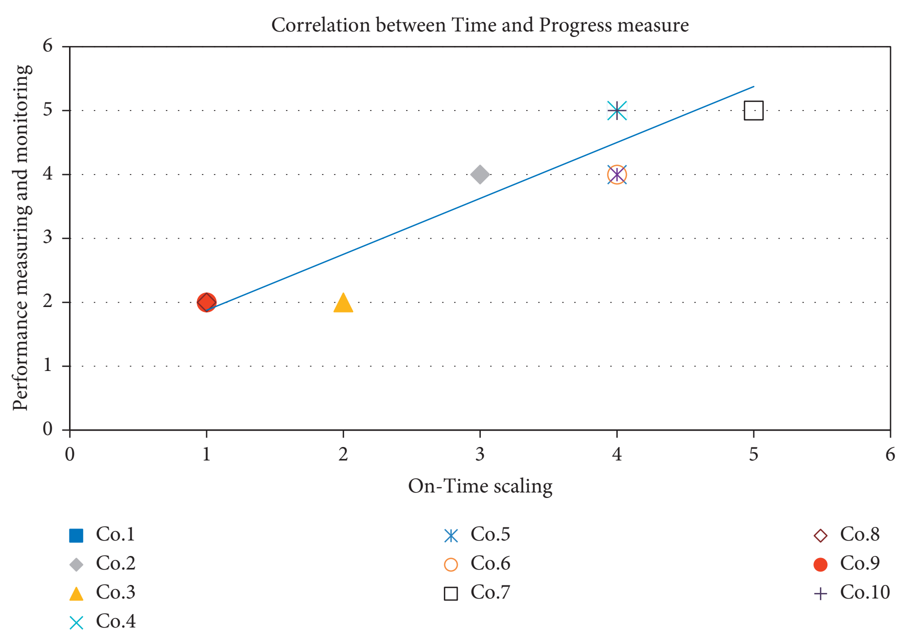

Figure 5: Correlation between the time and progress measure among the firms.

figure illustrates that the output variable has the highest sensitivity on the CS when DR has a high value from 4 to 6. When CS has a low value, in the range of 1 to 3, PM has a low value and when CS gets a high value, in the range of 3 to 5, PM gets a high value; otherwise, the output parameter has an average value.

The same impact as that in Figure 9(a) can be seen in Figure 9(f) just by changing the input variable of performance measuring (PE) to time as a measuring tool (TM). Such an impact can be seen in Figure 9(g) just after substituting TM by delay factors visibility (DV). Finally, Figure 9(h) illustrates the impact of management information (MI) system and doing things right first (DR) on performance measuring (PM). It is displayed that, for the values in the range of 3 to 5 for MI and a high-level value for DR in the range of 4 tp 6, PM gets a high value of 4.

5. Discussion

Many companies tend to be on budget rather than being on time. They believe that being on a budget is the goal and the other characteristics should be under control. This research shows that although projects tend to be on a budget, lead users' involvement plays a greater role, and, consequently,

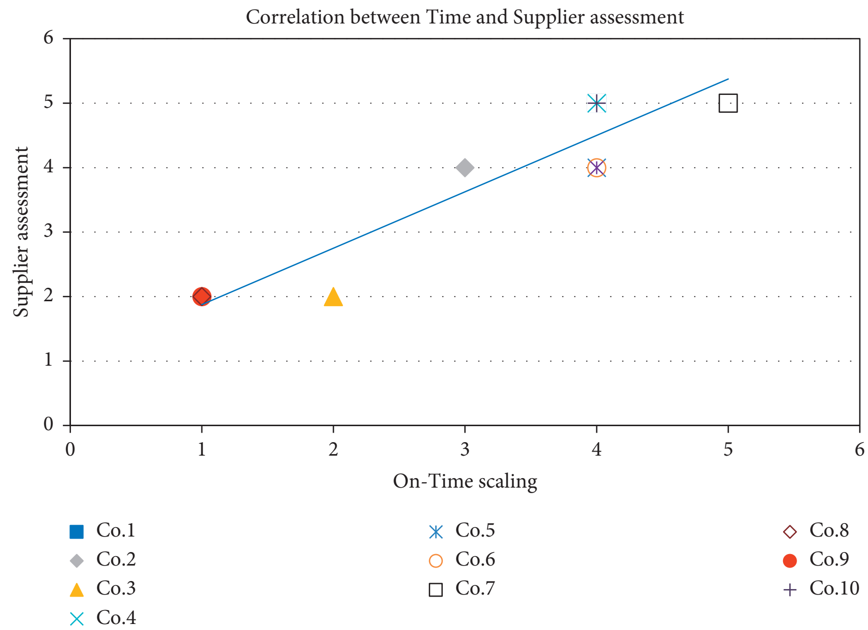

Figure 6: Correlation between the time and supplier assessment among the firms.

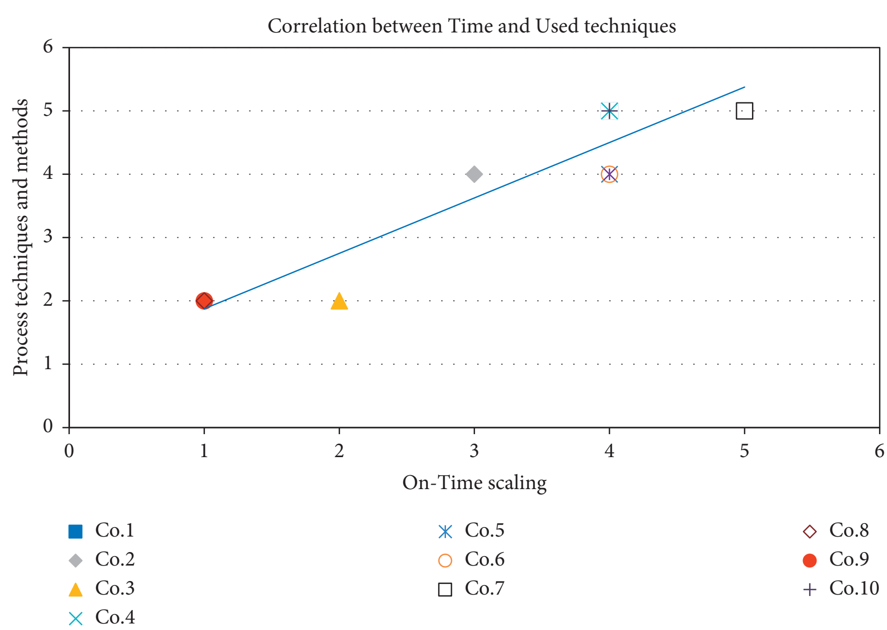

Figure 7: Correlation between the time and used techniques among the firms.

the timing of the project should be as important as being on budget. Perhaps the development programs are carried out on budget nominally, but analyzing the time value of the project reveals the actual cost of the total plan. Moreover, the results illustrated that the extent of lead user content is a good sign of creating real value for the companies. From a strategic point of view, not only is the short-term success of firms declined, but also firms are the victim of their temporary achievements. Creating value is a long-term mission for firms seeking to maximize their wealth. To find where a firm value could be created is the key success of the organization to survive in today's rapid environmental changes. For instance, many successful firms are providing ways for customers to participate as an integral part of development programs.

Companies struggle to define clear objectives and establish common sense, credible schedules, and visibility of delay factors, as all of them are needed for making rich preplanning before the development program begins. A reliable planning and scheduling process could contribute to the timing of a project. In project-based organizations, it is found that although the companies establish the work

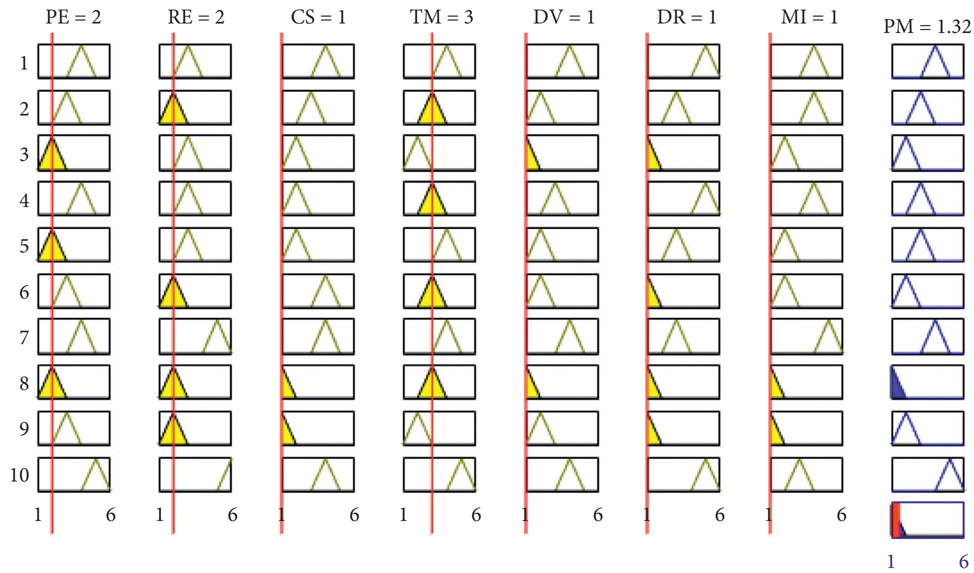

Figure 8: Rules set for the given data.

Table 9: The experimental and fuzzy predicted results.

Run	Obtained data	Fuzzy predicted results
1	4	4
2	3	3
3	2	2
4	3	3
5	3	3
6	2	2
7	4	4
8	1	1.32
9	2	2
10	5	5

breakdown structure (WBS), they suffer from a rich project planning wherein the definition of the activities is not identified. In other words, the link between activities and the expected duration to accomplishment is artificial. Each activity needs to be designed in detail, where its inputs and outputs should be defined based on the nature of the activity. This shortcoming results in decreasing the creditability of the schedule and, consequently, the project delay. Although the supplier assessment strategy could not have a straight impact on the product design and development timing, it influences projects through the quality perceived by the lead users. Therefore, product development teams cannot ignore the capability of their suppliers. For instance, the product design team must consider whether their suppliers can provide the required new parts within a reasonable time, at the expected cost, and with the required quality level. On the other hand, when reliable suppliers are involved in the development programs, the project risk is shared. It appears that firms should rate their suppliers based upon their specific needs.

The evaluation of project progress is important in monitoring the achievement of interconnected activities, warning the potential delay problems, the performance of the activities, and the timing of the program. This causes a recovery or improvement action to be proactively taken. On the other hand, poor progress measure results in misleading the evaluation of the project in terms of time, quality, and cost. Likewise, when rework occurs, its potential of shortcomings is added to this imprecision. Project-based organizations pay little attention to the power of communication in their entire systems, where this results in a significant amount of delay in the timing of the development programs.

Various types of information are exchanged in product development including design requirements, decisions, test results, manufacturing issues, and knowledge shared. Perhaps one could say that, in a product development program, information is the main chain that interconnects the mentioned components to each other. With this definition, the significance of correct and updated information is revealed more. Preparing the information at the right time, right place, and right format is the key to enhancing communication. In addition, poor communication cannot discover the potential of rework and delays and allows the proceeding activities to continue their work based on poorly defined or old transferred information from preceding activities. This causes a greater impact on the timing of the project, while the activities are interdependent rather than dependent or sequential.

Other important matters to be considered are the techniques used for shaping a database for storing information at the right place, right time, and right format. There is no doubt that, in each development program, based on its nature, special facets are going to emerge, while the proper accumulation of them constantly improves the knowledge and experience of the involved players. Weak design and poor manufacturing techniques are the other factors that contribute to delay in the projects. The poor design creates changes especially when the detailed design has been carried out. However, sometimes changes are unavoidable, while the customers' needs are changed. In this situation, the impact of

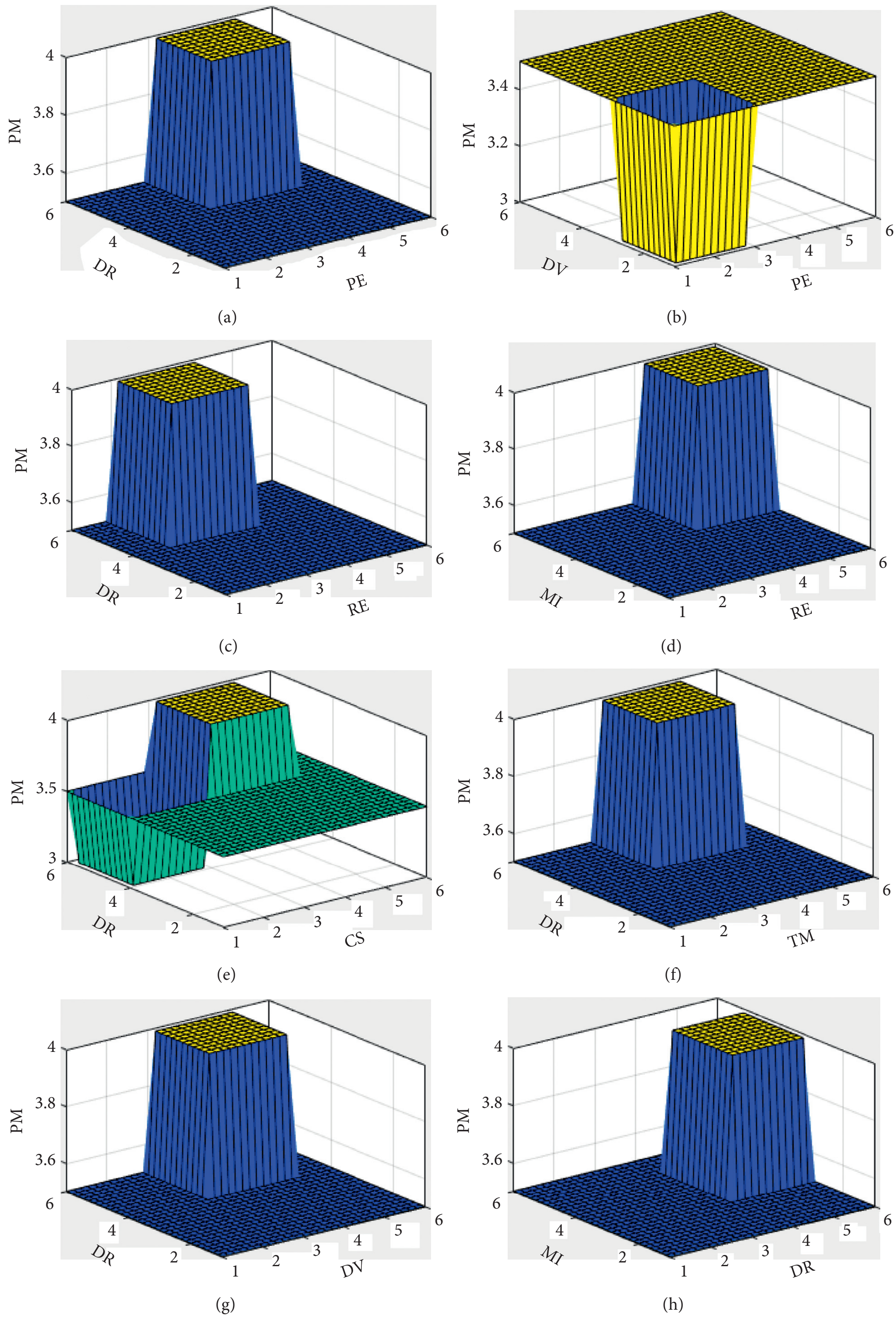

FIGURE 9: Illustration of the effects of input variable on the output variable.

change on different parts of the design should be identified and a trade-off analysis should be made.

6. Conclusion

In this study, four main parameters to characterize the process of lead-time reduction, organizational issues, firm resources, used methods and techniques, and performance measuring, in different EPC project-based organizations were considered. Using surveys and questionnaires, by getting help from the experts and managers in project-based organizations and companies, the correlations among them and the lead-time reduction were calculated. The finding was also discussed in the format of lesson-learned and courses of action to improve the development process. Moreover, a mathematical model based on the fuzzy approach to deal with performance measurement parameters is developed. The results of the analysis of the survey show that all the four considered factors are correlated to the lead time and affect the quality perceived by the main client and the cost of the project. Moreover, the results of the proposed fuzzy model illustrated that it may be an effective approach to predict the impact level of the performance measurement by having the levels of its attributes.

As fuzzy models work with predefined rules obtained from experts and managers, having more samples, having more filled surveys, and using more companies active in project-based activities may give better results to analyze the model. Therefore, having wider samples may be considered as a guideline for future studies. Moreover, the proposed mathematical model can be applied to study different parameters such as organizational issues, firm resources, and used methods and techniques based on their subfactors.

Data Availability

No data were used to support this study.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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Research Article

Application of Circular Economy and Uncertainty Planning in Analyzing the Sustainable Closed-Loop Supply Chain Network Design

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Supply chain sustainability as a new and very effective approach has recently attracted the attention of researchers in the field of supply chain management. Also, a circular economy helps to reduce the waste materials and products in a supply chain. In order to include circular economy in supply chain network design, it is necessary to use the concept of closed-loop network design. Therefore, designing a sustainable closed-loop supply chain network that works well even by changing some parameters seems to be necessary. This paper presents a multiproduct, sustainable closed-loop supply chain network under uncertainty. First, a mathematical model is proposed to design a closed-loop network, and then a set of possible scenarios is used to deal with the uncertainty of the parameters. In order to show the validity and applicability of the proposed model, numerical examples are presented and analyzed. In this regard, numerical results show the appropriate performance of the proposed model. Finally, sensitivity analysis is performed to assess the role of customer demand in different aspects of sustainability. It is revealed that increasing customer demand will have a strong impact on economic and environmental objectives.

1. Introduction

The importance of significant changes in the current business environment and competitive market as well as transportation costs has led to the issue of designing a sustainable supply chain network. Supply chain management is not limited to product manufacturing companies. However, service businesses can benefit from this approach [1]. The supply chain examines material flows and financial information from beginning to end, so the success of a supply chain depends on the integration and coordination of all entities in that chain in the form of an efficient and effective network structure [2]. According to [3], network design is the first management decision in the supply chain that affects all subsequent decisions and has the most significant impact on overall performance and return on investment in the supply chain. In addition to all the issues related to material flow planning along the supply chain, these decisions also include location, allocation, distribution, inventory, and purchase policy.

In recent years, the necessity and importance of a sustainable supply chain have led managers and planners of organizations and companies to take particular emphasis on this issue in the perspectives and strategies of their organization and company. Critical aspects of sustainable supply chain management include the sustainability of the supply chain network and supply chain environment, the application of environmentally friendly strategies, and the acceptance of social responsibility, so considering supply chain sustainability can be considered in addition to profitability

[4]. Financial considerations also considered and minimized adverse environmental and social adverse effects [5].

Recently, due to government measures, environmental issues and pollution, social issues, and customer pressures, there has been a growing focus on circular economy (CE) as well as sustainability. CE has been introduced as a new and efficient tool in supply chain optimization [6].

Since supply chains are undeniable entities in the current markets, their importance is increasing day by day due to shorter product life cycle, technology development, globalization, and competitive markets and because uncertainty is a separate component. It is the impossibility of real systems that can turn an appropriate decision into a lousy guarantee in the future. Therefore, designing a sustainable supply chain network based on a CE that can be compatible with a variety of natural changes seems to be necessary.

In the following and in Section 2, a comprehensive review of the literature is given. In Section 3, the proposed mathematical model is presented, in Section 4, the validation of the mathematical model and numerical results are provided, and finally, in Section 5, conclusions and future studies are given.

2. Literature Review

Although more attention has recently been paid to the environmental impact of the supply chain, limited research has considered the concept of a circular supply chain.

Pishvaei et al. [7] proposed a multiobjective stochastic programming model for designing a sustainable drug supply chain under uncertain conditions. Since the model was NP-hard, an accelerator decomposition algorithm was designed to deal with the computational complexity of the predetermined model. The results indicated the validity of the model and its solution method. Ghaderi et al. [8] presented a multiobjective model for designing a sustainable biotechnical supply chain based on the sustainability of the chain under uncertainty of the input data and taking into account economic, environmental, and social goals. The life cycle assessment (LCA) method was applied to the proposed model to estimate environmental and social impacts, of which computational analysis using a real case study demonstrates the validity of the proposed model. Eskandari et al. [9] presented an optimization model for a multiobjective sustainable supply chain with uncertain data due to adverse conditions during and after a disaster. The echelons of the studied supply chain were donor groups, blood collection facilities, distribution centers, and hospitals as points of demand.

An important way to deal with uncertainty is to use a fuzzy programming approach. Soleimani et al. [10] used a fuzzy approach to solve a multilevel, multipurpose model that included almost all activities from suppliers to recycling centers and customers. Özkır and Başlıgil [11] used fuzzy programming to model the problem of mutual and customers' satisfaction in the supply chain. Su [12] conducted a study focusing on the relationship between new and recycled materials with respect to variable production costs, device efficiency, and energy consumption. In this research, a linear multifunctional fuzzy planning model was used to analyze the relationship between the factors involved in effective costs and CO2 emissions. Mohammadi et al. [13] optimized the environmental effects of industry and total cost to design and plan a multicycle closed-circuit supply chain network. Their model evaluated the exchanges between carbon emissions as the impact of the industrial environment and total cost. It was concluded that although multistage scenario-based stochastic approaches can provide robust solutions, optimal approaches must be developed to solve real cases.

In the field of closed-loop supply chain network design, Devika et al. [14] proposed a mixed-integer linear programming model for the closed-loop supply chain network design. To solve this NP-hard problem, they used imperialist competitive algorithms (ICA) and variable neighborhood search (VNS). To test the performance of these algorithms, they were compared not only with each other but also with other powerful algorithms. The results show that the proposed approach achieves better solutions compared to others. Zhang and Jiang [15] presented a comprehensive approach to designing a sustainable closed-loop supply chain network based on economic, environmental, and social requirements. The objectives of the model were (1) to minimize total costs, (2) to minimize environmental impacts, and (3) to maximize social benefits. In that study, a multiobjective linear programming model was developed, and simulated annealing (SA) algorithm was used to solve the NP-hard problem. The results of implementing these algorithms showed that SA is almost the most efficient method.

Amin et al. [16] have optimized the closed-loop supply chain based on rubber production options. Their model analyzes a real case study in Canada by calculating the net present value of the problem. Rezaei and Kheirkhah [17] formulated a mathematical model of the TBL-based supply chain network. The objectives were (1) to maximize total profits, (2) to minimize overall environmental impacts, and (3) to maximize social benefits. They used the improved particle swarm optimization (PSO) algorithm to solve the problem, which gave appropriate results. Soleimani et al. [18] examined a sustainable closed-loop supply chain network with multiple levels, multiple products, and multiple cycles and determination of all components and raw materials of products. Modeling was done with an emphasis on high profitability and customer satisfaction by responding to demand and at the same time adhering to environmental and social responsibilities. A genetic algorithm (GA) was proposed to investigate various cases in this field. Based on the results, the proposed algorithm was able to provide a solution with a large approximation at the right time.

The multiplicity of goals in supply chain design is an issue that has been highly regarded by researchers in this field. Li and Hu [19] developed a two-stage randomized mixed-integer linear programming model based on petroleum biodegradation of which parameters such as biomass access, technological progress, and biofuel price are considered under uncertainty. Montoya-Torres et al. [20] focused on the effects of carbon in a supply chain and showed how to determine and optimize carbon effects throughout the supply chain and life cycle. Ahn et al. [21] proposed a linear mixed-integer linear programming model for the design of microalgae in the biodiesel supply chain to help with the estimated cost per hectare, including costs. Gonela et al. [22] proposed a linear programming model of different uncertain types for the design of bioethanol production supply chains based on industrial coexistence. In their model, the total profit is maximized due to the total emission limit of greenhouse gases and other reasonable limits. In order to realize this issue, the economic, social, and environmental pressures resulting from the construction of the mentioned supply chain were studied and modeled with three-objective functions of increasing profit, increasing social responsibility, and reducing carbon emission, respectively.

Lahane et al. [23] described the concept of circular economy in the supply chain. This research, which is the result of reviewing articles in the last ten years, shows that multicriteria optimization and decision-making techniques can create new frameworks in this area. Del Giudice et al. [24] investigated the application of big data in circular supply chain management and provided a circular supply chain. For this purpose, 378 Italian companies have been studied. The results of this study show that a supply chain based on big data as a modulator of the relationship between human resource management and company performance can provide good performance for a circular supply chain. Hussain and Malik [25] combined the paradigm of sustainability and circular economy in supply chain management. In this regard, structural equation modeling has been used to test the hypotheses. The research results show that the circular supply chain can provide a high level of stability for the supply chain.

Mastos et al. [26] have introduced the application of industry 4.0 in circular supply chain management. In this research, it is pointed out that, in order to manage a circular supply chain, it is necessary to study and evaluate the principles of supply chain sustainability. An industry 4.0-based solution is also proposed to evaluate the performance of circular supply chain sustainability.

Rentizelas et al. [27] proposed a mathematical formulation for the multiechelon supply chain network design by considering the circular economy of the wind turbine in Europe. They investigated the feasibility of the circular economy pathway of mechanical recycling for the reuse of end-of-life blades at composite material manufacturing while optimizing the required reverse supply network design in Europe for 2020 and for 2050.

After reviewing past research items, the main contribution of this research can be summarized as follows:

(i) Designing a design of a closed-loop supply chain network in multiperiod and multiproduct conditions

(ii) Considering the role of circular economy in supply chain network design

(iii) Analyzing the effect of circular economy in achieving the optimal solution of the supply chain

3. Problem Statement

In this research, a closed-loop supply chain is assessed. In the forward flow of this supply chain, there are four echelons, including suppliers, manufacturing centers, distribution centers, and customers. In the reverse flow, there are six echelons, including collection and inspection centers, repair centers, disposal centers, recycling centers, redistribution centers, and second-category consumers. The network of this supply chain is depicted in Figure 1.

Suppliers are in charge of obtaining raw materials in the forward network. The items are manufactured at production facilities and then distributed to clients in the first market via forwarding flow networks. After collection and examination, returned items are separated into two categories: separable products and nonseparable products. Products that can be separated into components are sent to a separate facility and turned into different parts. Parts are separated into two groups, recoverable and nonrecoverable, and transported to inspection, cleaning, and sorting centers.

Next, these items are transferred to manufacturers after inspection, cleaning, and sorting in these facilities, where they are combined with other parts and changed into new goods before being returned to the distribution loop. The recyclable separated items are transported throughout the recycling process. Repairable items are gathered from the centers during the repair process and, following inspection, are sent to these centers based on the capacity of the repair centers. Faulty and defective components of returned products can be retrieved, fixed, or replaced with healthy ones in these centers.

Finally, the repaired items are subsequently transferred to redistribution centers, where they are sold on the secondary market.

In order to design the network of this supply chain, a multiobjective mathematical model is proposed, which is presented as follows.

3.1. Notations

3.1. Notations. The notations used in the mathematical model of the closed-loop network are presented as follows.

3.2. Objective Functions

3.2.1. Maximizing the Profit of the Whole Chain. The profit performance is as follows:

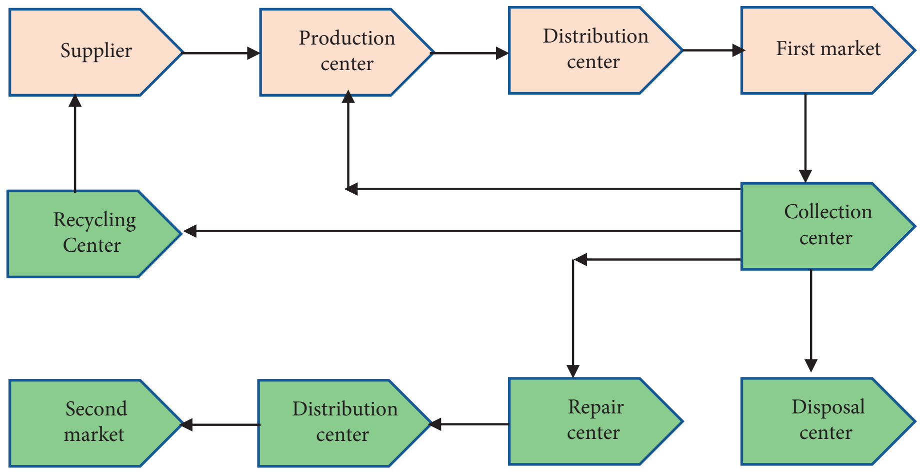

Figure 1: The proposed closed-loop supply chain.

$$
\begin{aligned}
MAX\,Z_1 = {} & \Bigg(\sum_s pb_s \Bigg[\sum_i \sum_c \sum_p QJC^s_{JCP}.\mathrm{Pr}^s_{cp} + \sum_s \sum_u \sum_p prr^s_{qpP}.Q\overline{D}Q^s_{uqp} \Bigg) \\
& - \Bigg(\sum_v \sum_{\check{m}} \sum_e QV\check{M}^s_{v\check{m}e}.TV\check{M}^s_{v\check{m}e} + \sum_{\check{m}} \sum_J \sum_p Q\check{M}J^s_{IJP}.T\check{M}J_{\check{m}jp} \\
& \quad + \sum_J \sum_C \sum_P QJC^s_{jcp}.TJC_{\check{m}jp} + \sum_C \sum_K \sum_p QCK^s_{ckp}.TCK_{ckp} \\
& \quad + \sum_J \sum_C \sum_P QK\check{M}^s_{k\check{m}p}.TK\check{M} + \sum_{\check{m}} \sum_J \sum_p QKD^s_{k\,dp}.TKD_{kdp} \\
& \quad + \sum_l \sum_{\overline{d}} \sum_p QL\overline{D}^s_{l\overline{d}p}.TL\overline{D} + \sum \overline{d} \sum_q \sum_p Q\overline{D}Q^s_{\overline{d}qp}.T\overline{D}Q_{\overline{d}qp} \\
& \quad + \sum_r \sum_v \sum_e QRV^s_{rve}.TV_{rve} \Bigg) \\
& - \Bigg(\sum_v \sum_{\check{m}} \sum_e QV\check{M}^s_{c\check{m}p}.\overline{D}C_{ve} \\
& \quad + \sum_{\check{m}} \sum_j \sum_p Q\check{M}J^s_{j\check{m}p}.MC^s_{\check{m}p} + \sum_j \sum_c \sum_p QJC^s_{jcp}.DC_{jp} \\
& \quad + \sum_c \sum_k \sum_p QCK^s_{k\,dp}.CC_{kp} + \sum_k \sum_{\check{m}} \sum_p QK\check{M}^s_{jkp}.RMC^s_{\check{m}p} \\
& \quad + \sum_k \sum_d \sum_p QKD^s_{k\,dp}.DP\;C_{dp} + \sum_k \sum_l \sum_p QKL^s_{klp}.RPC_{lp} \\
& \quad + \sum_k \sum_r \sum_p QKD^s_{krp}.RC_{rp} + \sum_k \sum_r \sum_p QKD^s_{krp}.RC_{rp} \\
& \quad + \sum_l \sum_{\overline{d}} \sum_p QL\overline{D}^s_{l\overline{d}p}.R\;DC_{\overline{d}p} \Bigg] \Bigg) \\
& + \Bigg[\Bigg(\sum_{\check{m}} \sum_h FX_{\check{m}h}.X_{\check{m}h} \\
& \quad + \sum_j \sum_h FY_{jh}.Y_{jh} + \sum_k \sum_h FH_{kh}.T_{kh} + \sum_l \sum_h FW_{lh}.W_{lh} \\
& \quad + \sum_{\overline{d}} \sum_h FO_{\overline{d}h}.O_{\overline{d}h} + \sum_r \sum_h FN_{rh}.N_{rh} \Bigg) \\
& + \Bigg(\sum_s pb_s \Bigg[\sum_{i \in \widehat{M} \bigcup \widetilde{M}} \sum_{\overline{w} \in \overline{w}} \sum_{t \in T} \overline{f}_i.l_i^{\overline{w}t^s} + \sum_{i \in \widehat{M} \bigcup \widetilde{M}} \sum_{\overline{w} \in \overline{w}} \sum_{t \in T} h_i.T\mathfrak{y}_i^{\overline{w}t^s-1} + \sum_{i \in \widehat{M} \bigcup \widetilde{M}} \sum_{p \in P} \sum_{t \in T} v_i^p. + \zeta_i^{pt^s} \\
& \quad + \sum_{i \in \widehat{D} \bigcup \widetilde{D}} \sum_{t \in T} \overline{h}_i.T\overline{\mathfrak{y}}_i^{t^s} + \sum_{i \in \check{D}} \sum_{p \in P} \sum_{t \in T} \overline{v}_i^p. + \pi_i^{pt^s} \Bigg] \Bigg). \qquad (1)
\end{aligned}
$$

Equation (1) displays the profit maximization from the supply chain in the form of total revenue minus total chain expenses. The income from the sale of items in the first- and second-category markets is shown in the first parenthesis. The shipping charges of each facility are shown in the second parenthesis. The supply chain's operational expenses are included in the third parenthesis. The cost of raw materials, the cost of product production and reproduction in production centers, operating costs in distribution and redistribution centers, inspection costs for products returned to collection centers, disposal costs, repair costs, and costs related to recycling are all included in these costs.

The fixed costs of establishing, distribution and redistribution, collection, and recycling are shown in the fourth parenthesis. The cost of working each employee, the cost of employing connected to the factory, the cost of jobless labor, contracting costs, and inventory costs in the distribution centers are all represented in the fifth parenthesis, respectively.

3.2.2. Second Objective Function: Reduction of Environmental Effects.

$$\begin{aligned}\text{MAX}\, Z_2 = \Bigg(\sum_s pb_s \Bigg[& \sum_v \sum_{\check{m}} \sum_e QV\check{M}^s_{v\check{m}e}.\text{ETV}\check{M}^s_{v,\check{m},p} + \sum_{\check{m}} \sum_j \sum_p Q\check{M}J^s_{j\check{m}p} \left(ET\check{M}J^s_{\check{m},j,p} + EM^s_{\check{m},p} \right) \\ & + \sum_j \sum_c \sum_p QJC^s_{jcp}.ETJC^s_{j,c,p} + \sum_c \sum_k \sum_p QCK^s_{ckp}.ETCK^s_{c,k,p} + \sum_k \sum_{\check{m}} \sum_p QKI^s_{k\check{m}p} \left(ETK\check{M}^s_{k,\check{m},p} + ER\check{M}^s_{\check{m},p} \right) \\ & + \sum_k \sum_d \sum_p QKD^s_{k\,dp}.ETKD^s_{k,d,p} + \sum_r \sum_v \sum_e QRV^s_{rve}.ETRV^s_{r,v,e} + \sum_k \sum_l \sum_p QKL^s_{klp} \left(ETKL^s_{K,L,p} + ERP_{lp} \right) \\ & + \sum_k \sum_r \sum_p QKR^s_{krp} \left(ETKR^s_{K,r,p} + ERC_{rp} \right) + \sum_l \sum_{\overline{d}} \sum_p QL\overline{D}^s_{l\overline{d}p}.ETL\overline{D}^s_{l,\overline{d},p} + \sum_{\overline{d}} \sum_q \sum_p Q\overline{D}Q^s_{\overline{d}qp}.ET\overline{D}Q^s_{\overline{d}q,p} \Bigg] \Bigg). \end{aligned} \tag{2}$$

The second objective function in (2) represents the minimization of environmental impacts based on the carbon emission index caused by the transportation of products between each of the centers as well as the carbon produced from the processes of production, reproduction, repair, and recycling.

3.2.3. Third Objective Function: Maximizing Social Effects.

$$\begin{aligned}\text{MAX}\, Z_3 = \Bigg(& \sum_s pb_s \left[\theta^s_{j,0} \left(\begin{array}{c} \sum_{\check{m}} \sum_h JOJ^s_{\check{m},h}.X_{\check{m}h} + \sum_j \sum_h JOJ^s_{j,h}.Y_{jh} + \sum_k \sum_h JOK^s_{k,h}.T_{kh} \\ + \sum_l \sum_h JOL^s_{l,h}.W_{lh} + \sum_{\overline{d}} \sum_h JO\overline{D}^s_{\overline{d},h}.O_{\overline{d}h} + \sum_r \sum_h JOR^s_{r,h}.\gamma_{rh} \end{array} \right) \right] \\ & - \sum_s pb_s \left[\theta^s_{ld} \left(\sum_{\check{m}} \sum_h L\, D\check{M}^s_{\check{m},h}.X_{\check{m}h} + \sum_l \sum_h L\, DL^s_{lh}.W_{lh} + \sum_r \sum_h L\, DR^s_{r,h}.\gamma_{rh} \right) \right] \\ & + \left(\sum_s pb_s \left[\begin{array}{l} \left(\sum_{\left\{ (i,\overline{j},\overline{r}) \in \overline{A} | i \in V_{\overline{k}},\, j \in \widehat{M}_{\overline{k}},\, \overline{k} \in \overline{K},\, \overline{k} \neq \overline{K} \right\}} \sum_{e \in E} \sum_{t \in T} \widehat{H}^e_i.\widetilde{W}^{et^s}_{i\overline{j}\overline{r}} \right) \\ + \left(\sum_{i \in \left\{ \widehat{M}_{\overline{k}} \cup \widehat{M}_{\overline{k}} | \overline{k} \in \overline{k}^d \right\}} \sum_{\overline{w} \in \overline{W}} \sum_{t \in T} \widetilde{H}^{\overline{w}}_i.\delta^{\overline{w}t^s}_i + \sum_{i \in \left\{ \overline{D}_{\overline{K}} \cup \overline{D}_{\overline{K}} | \overline{k} \in \overline{k}^d \right\}} \sum_{t \in T} \overline{\overline{H}}_i.\overline{\delta}^{t^s}_i \right) \\ + \left(\sum_{i \in \left\{ \widehat{M}_{\overline{k}} \cup \widetilde{M}_{\overline{k}} | \overline{k} \in \overline{k}^d \right\}} \sum_{\overline{w} \in \overline{W}} \sum_{t \in T} T\eta^{\overline{w}t-1}_i.\delta^{\overline{w}t^s}_i + \sum_{i \in \left\{ \overline{\widehat{D}}_{\overline{K}} \cup \widetilde{D}_{\overline{K}} | \overline{k} \in \overline{k}^d \right\}} \sum_{t \in T} T\eta^{-t^s}_i \right) \\ + \left(\sum_{i \in \left\{ \widehat{M}_{\overline{k}} \cup \widetilde{M}_{\overline{k}} | \overline{k} \in \overline{k}^u \right\}} \sum_{\overline{w} \in \overline{W}} \sum_{t \in T} L^{\overline{w}t-1}_i + \sum_{i \in \left\{ \overline{\widehat{D}}_{\overline{K}} \cup \widetilde{D}_{\overline{K}} | \overline{k} \in \overline{k}^u \right\}} \sum_{t \in T} \overline{L}^{-t^s}_i \right) \\ + \left(\sum_{i \in \left\{ \overline{M}_{\overline{k}} | \overline{k} \in \overline{k}^d \right\}} \sum_{p \in P} \sum_{t \in T} \overline{H}^p_i.\zeta^{pt^s}_i + \sum_{i \in \left\{ \check{\overline{D}}_{\overline{K}} | \overline{k} \in \overline{k}^d \right\}} \sum_{p \in P} \sum_{t \in T} \check{H}^p_i.\pi^{pt^s}_i \right) \end{array} \right] \right. \end{aligned} \tag{3}$$

The third objective function in (3) reflects the maximum of the supply chain network social impacts, which include maximizing new employment opportunities and limiting total days lost due to workplace injuries, acquiring raw materials from nonlocal suppliers, and growing the plant in the areas. Less developed, factory-owned distribution facilities in less developed areas are being closed down. All on contract factory employees are in more developed areas.

3.3. Constraints.

$$\sum_{J}\sum_{P} Q\check{M}J^{s}_{\check{m}JP} = \sum_{v}\sum_{e} QV\check{M}^{s}_{v\check{m}e} + \sum_{k}\sum_{p} QK\check{M}^{s}_{k\check{m}p}\ \forall_{\check{m}} \in \check{M}, s \in S, \quad (4)$$

$$\sum_{\check{m}} Q\check{M}j^{s}_{\check{m}jp} = \sum_{\check{m}} Qjc^{s}_{jcp}\ \forall j \in J, p \in P, s \in S. \quad (5)$$

Equation (4) states that, for any product, the sum of all inflows from all suppliers and collecting centers to each production center equals the outflows from that center. Equation (5) states that the sum of inflows from all production centers to each distribution center is equal to the sum of outflows from this distribution center for each product.

$$\sum_{j} Qjc^{s}_{jcp} \geq \mathrm{DE}_{cp}\ \forall c \in C, p \in P, s \in S. \quad (6)$$

Equation (6) indicates that it is necessary to meet the whole demand of all customers in the first market.

$$\sum_{\check{m}} QCK^{s}_{ckp} = \mathrm{DE}_{cp}.RT^{s}\forall c \in C, p \in P, s \in S. \quad (7)$$

Equation (7) depicts the link between consumer demand in the first market and items which are returned to all collection centers.

$$\sum_{d} QKD^{s}_{k\ dp} = \sum_{c} QcK^{s}_{ckp}.RD\ \forall k \in K, p \in P, s \in S. \quad (8)$$

Equation (8) indicates that, for each product, the number of products shipped from the collection centers to disposal centers is equal to the number of products shipped from customers in the first market to collection centers by considering the disposal ratio.

$$\sum_{l} QKl^{s}_{kLp} = \sum_{c} QcK^{s}_{ckp}.RR\ \forall k \in K, p \in P, s \in S. \quad (9)$$

Equation (9) states that the inflows to each collection center from all consumers in the first category market regions multiplied by the repair ratio equal the outflows from each collection center to all repair facilities for each product.

$$\sum_{r} QKR^{s}_{krp} = \sum_{c} QcK^{s}_{ckp}.RU\ \forall k \in K, p \in P, s \in S. \quad (10)$$

Equation (10) states that the inflows to each collection center from all consumers in the first category market regions multiplied by the recycling ratio equal the outflows from each collection center to all recycling centers for each product.

$$\sum_{\check{m}} QK\check{M}^{s}_{k\check{m}p} = \sum_{c} QcK^{s}_{ckp}.RM\ \forall k \in K, p \in P, s \in S. \quad (11)$$

Equation (11) shows that, for each product, the outflows from the collection centers to all production centers are equal to the inflows to each collection center from all customers in the first category market areas multiplied by the reproduction ratio.

$$\sum_{c} QcK^{s}_{ckp} = \sum_{d} QKD^{s}_{k\ dp} + \sum_{p} QKR^{s}_{kp} + \sum_{e} QK\check{M}^{s}_{kip} + \sum_{k} QKL^{s}_{k\check{m}p}\ \forall k \in K, p \in P, s \in S. \quad (12)$$

Equation (12) demonstrates the relation between the inflow and outflow in the collection center based on the products received from customers and sent to the repair centers or disposal centers.

$$\sum_{l} QKl^{s}_{klp} = \sum_{c} QL\overline{D}^{s}_{l\overline{d}p}\quad \forall l \in L, p \in P, s \in S. \quad (13)$$

Equation (13) states that the total of all inflows from all collection centers to each repair center is equal to the sum of all outflows from this repair facility for each product.

$$\sum_{l} QL\overline{D}^{s}_{l\overline{d}p} = \sum_{p} Q\overline{D}Q^{s}_{\overline{d}qp}\ \overline{\forall d} \in \overline{D}, p \in P, s \in S. \quad (14)$$

Equation (14) states that the total products received by redistribution centers from all repair centers should be equal to the total products shipped from redistribution centers

$$\sum_{l} Q\overline{D}Q^{s}_{\overline{d}qp} \geq DDE_{qp}\quad \forall q \in Q, p \in P, s \in S. \quad (15)$$

Equation (15) indicates that the demand of all customers in the second-category market areas is satisfied.

$$\sum_{k}\sum_{p} QKR^{s}_{krp} = \sum_{v}\sum_{e} QRV^{s}_{rve}\quad \forall r \in R, p \in P, s \in S. \quad (16)$$

Equation (16) states that the sum of inflows from all collecting centers to each recycling center is equal to the sum of outflows from these recycling centers for each raw material.

$$\sum_{e}\sum_{i} QV\check{M}^{s}_{v\check{m}e} \leq \mathrm{CAPV}_{v}\forall v \in V. \quad (17)$$

Equation (17) states that, for each supplier, the provided capacity should be of concern.

$$\sum_{j}\sum_{p} Q\check{M}J^{s}_{\check{m}jp} \leq \sum_{h} \mathrm{CAP}\check{M}_{\check{m}h}.X_{\check{m}h}\forall_{\check{m}} \in L. \quad (18)$$

Equation (18) shows the relation between the products sent from production centers and the products received by distribution centers as well as the shipment capacity.

$$\sum_{c}\sum_{p} QJC^{s}_{jcp} \leq \sum_{h} \mathrm{CAP}J_{\check{m}h}.Y_{\check{m}h}\forall j \in J. \quad (19)$$

Equation (19) states that all products sent from each distribution center should be less than the holding capacity in that distribution center.

$$\sum_{k}\sum_{p} QCK^{s}_{ckp} \leq \sum_{h} \text{CAP}K_{kh}.T_{kh} \forall k \in K. \quad (20)$$

Equation (20) states that all products received by the collection center should be less than the holding capacity of that collection center.

$$\sum_{k}\sum_{p} QKL^{s}_{klp} \leq \sum_{h} \text{CAP}K_{lh}.W_{lh} \forall l \in L. \quad (21)$$

Equation (21) states that the aggregate of all collecting centers inflows to repair centers for each product does not exceed the capacity.

$$\sum_{l}\sum_{p} QL\overline{D}^{s}_{l\overline{d}p} \leq \sum_{h} \text{CAP}\, L_{\overline{d}h}.O_{\overline{d}h} \forall_{\overline{d}} \in \overline{D}. \quad (22)$$

Equation (22) indicates that, for each product, the sum of the inflows to the redistribution centers by all collection centers does not exceed the capacity of the redistribution centers.

$$\sum_{k}\sum_{p} QKR^{s}_{krp} \leq \sum_{h} \text{CAP}R_{rh}.\gamma_{rh} \forall r \in R. \quad (23)$$

Equation (23) indicates that, for each product, the sum of the inflows to the recycling centers by the collection centers does not exceed the capacity of the recycling centers.

$$\sum_{h} X_{\check{m}h} \leq 1 \forall_{\check{m}} \in I, \quad (24)$$

$$\sum_{h} Y_{\check{m}h} \leq 1 \forall j \in J, \quad (25)$$

$$\sum_{h} T_{kh} \leq 1 \forall k \in K, \quad (26)$$

$$\sum_{h} W_{lh} \leq 1 \forall l \in L, \quad (27)$$

$$\sum_{h} O_{\overline{d}h} \leq 1 \forall_{\overline{d}} \in \overline{D}, \quad (28)$$

$$\sum_{h} \overline{D}_{rh} \leq 1 \forall r \in R. \quad (29)$$

Equations (24)–(29) ensure that production, distribution, collection, repair, redistribution, and recycling centers are built to a maximum capacity level, respectively.

$$\begin{gathered} T\overline{\mathfrak{y}}^{t^s-1}_{i} + \overline{\mathfrak{y}}^{t^s}_{i} - \overline{L}^{t^s}_{i} = T\overline{\mathfrak{y}}^{t^s}_{i} \\ \forall i \in \widehat{D} \bigcup \widetilde{D}, t \in T, s \in S. \end{gathered} \quad (30)$$

The number of employees working each period and at each distribution center is expressed by (30).

$$\begin{gathered} T\overline{\mathfrak{y}}^{t^s-1}_{i} \geq \overline{L}^{t^s}_{i} \\ \forall i \in \widehat{D} \bigcup \widetilde{D}, t \in T, s \in S. \end{gathered} \quad (31)$$

Equation (31) indicates that the number of fired workforces in each distribution center is fewer than the number of those who were previously employed.

$$\begin{gathered} T\mathfrak{y}^{\overline{w}t^s-1}_{i} + \mathfrak{y}^{\overline{w}t^s}_{i} - L^{\overline{w}t^s}_{i} = T\mathfrak{y}^{\overline{w}t^s}_{i} \\ \forall i \in \widehat{M} \bigcup \widetilde{M}, t \in T, s \in S. \end{gathered} \quad (32)$$

Equation (32) expresses the number of employees working in each period and in each production center. These workforces include people in the previous period, plus those hired and minus those fired.

$$\begin{gathered} T\mathfrak{y}^{\overline{w}t^s-1}_{i} \geq L^{\overline{w}t^s}_{i} \\ \forall i \in \widehat{M} \bigcup \widetilde{M}, t \in T, s \in S. \end{gathered} \quad (33)$$

Equation (33) states that in each distribution center, the number of those fired is less than the number of those who were previously employed.

$$\begin{gathered} \sum_{p} T\mathfrak{y}^{\overline{w}t^s}_{i}.\left(\overline{H}^{p}_{i} + \overline{H}^{p}_{i}\right) \leq \overline{\overline{H}} \\ \forall i \in \widehat{M} \bigcup \widetilde{M}, \overline{w} \in \overline{W}. \end{gathered} \quad (34)$$

Equation (34) refers to the fact that employees in the production centers must work as much as possible during shift work in order to expand and produce items.

$$\begin{gathered} T\mathfrak{y}^{\overline{w}t^s}_{i}.\left(\overline{H}^{p}_{i}\right) \geq \sum_{j} Q\check{M}J^{s}_{i,j,p} \\ \forall i \in \widehat{M} \bigcup \widetilde{M}, \overline{w} \in \overline{W}, s \in S, p \in P. \end{gathered} \quad (35)$$

Equation (35) expresses the relationship between production and manpower. In this regard, the total amount of goods produced by the workforces in each production center should be more than the amount of goods shipped from that center.

$$\sum_{p} T\overline{\mathfrak{y}}^{t^s}_{i}.\left(H^{''}_{i} + \widehat{H}^{p}_{i}\right) \leq \overline{\overline{H}} \quad \forall i \in \widehat{D} \bigcup \widetilde{D}. \quad (36)$$

Equation (36) refers to the fact that individuals working in the distribution center are responsible for expanding and maintaining items and must work for the whole shift.

$$T\overline{\mathfrak{y}}^{t^s}_{i}.\left(\widehat{H}^{p}_{i}\right) \geq \sum_{q} Q\overline{D}Q^{s}_{i,q,p} \forall i \in \widehat{D} \bigcup \widetilde{D}. \quad (37)$$

The connection between inventory and workforce planning is expressed in (37). The total quantity of goods sent by the workforces in each distribution center should be more than the total amount of products shipped from that center.

Table 1: Approximate parameters of the mathematical model.

Parameter	Low limit	Upper line	Parameter	Low limit	Upper line	Parameter	Low limit	Upper line
Pr^{s}_{cp}	600	800	$\mathrm{RMC}^{s}_{\check{m},p}$	0.2	0.3	$\mathrm{TKD}_{k,d,p}$	2	3
$Pr\,r^{s}_{qp}$	400	500	$DC_{j,p}$	0.3	0.4	$TKL_{k,l,p}$	2	3
DE^{s}_{cp}	50	60	$CC_{k,p}$	0.2	0.4	$TK\widehat{M}_{k}, \check{m}_{p}$	2	3
$\mathrm{FX}_{\check{m},h}$	10	20	$RPC_{l,p}$	0.1	0.2	$TL\overline{D}_{l,\bar{d},p}$	2	3
$Fy_{j,h}$	15	20	$R\,DC_{\bar{d},p}$	0.3	0.4	$T\overline{D}Q_{\bar{d},q,p}$	1	3
$FH_{k,h}$	5	15	$RC_{r,p}$	0.1	0.3	$TRV_{r,v,e}$	1	3
$FO_{\bar{d},h}$	5	15	$TK\check{M}_{v}, \check{m}_{e}$	2	3	$\bar{h}_{i}$	0.2	0.4
$FU_{r,h}$	10	15	$T\check{M}J\,\check{m}_{p}$	2	3	h_{i}	0.2	0.4
$\bar{v}^{p}_{i}$	0.1	0.3	$\widehat{M} \bigcup \widetilde{M}$	800	1000	$\mathrm{CAP}\,V_{u}$	500	800
$\mathrm{CAP}\,K_{l,h}$	700	1000	$\mathrm{CAP}\,J_{j,h}$	800	1000	$\mathrm{CAP}\,U_{\bar{d},h}$	800	1000
$CAP\,J_{j,h}$	900	1200						

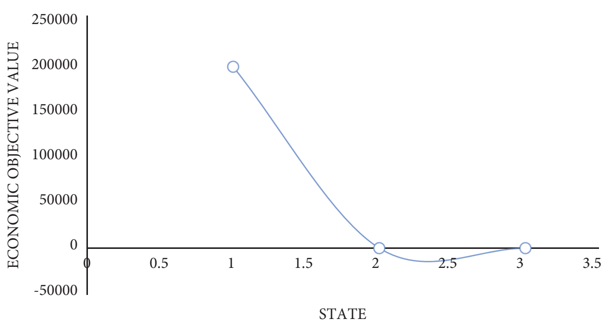

Figure 2: The value of the economic objective function under different scenarios.

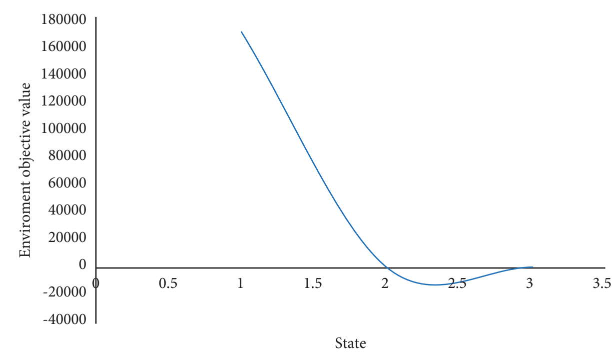

Figure 3: The value of the environment objective function under different scenarios.

$$X_{\check{m}h}, Y_{\check{m}h}, T_{kh}, W_{lh}, O_{\bar{d}h}, U_{rh} \in \{0,1\},$$
$$QVI_{v\check{m}h}, QIJ_{\check{m}jp}, QJC_{jcp}, QCK_{ckp}, QKI_{k\check{m}p}, QKD_{k\,dp}, \quad (38)$$

$$QKL_{klp}, QKR_{krp}, QLU_{j\bar{d}p}, QRV_{rve} \geq 0. \quad (39)$$

Equations (38)-(39) show the kind of each decision variable.

4. Numerical Results

4.1. Validation of the Mathematical Model. The validity of the proposed multiobjective model developed in this study is evaluated using the GAMS software and a randomly generated test problem. The simulated data are used to create a numerical example, which is subsequently incorporated into the mathematical model. The following is the data in this numerical example.

The supply chain is thought to contain two raw material sources. There are five first markets and three second markets. There are three disposal centers, three possible distribution centers, two potential collecting centers, and two potential repair and recycling centers.

The goal is to produce and supply one specific product. There is only one production unit to produce this product. The repair rate in the repair centers is equal to 40%, the disposal rate in the disposal centers is equal to 30%, the recycling rate in the recycling centers is equal to 20%, and finally, the reproduction rate in the production center is equal to 10%. Other parameters of the mathematical model are generated based on a continuous uniform distribution. The upper limit and the lower limit are the values of each of the parameters according to Table 1.

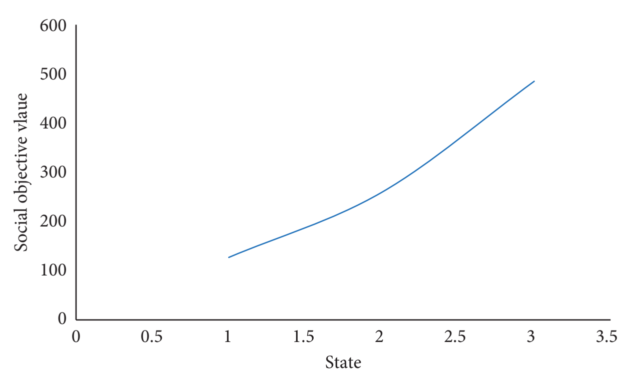

Figure 4: The value of social objective function under different scenarios.

Figure 2 shows that the maximum value of the objective function is obtained in the first case (maximizing the economic effect of the supply chain), and in no other case is the equivalent value obtained. Figure 3 also shows that the lowest value of the environmental impact objective function is obtained in the second case (supply chain environmental impact minimization mode), and in no other case is the equivalent value obtained. In a similar way, the trend of the third objective function in different scenarios is illustrated in Figure 4.

Table 2: Dimensions of designed examples.

Dimensions	Name	Number of suppliers	The number of the first market	Second market number	Number of disposal centers	Number of distribution centers	Number of collection centers	Number of repair centers	Number of recycling centers	Number of products	Number of scenarios
Small	P1	2	6	3	2	3	2	2	2	2	2
	P2	3	7	4	2	3	2	3	3	3	3
	P3	4	8	6	3	4	3	5	5	5	6
Medium	P4	7	9	8	5	5	5	5	6	6	7
	P5	7	12	10	5	6	4	7	6	6	10
	P6	8	11	10	6	8	5	8	8	8	10
	P7	10	14	10	6	8	6	9	8	8	13
Large	P8	11	17	15	6	10	11	11	11	11	16
	P9	13	21	17	8	13	11	14	14	17	19
	P10	15	29	21	9	15	12	14	15	22	21

Table 3: Results of solving different numerical examples.

	Optimal economic value	The optimal amount of social	Optimal environmental value	Solution time
P1	183712.6	234.6762	6863.064	33.02988
P2	245961.5	281.6311	13128.02	54.96419
P3	259506.8	421.6442	17239.34	115.0335
P4	410597.6	398.0413	23185.15	337.9464
P5	646575.7	414.8581	27424.11	455.4346
P6	1036983	692.0819	28936.21	534.6852
P7	1285350	1165.829	42623.64	1255.487
P8	1336998	1302.29	44986.48	2051.522
P9	2007278	1402.862	49408.82	3178.191
P10	1925290	1488.242	50817.1	3854.694

As a result, improving one of the three objectives will not bring all other ones to the optimal level, nor will optimizing two of the three objectives. Therefore, it may be argued that the objectives are in conflict. Because when the supply chain's economic effect is optimized, other objectives are not in their ideal value. As a result, the same is valid for social and environmental impact optimization.

4.2. CE Performance in Sustainability Supply Chain. In order to evaluate the performance of CE in a sustainable supply chain, the mathematical model is solved using several numerical examples in various dimensions. In this regard, a total of ten numerical examples have been generated. Table 2 provides dimensional information for these test problems. Additional information is based on Table 1. The weighted sum technique is utilized to optimize the suggested three-objective problem. Three objectives with the same weight of 0.33 are combined, and their total objective is optimized.

These instances are then optimized in GAMS software using the optimization model. Table 3 summarizes the findings. The model information shown in Table 2 is given to the GAMS program in each of problems P1 through P10. After that, their weight distribution is optimized. Finally, the optimum value for each of the software's aims is shown. Table 3 summarizes the findings of this research.

According to Table 3, the proposed mathematical model can identify the best value for all three objectives in a variety of scenarios. This demonstrates the mathematical model's effectiveness. In Figures 5, 6, and 7, the method of determining the values of various functions is depicted in ten cases.

The ideal value of each of the objective functions grows as the dimensions of the issue expand from small to large, as seen in Figures 5, 6, and 7. These increases are not in a linear trend, and the rate of rising varies depending on the case. As the weight combination technique only offers the ideal value for each objective, it is not feasible to compare two objectives on the same problem, and only the trend of the values of each of the investigated goals is evaluated.

4.3. Sensitivity Analysis. In this section, the effect of raising the demand parameter as one of the key parameters of the model on the values of each objective function is explored using sensitivity analysis in two ways. Because the demand parameter is important in supply chain concerns, the pattern of changes in the proposed model's objective functions with rising customer demand in the first and second markets has been investigated.

Figure 8 shows the trend of changes in the economic objective function against the increase in changes in customer demand in the first and second markets. As can be seen, the slope of the increase in the first objective function is nonlinear and nonparabolic. Therefore, with increasing changes in customer demand, the amount of the economic

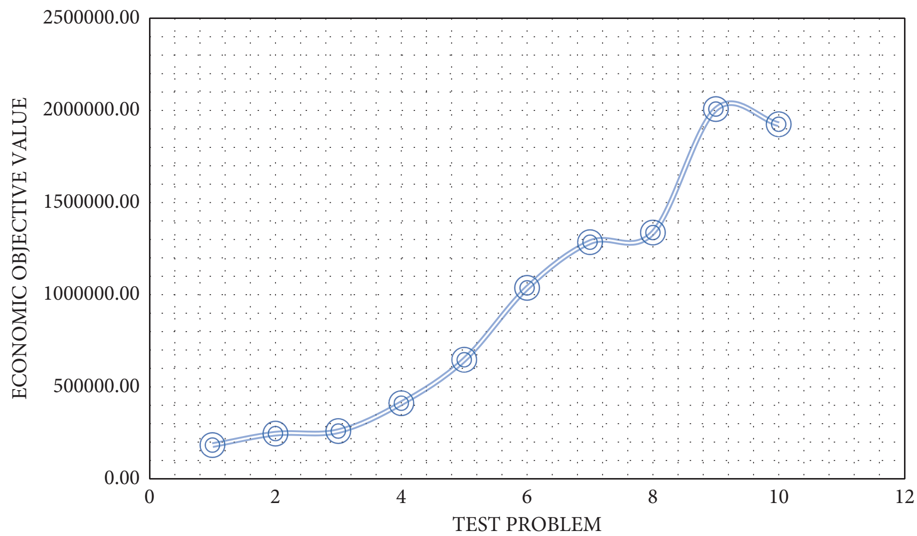

Figure 5: The trend of the first objective function on different numerical examples.

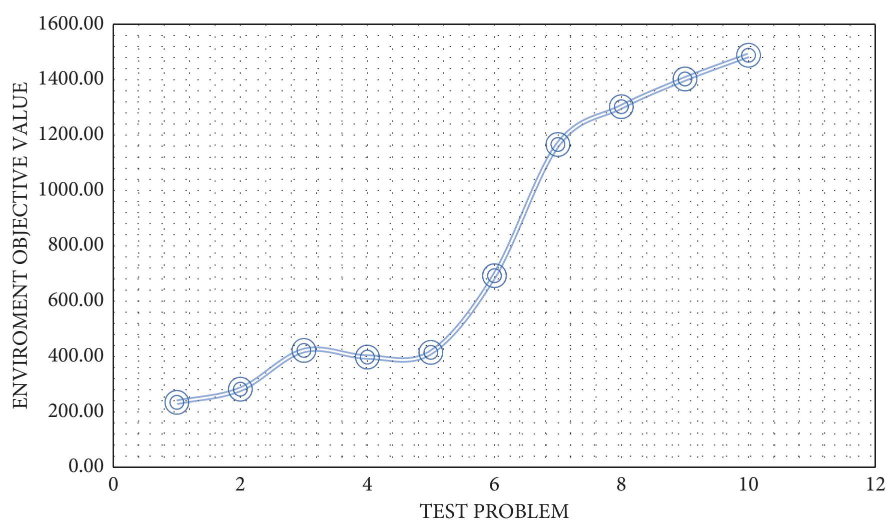

Figure 6: The trend of the second objective function on different numerical examples.

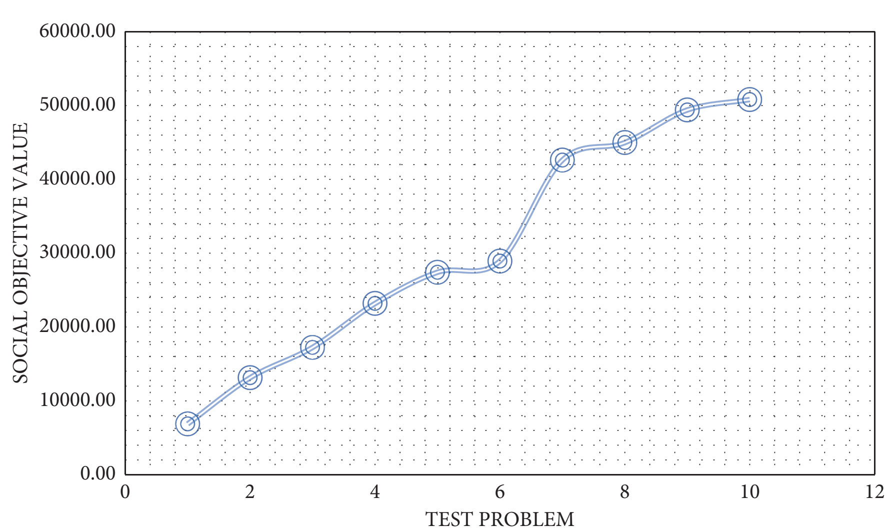

Figure 7: The trend of the third objective function on different numerical examples.

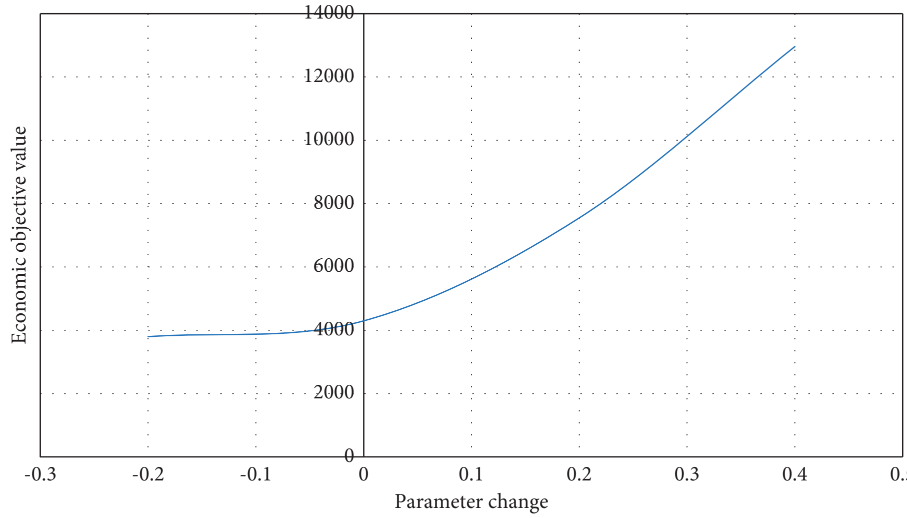

Figure 8: Sensitivity analysis of economic objective function.

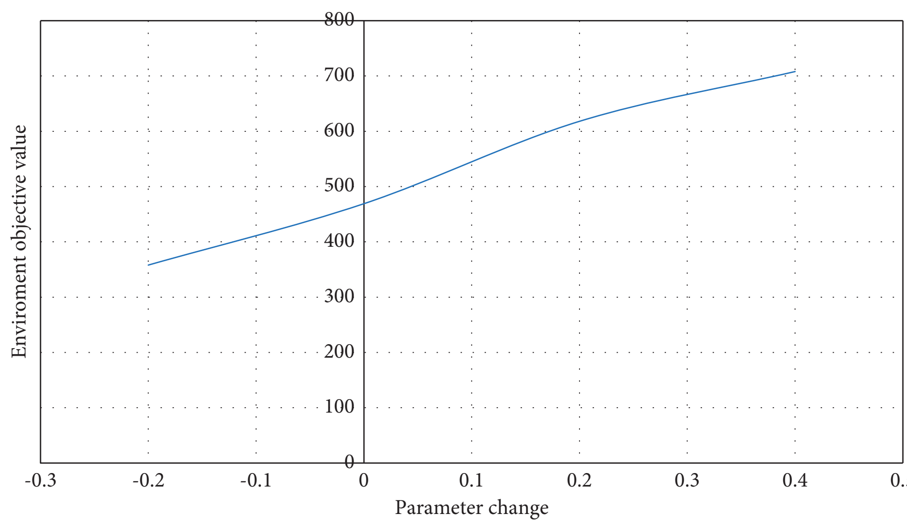

Figure 9: Sensitivity analysis of the environmental objective function.

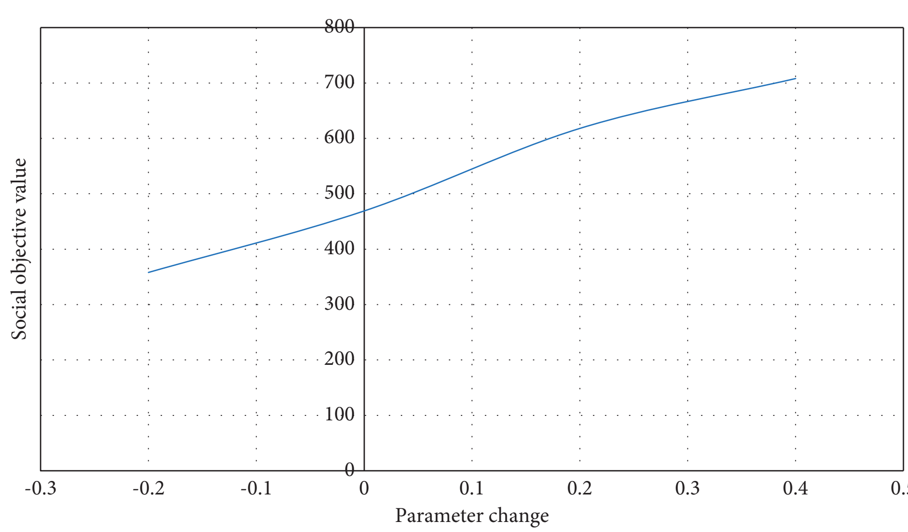

Figure 10: Sensitivity analysis of social objective function.

objective function has an increasing trend. Figures 9 and 10 show the trend of changes in the environmental and social objective function, respectively, against the increase in customer demand in the first and second markets, and in both cases, changes in both functions can have an increasing trend. The results obtained in this section indicate that the sharp increase in target functions with changes in demand indicates that it is essential that changes in demand can make optimal supply chain decisions, affecting whether in the economic, environmental, or social fields.

5. Conclusions and Future Directions

In this study, first, the previous related studies were reviewed. Next, inspired by the latest research items, a supply chain based on the circular economy was developed. This supply chain is closed-loop and consists of suppliers, manufacturers, distributors, customers, collection centers, repair centers, recycling centers, and disposal centers. Considering the multidimensional concept of sustainability, maximum profit according to the revenue and costs of the whole chain, minimizing environmental effects according to carbon emission index, and maximizing social effects according to the criteria of the number of job opportunities created and the number of lost days, is formulated in the proposed mathematical model. In this regard, purchasing raw materials from nonlocal suppliers, expanding the plant in less developed areas, firing employees from factory-owned distribution centers in less developed areas, location and allocation, and distribution are optimized through this model. To deal with the uncertainty of the parameters in the proposed closed-loop supply chain optimization model, the probabilistic method has been used. In the next step, the validation and the results of the model were examined. In the validation section, the results show that the individual optimization of each objective does not lead to the ideal level of other objectives, so the result is that economic, environmental, and social goals are in conflict with each other. Also, several examples were solved in small, medium, and large dimensions, which show that the designed mathematical model has the ability to find the ideal solution in different situations and conditions. At the end of the research, sensitivity on the customer demand parameter shows that increasing customer demand will have a substantial impact on all three objectives.

There was a key limitation in this study. Considering the circular economy for the supply chain requires a holistic view of all supply chains. In supply chain network design, however, only members of a chain are considered. Therefore, adding a circular economy to the supply chain network design problem is always a major constraint for real-world implementation. Because this requires the participation of a large number of supply chains, the complexity of the model makes it more challenging to optimize, and this is another limitation of the research. Some future suggestions for developing this study and presenting new research include using an improved GA or PSO algorithm to optimize a large-scale model and designing a hybrid metaheuristic algorithm.

Abbreviations

Indices

$v \in V$: Set of fixed locations for suppliers
$c \in C$: Set of fixed locations for the first market
$q \in Q$: Set of fixed locations for the secondary market
$d \in D$: Set of fixed locations for disposal centers
$k \in K$: Set of potential locations for collection and inspection centers
$l \in L$: Set of potential locations for repair centers
$r \in R$: Set of potential locations for recycling centers
$p \in P$: Set of products
$s \in S$: Set of scenarios
$e \in E$: Set of raw materials
$h \in H$: Set of capacity levels for potential locations
$\tilde{m} \in \tilde{M}$: Set of inventories owned by the factory
$\hat{m} \in \hat{M}$: Set of new facilities owned by the factory
$\check{m} \in \check{M}$: Set of possible factories
$\overline{w} \in \overline{W}$: Set of types of departments owned by the factory
$\overline{d} \in \overline{D}$: Set of potential locations for distribution centers
$\tilde{d} \in \tilde{D}$: Set of existing distribution centers
$\hat{d} \in \hat{D}$: Set of new redistribution centers
$\check{d} \in \check{D}$: Set of conventional distribution centers
$\overline{A} = \{(i,\overline{j},\overline{r})\}$: Types of transportation whose origin is i and destination is j
$\overline{K} = \overline{k}^d \bigcup \overline{K}^u$: A set of areas. d includes more developed areas, and u includes less developed areas.

Parameters

Pr^s_{cp}: The selling price of product p in the first market c in scenario s
prr^s_{qp}: The selling price of product p in the secondary market q in scenario s
DE^s_{cp}: Demand for product p in the first market c in scenario s
$D\ D\ E^s_{qp}$: Demand for product p in the secondary market q in scenario s
$\mathrm{FX}_{\check{m},h}$: Fixed cost of construction of production center $\check{m}$ with capacity level h
$Fy_{j,h}$: Fixed cost of constructing distribution center j with capacity level h
$FH_{k,h}$: Fixed cost of constructing a collection and inspection center k with capacity level h
$FO_{\overline{d},h}$: Fixed cost of construction of distribution center $\overline{d}$ with capacity level h
$FU_{r,h}$: Fixed cost of constructing a recycling center r with capacity level h
$SC_{v,e}$: Preparing cost of each unit of raw materials e with capacity level h
$MC^s_{\check{m},p}$: Production cost per unit of product p in the production center $\check{m}$ in scenario s
$RMC^s_{\check{m},p}$: Reproducing cost per unit of product p at the production center $\check{m}$ in scenario s

$DC_{j,p}$: Distribution and holding cost per unit of product p in the distribution center j

$CC_{k,p}$: Inspection and testing cost per unit of product p in the collection center k

DPC_{d,p^R}: Disposal cost per unit of product p in the disposal center d

RPC_{l,p^R}: Repairing cost per unit of product unit p in the repair center l

RDC_{d,p^R}: Redistribution cost per unit of product p in the redistribution center $\overline{d}$

RC_{r,p^R}: Redistribution cost per unit of product p in the recycling center r

$TVM_{\check{m},v,e^R}$: Transportation and purchasing cost per unit of raw materials e from the supplier v to the production center $\check{m}$

$TMJ_{\check{m},j,p^R}$: Transportation cost per unit of product p from the production center $\check{m}$ to the distribution center j

TJC_{j,c,p^R}: Transportation cost per unit of product p from the distribution center j to the first market c

TCK_{k,c,p^R}: Transportation cost per unit of used product p from the first market c to the collection center k

TKD_{k,d,p^R}: Transportation cost per unit of used product p from the collection center k to the disposal center d for disposal

TKL_{k,l,p^R}: Transportation cost per unit of used product p from the collection center k to the repair center l for repair

$TKM_{k,\check{m},p^R}$: Transportation cost per unit of used product p from the collection center k to the production center $\check{m}$ for reproduction

TKR_{k,r,p^R}: Transportation cost per unit of used product p from the collection center k to the recycling center r for recycling

TLD_{d,l,p^R}: Transportation cost per unit of repaired product p from the repair center l to the redistribution center $\overline{d}$

TDQ_{d,q,p^R}: Transportation cost per unit of repaired product p from the redistribution center $\overline{d}$ to the secondary market q

TRV_{r,v,e^R}: Transportation cost per unit of recycled raw materials e from the recycling center r to the supplier v

$\overline{h}_i$: Hiring cost per unit for each employee with a distribution center belongs to $i \in \overline{d} \cup d$

h_i: The cost of hiring for each new hire related to the factory $i \in \check{m} \cup \widetilde{m}$

$\overline{f}_i$: The cost of dismissal of each dismissed employee belonging to the factory belongs to $i \in \check{m} \cup \widetilde{m}$

v_i^p: Subcontracts cost for each unit of the p family related to factory $i \in \check{m} \cup \widetilde{m}$

$\overline{v}_i^p$: Storage cost in each time period of the product family related to the distribution center belongs to $i \in \overline{d} \cup d$

$CAPV_{v^R}$: Maximum supplier capacity v

$CAPM_{\check{m}h^R}$: Maximum production center capacity $\check{m}$ with capacity level h

$CAPJ_{jh^R}$: Maximum capacity of distribution center j with capacity level h

$CAPK_{kh^R}$: Maximum capacity of collection center k with capacity level h

$CAPL_{lh^R}$: Maximum capacity of repair center l with capacity level h

$CAPU_{\overline{d}h^R}$: Maximum capacity of the redistribution center $\overline{d}$ with capacity level h

$CAPR_{rh^R}$: Maximum capacity of recycling center r with capacity level h

RT^s: Collection center usage rate in scenario s

RM: Reproduction rates in production centers

RU: Recycling rates at recycling centers

$R\ D$: Disposal rates at disposal centers

RR: Repair rates at repair centers

pb_s: Probability of scenario s

$\theta_{j,0}^s$: The normalized weighted for the total number of job opportunities created in the facility in scenario s

θ_{1,d^R}^s: The normalized weighted for the total number of working days lost in the facility in scenario s

$JO\check{m}_{\check{m},h^R}^s$: The number of job opportunities created in case of construction of production center $\check{m}$ with capacity level h in scenario s

JOJ_{j,h^R}^s: The number of job opportunities created in case of construction of distribution center j with capacity level h in scenario s

JOK_{k,h^R}^s: The number of job opportunities created in case of construction of collection center k with capacity level h in scenario s

JOL_{l,h^R}^s: The number of job opportunities created in case of construction of repair center l with capacity level h in scenario s

$JO\overline{D}_{\overline{d},h^R}^s$: The number of job opportunities created in case of construction of redistribution center $\overline{d}$ with capacity level h in scenario s

JOR_{r,h^R}^s: The number of job opportunities created in case of construction of recycling center r with capacity level h in scenario s

$J\ D\check{M}_{\check{m},h}^s$: Average lost working days in case of construction of production center $\check{m}$ with capacity level h, which is sent to scenario s

$J\ DL_{l,h}^s$: Average lost working days in case of construction of repair center l with capacity level h, which is sent to scenario s

$J\ DR_{r,h}^s$: Average lost working days in case of construction of recycling center r with capacity level h, which is sent to scenario s

$\widehat{H}_i^e$: The number of employees required to produce e raw materials by $i \in V$ supplier

$\widetilde{H}_i^{\overline{w}}$: The number of employees required to expand a unit of capacity from the $\overline{w} \in w$ section of the factory belongs to $i \in \check{m} \cup \widetilde{m}$

$\overline{H}_i^p$: The number of employee periods required to produce a unit of the product p is in the subcontract of factory $i \in \breve{m}$

$\overset{=}{H}$: The number of working time units an employee has available for each course

$H_i^{''}$: The number of employee courses required to expand a distribution center belongs to the $i \in \overline{d} \cup$d unit

$\hat{H}_i^p$: The number of employee periods required to store one p product unit per time period in the $i \in \overline{d}$ subdistribution center

$ETV\breve{M}_{v,\breve{m},e}^s$: Carbon emission rate per shipment of raw materials e from supplier v to production center $\breve{m}$ in scenario s

$ET\breve{M}J_{\breve{m},j,p}^s$: Carbon emission rate per shipment of product p from the production center $\breve{m}$ to the distribution center j in scenario s

$ETJC_{j,c,p^R}^s$: The amount of carbon emissions per unit of product p transported from the distribution center j to the first market c in scenario s

$ETCK_{c,k,p^R}^s$: The amount of carbon emissions per shipment of used product p from the primary market c to the collection center k in scenario s

$ETK\breve{M}_{k,\breve{m},p^R}^s$: Carbon emission rate per shipment of used product p from the collection center k to the production center $\breve{m}$ for reproduction in scenario s

$ETKD_{k,d,p^R}^s$: Carbon emission rate per transport of product unit used p from collection center k to disposal center d for disposal in scenario s

$ETL\overline{D}_{l,\overline{d},p^R}^s$: Carbon emission rate per shipment of repaired product p from repair center l to redistribution $\overline{d}$ in scenario s

$ET\overline{D}Q_{\overline{d},q,p^R}^s$: Carbon emission rate per shipment of repaired product p from redistribution center $\overline{d}$ to secondary market q in scenario s

$ETRV_{r,v,e^R}^s$: Carbon emission rate per shipment of raw materials e from recycling center r to supplier v in scenario s

$EM_{\breve{m},p^R}^s$: The amount of carbon emissions per unit of product p produced at the production center $\breve{m}$ in scenario s

$ERM_{\breve{m},p^R}^s$: Carbon emission rate per reproduction per unit of product p at production center $\breve{m}$ in scenario s.

Decision variables

$QV\breve{M}_{v,\breve{m},e}^s$: The number of raw materials shipped e sent from supplier v to the production center $\breve{m}$ in scenario s

$Q\breve{M}J_{\breve{m},j,p}^s$: The number of products p shipped from supplier v to the production center $\breve{m}$ in scenario s

$QJC_{j,c,p}^s$: The number of products shipped p that is sent from distribution center j to the first market c to scenario s

$QCK_{c,k,p}^s$: The number of products shipped p that is sent from the first market c to the collection center k to scenario s

$QK\breve{M}_{k,\breve{m},p}^s$: The number of products transported p that is sent from the collection center k to the production center $\breve{m}$ for reproduction in scenario s

$QKD_{k,d,p}^s$: The number of products transported p that is sent from collection center k to disposal center d for disposal in scenario s

$QKR_{k,r,p}^s$: The number of products p shipped from collection center k to the recycle center r in scenario s

$QL\overline{D}_{l,\overline{d},p}^s$: The number of products shipped p that is sent from distribution center j to the first market c to scenario s

$QUQ_{\overline{d},q,p}^s$: The number of products shipped p that is sent from the first market c to the collection center k to scenario s

$QRV_{r,q,p}^s$: The number of products transported p that is sent from the collection center recycle center r to second market q in scenario s

$X_{\breve{m},h}$: Binary variable and equal to 1 if the production center $\breve{m}$ is established with capacity level h

$Y_{j,h}$: Binary variable and equal to 1 if the distribution center j is established with a capacity level of h

$T_{k,h}$: Binary variable and equal to 1 if the collection center k is established with a capacity level of h

$W_{l,h}$: Binary variable and equal to 1 if the repair center l is established with a capacity level of h

$O_{\overline{d},h}$: Binary variable and equal to 1 if redistribution center $\overline{d}$ with capacity level h is established

$\gamma_{r,h}$: Binary variable and equal to 1 if the recycling center r is established with capacity level h 1, otherwise zero

$L_i^{\overline{w}t^s}$: The number of dismissed employees related to the $\overline{w} \in w$ part, belonging to $i \in \breve{m} \cup \tilde{m}$ in the period t under scenario s

$\mathfrak{y}_i^{\overline{w}t^s}$: The number of employees hired for the $\overline{w} \in w$ part, belonging to $i \in \breve{m} \cup \tilde{m}$ in the period t under scenario s

$T\mathfrak{y}_i^{\overline{w}t^s}$: The number of employees working in the $\overline{w} \in w$ part, belonging to $i \in \breve{m} \cup \tilde{m}$ in the time period t under scenario s

$\overline{\mathfrak{y}}_i^{t^s}$: The number of employees of the distribution center owned by $i \in \overline{d} \cup \tilde{d}$ in the period t under scenario s

$T\overline{\mathfrak{y}}_i^{t^s}$: The number of employees of the distribution center owned by $i \in \overline{d} \cup \tilde{d}$ in the period t under scenario s

$\overline{L}_i^{t^s}$: The number of employees fired from the distribution center owned by $i \in \overline{d} \cup \tilde{d}$ during the period t under scenario s

$\overline{W}_{i,j,r}^{et^s}$: The number of families of raw materials e that is sent by transport r through the transfer arc $(i,\overline{j},\overline{r})$ in period t under scenario s

$\delta_i^{\overline{w}_{t^s}}$: Expansion of production capacity in each time period of the $\overline{w} \in$w section, owned by $i \in \check{m} \cup \tilde{m}$ in the time period t under scenario s

$\overline{\delta}_i^{t^s}$: Expansion of storage capacity in the time period related to the distribution center owned by $i \in \overline{d} \cup \tilde{d}$ with the time start of period t under scenario s

$\zeta_i^{\mathrm{pt}^s}$: The number of products that each $i \in m$ plant produces in the period t under scenario s

$\pi_i^{\mathrm{pt}^s}$: The inventory of product p that the $i \in m$ distribution center maintains over the period t under scenario s.

Data Availability

The data are available upon the request.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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Research Article

Development of Machine Learning Methods in Hybrid Energy Storage Systems in Electric Vehicles

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The hybrid energy storage systems are a practical tool to solve the issues in single energy storage systems in terms of specific power supply and high specific energy. These systems are especially applicable in electric and hybrid vehicles. Applying a dynamic and coherent strategy plays a key role in managing a hybrid energy storage system. The data obtained while driving and information collected from energy storage systems can be used to analyze the performance of the provided energy management method. Most existing energy management models follow predetermined rules that are unsuitable for vehicles moving in different modes and conditions. Therefore, it is so advantageous to provide an energy management system that can learn from the environment and the driving cycle and send the needed data to a control system for optimal management. In this research, the machine learning method and its application in increasing the efficiency of a hybrid energy storage management system are applied. In this regard, the energy management system is designed based on machine learning methods so that the system can learn to take the necessary actions in different situations directly and without the use of predicted select and run the predefined rules. The advantage of this method is accurate and effective control with high efficiency through direct interaction with the environment around the system. The numerical results show that the proposed machine learning method can achieve the least mean square error in all strategies.

1. Introduction

Fuel usage, energy source diversification, and electric propulsion technologies are some of the measures increasingly adopted around the world to make vehicles cleaner and more efficient with the ultimate purpose of reducing greenhouse gas emissions and reaching a sustainable energy ecosystem [1–3]. Hybrid electric vehicles are expected to have significantly lower fuel consumption than conventional vehicles as well as substantially lower emissions [4–6]. It is essential to equip hybrid electric vehicles with advanced energy management systems to achieve these goals. Electric Vehicles (EVs) and Hybrid Electric Vehicles (HEVs) can operate in a variety of modes such as fully electric or power distribution, which are controlled by an energy management system based on driving conditions [7–10]. Accordingly, an energy management system tries to improve the power output of multiple sources and supply the necessary power while minimizing the most important and significant costs [11, 12].

In recent years, researchers have proposed a number of models and methods for energy management in HEVs and also several reviews summarizing the progress of research in this area. Currently, the greatest challenge in improving the energy management systems of HEVs is how to shorten their computational processes and improve their adaptability. These challenges can be overcome with the help of learning methods [13–16]. In particular, reinforcement learning can be used to achieve enhanced energy management in Hybrid Energy Storage Systems (HESSs) [17, 18]. Recently, researchers have shown a growing interest in energy management approaches that utilize novel methods like machine learning or artificial intelligence [19–21]. It should be noted that machine learning is a data analyzing technique used to solve all kinds of problems in many industrial-based problems [22].

This paper presents a comprehensive approach to reinforcement learning-based energy management strategies. In general, the applications of reinforcement learning in energy management can be classified into two categories: (1) "simple algorithms," which refers to using a single algorithm (e.g., Q-learning, dynamic learning, or SARSA) to produce energy management policies; (2) "hybrid algorithms," which refers to using a combination of reinforcement learning algorithms (e.g., forecasting algorithms, deep learning algorithms, and predictive control models) or data [23].

The content of this article is organized as follows. First, the paper provides a review of HESSs and discusses the challenges of energy management in these systems and the optimization constraints in this area. Next, the paper reviews the variety of reinforcement learning methods that can be utilized in HESSs, including simple and hybrid algorithms. The article attempts to cover various methods and vehicle types and compare their main functional features.

1.1. Hybrid Energy Storage System

1.1. Hybrid Energy Storage System. A Hybrid Energy Storage System (HESS) is an energy storage system comprised of two or more energy storage sources that meet the requirements of complex driving conditions. Considering their function, HESSs need to have a suitable energy management mechanism and topology to ensure well-coordinated power distribution among different energy sources. This also affects the lifespan of HESSs and the performance, efficiency, and cost-effectiveness of the broader system by determining how well power is distributed among different components. Energy management systems and topologies are the most popular topics of research into HESSs. Since different topologies have different power sources, there could be significant differences between different energy management systems. In recent years, many new studies have been conducted on the energy management system and topology of HESSs, but there have been few reviews of progress in this field.

The energy storage systems of EVs or HEVs have a wide range of features and functions. The performance of these systems is primarily indicated by rated power, charge/discharge rate, power density, energy density, self-discharge rate, response time, energy storage efficiency, and cycle life. With the help of these indicators, one can choose a suitable energy storage system based on performance requirements. Energy storage systems can be broadly divided into three categories of mechanical, electrical, and chemical, which are shown in Figure 1. The characteristic parameters of conventional energy storage systems are provided in Table 1.

Table 1 compares 6 energy storage systems. As can be seen, the highest power consumption is for air compressors, and the lowest is for lithium batteries. Also, the life cycle of each of these systems is presented, which can be an important criterion in choosing an energy storage system.

1.2. Energy Management Strategy. The main function of an energy management system is to balance the distribution of power between multiple energy sources and the power source so as to optimize a series of cost functions such as fuel consumption, battery life, emission, and driving control. This problem is usually formulated as a control optimization problem with specific control objectives and physical constraints. These control objectives may include one or more parameters such as exhaust temperature, emissions, fuel consumption, battery's state of charge (SOC) and state of health (SOH), and power consumption costs. Figure 2 shows the energy management problem for a typical HEV.

(1) Dynamics of power transmission systems: power transmission dynamic variables such as vehicle speed and acceleration, generator speed, power demand, battery SOC.

(2) Model and other components: basic mathematical formulations for transmission components such as electric motor, battery pack, generator, and supercapacitor, and their connections to other components.

(3) Control objectives: optimization objectives such as emission, fuel consumption, battery life, driving mobility, power costs, and shift frequency.

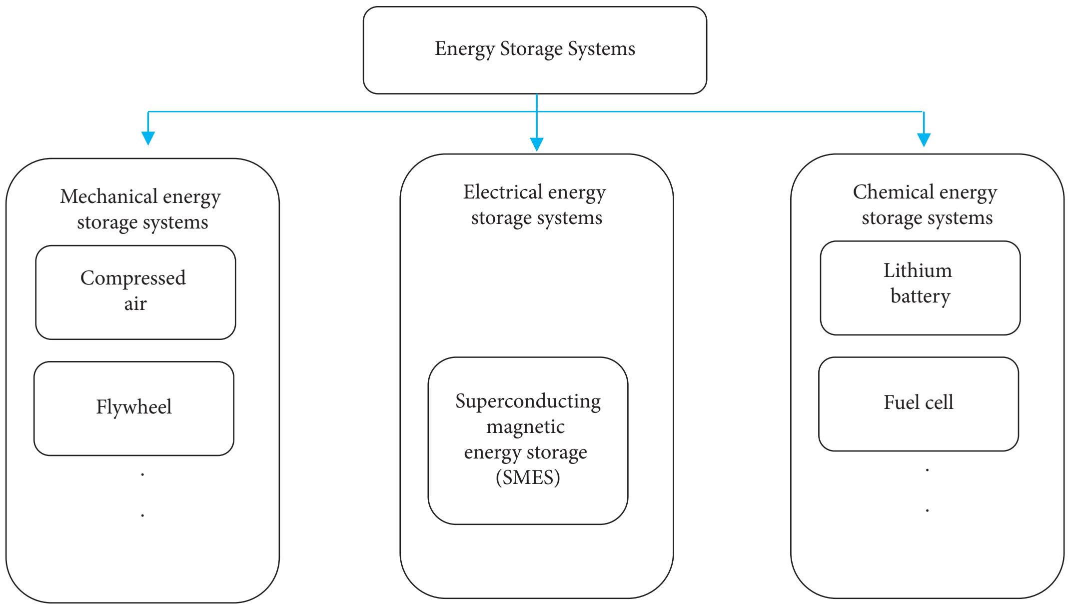

Figure 1: Classification of conventional energy storage systems.

Table 1: Typical characteristics of energy storage systems [24, 25].

Energy storage systems	Power consumption rate (MW)	Discharge time	Power density	Energy density	Self-discharge rate (%/day)	Response time	Efficiency (%)	Lifespan (years)	Cycle life (cycles)
Compressed air	100–300	1 day	—	30–60	—	minutes	40–70	20–40	-
Flywheel	0–250	s-h	400–1600	5–130	20–100	ms-sh	80–90	15–20	10^2–10^7
Battery-supercapacitor	0–0.3	ms-1h	0.1–10	0.1–15	2–40	ms	85–98	5–12	10^5–10^6
SMES	0.1–10	ms-8s	500–2000	0.5–5	10–15	ms	75–80	-	-
Lithium-ion batteries	0–0.1	minutes-h	200–340	130–250	0.1–0.3	ms	65–95	5–8	600–1200
Fuel cell	0–50	s-days	>500(W/L)	500–3000	0.5–2	ms-minutes	20–66	5–30	10^3–10^4

(4) Physical constraints: constraints imposed on important variables such as battery SOC, power demand, rotation speed, torque, and gears.

The optimal control problem is often subject to three types of physical constraints: propulsion dynamics, initial and final values of state variables, and constraints that apply to control and state variables. Once the inputs like power demand, vehicle speed, SOC, current, steering angle, and speed are given, the amount of power needed from each energy source and the corresponding fuel cost can be calculated with the help of propulsion dynamics formulations. It is common to consider battery SOC, gearbox position, and engine/generator speed as state variables. Also, it is typical to treat engine output torque with throttle position, gear shift, and clutch position (in multimode HEVs like Toyota Prius and Chevrolet Volt) as control measures. To solve this optimal control problem, it is necessary to define appropriate constraints for these parameters. In addition, to control objectives and constraints, it is necessary to build a comprehensive model of power transmission system components as part of the solution process.

2. Literature Review

In reinforcement learning, an agent's core element learns how to map inputs (states/modes) to outputs (optimal control measures) to maximize a cumulative reward. This reward maximization is usually done through a trial and error process, which involves observing how each action affects the reward at present and in the future (lagged effects). The basic steps of reinforcement learning include detecting the state of the environment, taking certain actions, and improving the actions with rewards serving as guidance [26].

Reinforcement learning has three characteristic features. The first feature is the balance and coordination between exploration and exploitation. The agent uses the exploration phase to gain knowledge about the environment and then

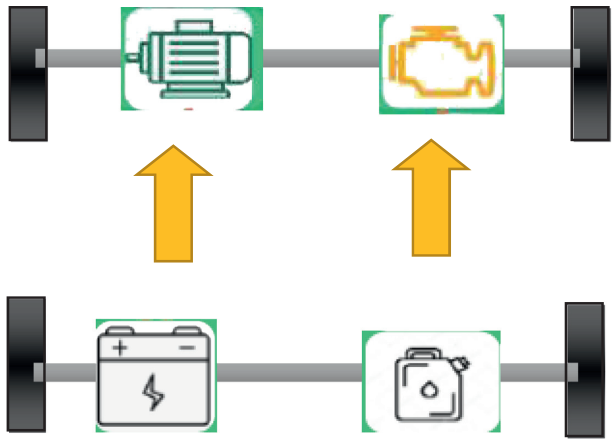

Figure 2: Classification of the energy management problem for HEVs.

proceed to exploitation, which means taking a control action based on the existing knowledge. The second feature of reinforcement learning is the ability to adapt measures without needing external control, which is essential in cases where the environment is vague or uncertain. Through its interactions with the environment, the agent can identify the state of the environment and take appropriate actions to affect it if needed. The third characteristic feature of reinforcement learning is that it is Markovian, meaning that the conditional probability distribution of future states of the environment depends only on the current state and not the sequence of events that precede it.

For the problem of energy management in HESSs, the environment can be modeled as propulsion dynamics and driving conditions. Also, the agent can be considered as a power distribution controller operating with a series of algorithms, the purpose of which is to search for a sequence of actions that maximize reward based on the available state and reward information.

To teach a reinforcement learning algorithm, it is necessary to define a value function for the agent. This value function is a function of state, action, and reward, which is typically denoted by Q(s, a) (where s is state and a is action). State, performance, and reward information can be collected in real driving conditions for the HESS energy management problem. Then, Markov decision processes (MDPs) can be used to mimic these variables, which means the next state and reward can be predicted based only on the current information and independent of historical data. Finally, the value function can be calculated to determine what will be the best control action. The difference between different reinforcement learning algorithms is in the criteria they use for updating the value function.

2.1. Application of Reinforcement Learning in HESS Energy Management. This section provides a summary of advanced reinforcement learning approaches used for the purpose of energy management in HESSs. The first part of the section is devoted to initial attempts to use simple algorithms in this field. Then, the section proceeds to review recent progress in the combined use of multiple algorithms and the development of hybrid algorithms for HESS energy management. Table 2 provides an overview of the variety of algorithms used in HESS energy management.

3. Methodology

3.1. Machine Learning. In machine learning, the subject is the design of machines that learn from the examples given to them and their own experiences. In fact, in this science, an attempt is made to design a machine using algorithms in such a way that it can learn and operate without explicitly planning and dictating each action. In machine learning, instead of programming everything, the data are given to a general algorithm, and it is this algorithm that builds its logic based on the data given to it. Machine learning has a variety of methods, including supervised, unsupervised, and reinforcement learning [2].

Machine learning is closely related to (and often overlaps with) computational statistics, the focus of which is computer prediction, and is linked to mathematical optimization, which also introduces methods, theories, and applications. Machine learning is sometimes integrated with data mining; the focus of this sub-category is on exploratory data analysis and is known as unsupervised learning. Machine learning can also be unsupervised and used to learn and recognize the basic form of the behavior of different creatures and then find significant abnormalities [3].

In data analysis, machine learning is a method for designing complex algorithms and models used for forecasting; in the industry, this is known as predictive analytics. Machine learning is beyond the realm of artificial intelligence. In the early days of artificial intelligence as a science discipline, some researchers made machines learn from data. They tried to solve this problem with various symbolic methods, like neural networks.

However, the growing emphasis on logical and knowledge-based methods has created a gap between artificial intelligence (AI) and machine learning. Probability systems were full of theoretical and practical problems with obtaining and displaying data. By 1980, cyber systems were gaining ground over AI, and statistics were no longer relevant. Work on knowledge-based learning continued within the realm of AI, leading to inductive logical programming, but the statistical trajectory of other research was beyond the realm of AI and was seen in pattern making and information retrieval. Research on neural networks was also rejected by AI and Computer Science (CS) at about the same time. This path was also pursued outside of AI/CS by researchers in other disciplines, including Hopfield, Rumelhart, and Hinton, under the name of connectionism. Their major success came in the mid-1980s with backpropagation [18].

Machine learning and data mining often use the same methods and overlap significantly, but while machine learning focuses on prediction based on known properties learned from training data, data mining focuses on discovering properties (formerly). The unknown focuses on the data (this is the step of analyzing knowledge extraction in the database). Data mining uses several machine learning

Table 2: Comparison of reinforcement learning algorithms used in HESSs.

Reference	Drawbacks	Advantages	Power transmission system	Algorithm
Hsu et al. [27]	Simplification of complex models	Adaptive to riding conditions	Electric bike	Q-learning
Qi and Wu [28], Liu and Murphey [29]	Dependence on driving data	High accuracy	Hybrid electric vehicle	Temporal-difference (TD) learning
Liu et al. [30]	Sporadic local optimization	Ability to run online	Plug-in hybrid electric vehicle	Q-learning
Hu et al. [31]	Computational load	Multiple control objectives	Hybrid electric vehicle	Q-learning
Kamet et al. [32]	Design complexity	Robust against variability	Hydraulic hybrid vehicle	Deep reinforcement learning and dynamic neural programming
Zhao et al. [33], Xiong et al. [34]	Complex mathematics	Real-time control	Hybrid truck	Dynamic learning
Kamet et al. [32] Zhao et al. [33]	Needs specific training	Data-driven model	Plug-in hybrid electric vehicle	Deep learning
Liu et al. [30], Hu et al. [31]	Sensitivity to driving cycle	Fast computation	Electric vehicle	Online reinforcement learning
Hay et al. [35], Lin et al. [36]	Data requirements	Improved battery life	Hybrid electric vehicle and plug-in hybrid electric vehicle	Reinforcement learning and Markov decision system

methods but with different purposes; machine learning, on the other hand, uses data mining techniques as "unsupervised learning" or as a preprocessing step to improve learner accuracy. Much of the confusion between the two disciplines (often with distinct conferences and journals, with the exception of the ECML PKDD) stems from their underlying assumptions: In machine learning, performance is usually assessed by the ability to reproduce known knowledge, while In knowledge extraction and data mining (KDD), the key activity is to discover previously unknown knowledge. Compared to known knowledge, one unsupervised method (an uninformed method) easily fails other monitored methods, while in a typical KDD activity, supervised methods can be accessed due to lack of access to training data.

Classification machine learning models can be accurately estimated using techniques such as the holdout method, which divides data into a training set and an experimental set (usually two-thirds of the data in the training set and one-third). Moreover, it evaluates the model's performance under training on the test set verified. In comparison, the N-fold cross-validation method randomly divides the data into k subsets, with $k-1$ of the data used for model training and $k-1$ for testing the model's predictive ability. In addition to holdout and cross-validation methods, bootstrap, which samples n items from the data set by pasting, can be used to evaluate the model accurately [18].

3.2. Learning Algorithms. In 2012, Hsu et al. [27] used the Q-learning algorithm to improve the power management system of electric or hybrid bikes. These researchers defined the power management objectives as improvement in riding safety and comfort and more efficient use of battery power. The simulation results of this study showed that the proposed power management system could offer 24% and 50% improvement in the riding quality and energy efficiency objectives, respectively. Since then, many researchers have started using reinforcement learning algorithms in HESS energy management rather than the control optimization theory. For example, Qi et al. used the Q-learning algorithm to optimize the battery SOC maintenance strategy of an HEV [28]. When combined with a sustainable strategy, this method can offer a balance between real-time performance and energy efficiency optimization. In [29], Liu used the reverse reinforcement learning method to create a probabilistic driving path prediction system, which predicts the suitable engine/battery power distribution ratio based on its forecast of driver behavior.

Over the past several years, Liu et al. have also conducted a number of studies on the use of reinforcement learning-based power distribution controls in hybrid transmission systems. First, they evaluated the adaptability, optimality, and learning capability of a Q-learning-based energy management strategy for a hybrid tracked vehicle [30]. Next, to develop real-time controls for a hybrid transmission system, they integrated an online recursive algorithm into the Q-learning structure so that control strategies can be updated in real-time [31]. However, these algorithms may not be robust against variability in driving conditions, i.e. different driving behaviors, driving areas, and road environments.

4. Proposed Hybrid Energy System

With the rapid development of deep learning and artificial intelligence in recent years, the energy management strategies of hybrid vehicles have become increasingly intelligent. It is now typical to embed two or more algorithms that process different types of information into a reinforcement learning framework in order to ensure more efficient, real-time controls based on speed and power requirement forecasts; information shared between vehicles or between vehicles and infrastructure, and interactions with smart grids and smart cities.

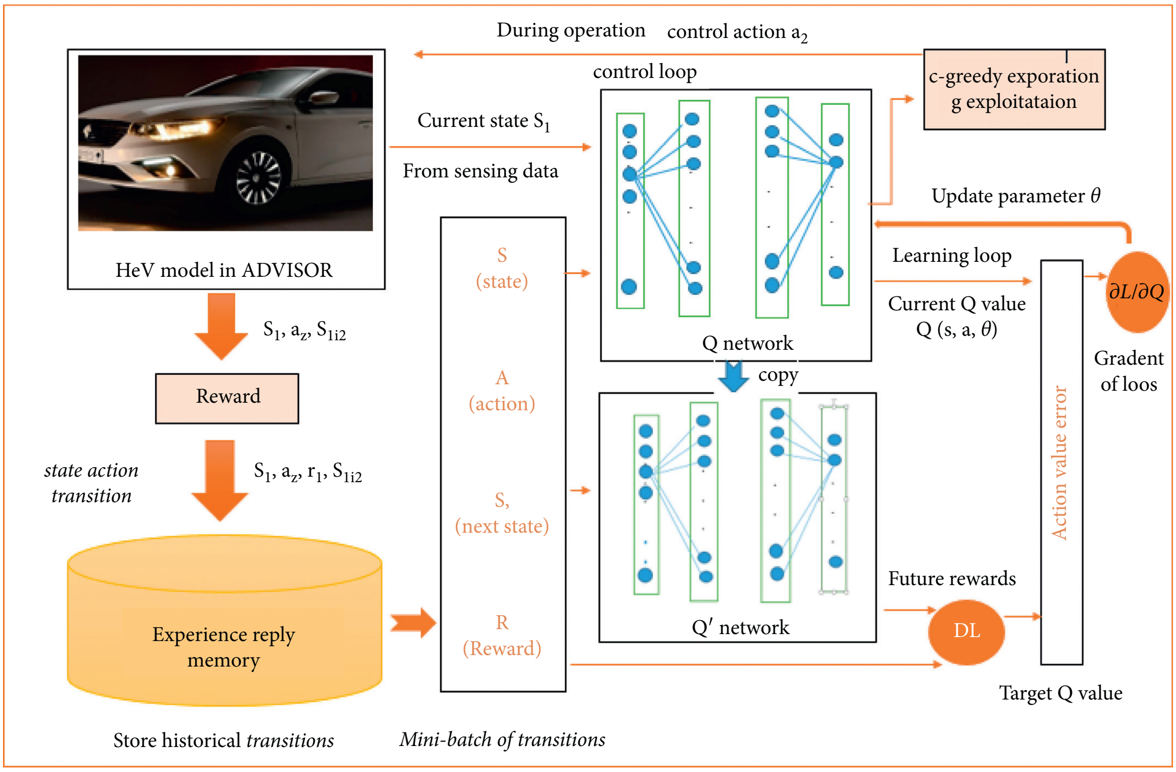

Figure 3: DRL-based control framework of [12] as an example of hybrid algorithms developed for energy management in HEVs.

Table 3: Machine learning implementation results for HESSs.

Strategy	Without transactions		With transactions		Gradient of loss	Action error	Mean square error
	Train	Test	Train	Test			
1	1500	500	1300	700	0.376	0.305	0.343
2	1700	300	1000	1000	0.360	0.450	0.303
3	1000	1000	1700	300	0.424	0.403	0.334
4	1300	700	1500	500	0.391	0.330	0.476
5	1500	500	1500	500	0.396	0.311	0.259

Deep reinforcement learning (DRL) has also proved to be an effective tool for designing an adaptive energy management strategy based on driving cycle data. In a study by Hu et al., they evaluated the performance of a DRL-based energy management strategy with online learning capability in comparison to a rule-based strategy [32]. The diagram of the DRL-based control strategy proposed in this study is illustrated in Figure 3. Moreover, the provided numerical results are illustrated in Table 3 and Figure 4.

According to Figure 3, there are two neural networks, a neural network for the nontransaction mode and a neural network for the transaction mode. Accordingly, Table 3 presents five different strategies for machine learning. In each strategy, the amount of data separation into two groups Train and Test (for each neural network) is specified. Also, three error indicators are presented after the implementation of the machine learning approach. The results in Table 3 and Figure 4 show that strategy 5 had the lowest error rate. This is because, in strategy 5, both neural networks are implemented in a similar way. Moreover, the highest error was reported for strategy 2, in which the data were evenly divided into two groups, train and test. Accordingly, it can be concluded that the proposed machine learning method can achieve the least mean square error in all strategies.

Real-time management under driving conditions must be achieved through the selection of the best adaptive strategies based on changes in the value function. In the case of hybrid algorithms, more data are needed for this purpose. In [33], researchers used a deep neural network (DNN) to train value functions offline and then used these functions in Q-learning for online control with adaptability to different transmission systems and driving conditions.

Xiong et al. developed a hybrid reinforcement learning-based real-time energy management system by combining the Q-learning algorithm with an online value function updating procedure. The product of this combination was a

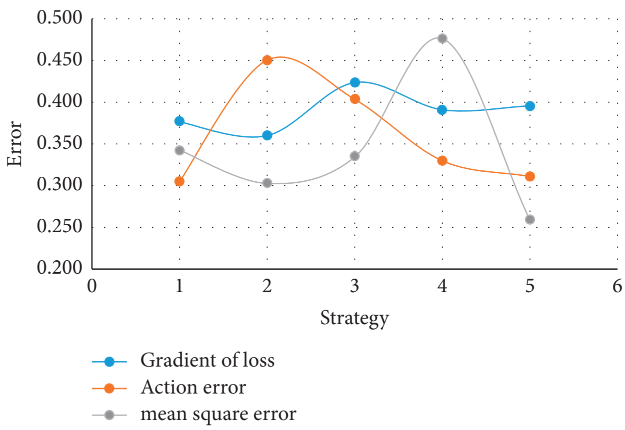

Figure 4: Different error indexes for all strategies.

real-time control system, where control measures can be updated in real time. They then validated this strategy by running simulations on a hardware operating system with batteries and super capacitors added to the circuit [34].

5. Conclusion

In machine learning, it is a broad discipline that has designed learning algorithms that can guide stimuli, detect spoken language, and discover hidden settings in data volume growth. Financial data are no exception. It works with data streams that capture company characteristics, corporate governance characteristics, audit reports, market data, and environmental variables. Machine learning algorithms detect complex patterns in this data, select the best variables to explain the variable, and use the appropriate combination of variables to predict the sample accurately. They are the keys to opening up big, growing data sources that can make better predictions and make smarter decisions. Machine learning has received a great deal of attention in the social sciences and denies the existing approaches to data analysis.

Although deep learning-based energy management strategies are superior to rule-based strategies, two issues limit their use in practice. The first issue is the limited computation power of the vehicle's CPU, which makes it necessary to install another computer on the vehicle to process the data. The second issue is collecting and storing the required information because deep learning requires substantial amounts of data to infer strategies for different driving conditions. However, with the development of network communication technologies and intelligent transportation systems (ITS), it is likely to become easier to use deep learning-based real-time energy management strategies in the future.

This paper provided a summary of reinforcement learning-based energy management strategies for Hybrid Energy Storage Systems (HESSs) of hybrid electric vehicles (HEVs). The paper started with an introduction to the problem of energy management in this field and how learning methods can be used to solve this problem. Then, the existing energy management schemes with multiple control objectives were discussed. In the end, the outlook for the further development of reinforcement learning-based energy management systems is as described.

A potentially rewarding line of research in this field is to work on the more efficient use of artificial intelligence techniques for energy management. It is also important to assess the theoretical and practical feasibility of the proposed methods through real-world testing and implementation as well as simulation. Considering the advancement of intelligent transportation systems, which also make it easier to gather traffic data, it might also be helpful to develop a method for adjusting strategies based on the behaviors of vehicles and infrastructure.

Data Availability

The data are available from the corresponding author on request.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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Research Article

Designing a Medical Supply Chain Network Considering the Risk of Supply and Flexible Production in Two-Stage Uncertain Conditions

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In the green supply chain approach, all the links that are put together to provide a product or service are considered, and strategic and operational decisions are made to increase the efficiency and effectiveness of the entire chain. At the same time, the environmental effects should be minimized. In this research, a nonlinear mixed-integer multiobjective model is developed to design a green closed-loop supply chain for medical products. In this supply chain, the echelons include supplier, manufacturer, warehouse, and customer in the forward supply chain and collection centers, repair services, and disposal centers in the reverse supply chain. In the proposed model, four objectives of customer satisfaction, environmental effects, supply risk, and total costs of the supply chain were considered. The developed model is implemented in a supply chain of medical products, and after optimizing the model, the main results including location and capacity of facilities, planning for flexible production, purchase of materials, service and maintenance plan, product transfer, and inventory level are determined and analyzed.

1. Introduction

Nowadays, many companies are trying to improve their business processes to meet customer expectations and satisfaction and be able to compete successfully in competitive environments. In this regard, supply chain management is one of the interesting and important issues among academic researchers and industry managers [1]. These processes begin with preparing raw materials and end with customer satisfaction by providing final products to customers. With the emergence of the concept of supply chain management and its recognition as an important competitive advantage, supply chain management has become an integral part of strategic decisions in each market. Supply chain management includes planning and managing the production/manufacture, transportation, and distribution of products, from the supply of raw materials to the delivery of finished products to customers [2]. In fact, supply chain management is looking for a solution to take these measures with the lowest cost as well as the highest productivity and efficiency in the face of a definite or uncertain environment.

Green supply chain management was introduced by the Michigan State University Industrial Research Association in 1996, which is a new management model for environmental protection [3, 4]. Studies show that supply chain management with emphasis on environmental protection has become one of the most critical issues for customers, shareholders, governments, employees, and global pressures.

A green supply chain often means reducing or not using harmful chemicals, which is a complete misconception because the parachain goes beyond this stage and considers all parts of an organization. In fact, the green supply chain is the result of linking economic goals with the organization's environmental goals. Minciardi et al. (2006) have designed the green supply chain intending to reduce waste materials. Jamshidi et al. [5] designed the green supply chain to reduce total supply chain costs, including raw material supply costs, maintenance costs, and transportation costs, as well as reducing emissions of carbon dioxide, carbon monoxide, and nitrous oxide. Chaabane et al. [6] designed a sustainable supply chain with the aim of reducing the production of toxic gases by pollutants, and in their work, sustainability through life cycle applications was considered. References [7, 8] have developed a model for the inventory system of a perishable commodity in the green supply chain.

References [9, 10] examined the chain of a perishable product with a fixed life cycle by an inventory-routing approach. In studies [10–13], waste materials are also considered while in studies [14] in 2013 and [9], products must be used for a fixed life before they break down. References [15–17] considered inventory routing with demand uncertainty.

Pishvaee et al. [18] have proposed a robust optimization model to consider the uncertainty of the closed-loop supply chain network design. They introduced a multilevel network that includes customers in the primary and secondary markets, collection, distribution, and disposal centers with limited capacity. There was uncertainty in the amount of returned products, demand for recycled products, and shipping costs. The model considers both recycling and landfill activities. Amin & Zhang [19] presented a closed-loop supply chain network model under uncertainty conditions. In this study, a network that includes manufacturing plants, customers, collection centers, and landfills was considered. The model includes two objective functions: minimizing costs and maximizing the use of environmentally friendly raw materials. Tehrani Soltani et al. (2015) designed a multiobjective, multiproduct, and multiperiod closed-loop supply chain.

References [20–22] proposed a mathematical model for a closed-loop supply chain with environmental effects.

Reference [23] presented a two-stage stochastic programming model for supply and production optimization in a revised logistic. Reference [24] developed an effective solution for a sustainable green supply chain network design model. Reference [25] presented a multiobjective model for a gold supply chain, considering the CO2 emissions. Reference [26] proposed a single stage to evaluate and optimize green supply chain performance in a closed-loop network.

Reference [27] proposed a two-dimensional mixed-integer programming model for the closed-loop network to minimize total cost and discontinuity delivery. Reference [28] has designed a MILP model to maximize the overall profitability of a closed network. References [29, 30] proposed a multiobjective model that is influenced by uncertain supply and demand. Reference [31] proposed a two-objective mathematical model for a pharmaceutical supply chain network design problem. The model helps to make several decisions about strategic issues, such as the opening of pharmaceutical manufacturing centers and distribution centers.

References [32–34] developed a MILP model for the design of the location/facility network. In the proposed model, CO2 emissions are achieved through the construction of network facilities, various production processes, and vehicle transportation. Reference [35] introduced a multicycle supply chain network design model in Turkey. Reference [36] developed a mixed-integer mathematical model for the network design of a pharmaceutical supply chain. The two objective functions of the presented model seek to minimize the total cost and the maximum unmet demand.

Reference [4] presented a green closed-loop supply chain model considering material discount conditions. The study included several periods and several products, and customer demand in the model was clearly defined. Reference [37] has provided an integer nonlinear programming model for supply chain network design with consideration of transportation cost reductions. A new hybrid algorithm called KAGA has been developed and implemented in the glass industry to optimize this mathematical model.

Reference [38] has designed a stable closed-loop supply chain for water reservoirs. For this purpose, a robust fuzzy optimization model has been developed. Sensitivity analysis is also performed on essential parameters of the mathematical model, and the results are evaluated.

Reference [39] designed a novel, reusable, half-face respirator in case conventional medical supply chain failed to meet demand. The authors provided a new collaboration between the hospital, physicians, medical school, and school of engineering. Reference [40] has developed a stochastic planning model for closed-loop supply chain network design. To optimize this model, the whale optimization algorithm (WOA) and particle swarm optimization (PSO) have been used as popular methods. In addition to this development, genetic algorithm (GA) and simulated annealing (SA) have been used as well-known metaheuristics for a comprehensive comparison.

After careful consideration of reviewed research items, the main contribution and the novelty of this paper can be summarized as follows:

(i) Incorporating the green supply chain network design for medical supply chain.

(ii) Optimizing all the fixed and variable costs, amount of carbon dioxide produced in the supply chain, costs of customer dissatisfaction, and total risk of the supply chain simultaneously.

(iii) Analyzing the effect of environmental issues in the green supply chain under different scenarios.

2. Methodology

Considering the issues raised in the field of the green supply chain, the main purpose of this study is to continue the research conducted by other researchers who, leaving aside some of the assumptions that facilitate and limit supply chain issues, present their proposed models. The problem should be developed in such a way that its assumptions are more compatible with real-world conditions, so the purpose of this study is to develop a multiobjective green supply chain model that includes supplier, manufacturer, and customer levels in the forward supply chain and collection, recycling, and disposal centers in the reverse supply chain.

In this study, the raw material supplier utilized quantitative discount assumptions to inspect the influence of these tactical decisions on the architecture of the green supply chain network. The proposed model's goals include minimizing overall network costs, CO2 emissions, customer discontent, and material supply risk.

2.1. Model Assumptions. We propose a multiproduct, multiperiod, and multiobjective green closed-loop supply chain network design model. Available locations for production, recovery, distribution, and collection centers are available.

(i) Customers' demands are different, and they must be completely satisfied in each period.
(ii) Suppliers and supply risk are considered.
(iii) Customer dissatisfaction is considered based on a lack of response to the demand.
(iv) Inventory holding costs are considered for production, distribution, and collection centers.
(v) The amount of discount in each supplier and the minimum order quantity are known.
(vi) Factory facilities (production site), warehouses, and collection centers all have specific capacities.
(vii) The two main sources of raw materials are supplied by suppliers: green and nongreen raw materials
(viii) In each period, only one supplier can be selected to supply each item. The discount amount applies to all products.

Considering the above assumptions, the important decisions that are made in the proposed mathematical model are as follows:

(i) Determining the locations of new facilities.
(ii) Assigning customers to facilities.
(iii) Determining shipping mode.
(iv) Determining the capacity level of each facility.
(v) Determining the quantity of raw materials purchased from suppliers.
(vi) Determining the amount of production in production centers.
(vii) Determining the inventory level of products in production, distribution, and collection centers.
(viii) Determining the amount of flow shipped between network facilities.

2.2. Mathematical Model. In this research, a four-echelon closed-loop supply chain network is considered. The forward network includes suppliers of semifinished products, production centers, warehouses (which store and deliver the products to customers), and customers. The reverse network also includes the collection centers, repair centers, and disposal centers.

In the forward flow path, the supplier sends the required semifinished product to the warehouses. After assembly, the parts are sent to the warehouse for sale in production centers. After receiving products from production centers, distribution centers (warehouses) send them to the customers. The customer submits initial service request (overhaul) to return the product, and the product is sent to the repair center (factory) by the collection center. In the repair center, after inspecting the products, those products that can be repaired are sent to the distribution centers (warehouse) after repair, and then the overhauled device is returned to its specific customer.

2.3. Sets, Parameters, and Decision Variables. According to the objectives, assumptions, and characteristics of the problem, for the proposed model, sets, parameters, and decision variables were defined as follows. Decision variables

2.4. Mathematical Model Formulation. The proposed mathematical model is divided into two sections, the first of which contains the objective functions and the second of which contains the constraints. In the section of objective functions, f1 denotes all fixed and variable costs (creating facilities, costs of processes in each facility, and moving between facilities), f2 is the amount of carbon dioxide produced in the supply chain flow due to processes and transfers between the facility and the delivery of products to customers, f3 represents the costs of customer dissatisfaction with the company, and f4 minimizes the total risk of the supply chain. (Table 1)

$$\operatorname{Min} f_1 = C1 + C2 + C3 + C4, \tag{1}$$

$$C1 = \sum_{f\in F} f_f' x_f' + \sum_{w\in W} f_w'' x_w'' + \sum_{i\in I} f_i''' x_i''', \tag{2}$$

Table 1: Model decision variables.

Decision variables		
f	Factories	$(f = 1, 2, \ldots, F)$
w	Warehouses	$(w = 1, 2, \ldots, W)$
c	Customers	$(c = 1, 2, \ldots, C)$
i	Collection centers	$(i = 1, 2, \ldots, I)$
t	Planning courses	$(t = 1, 2, \ldots, T)$
s	Intended scenarios in the model	$(s = 1, 2, \ldots, S)$
p	Supplied products	
su	Primary and semifinished parts suppliers	$(su = 1, 2, \ldots, \mathrm{SU})$
b	Piece/raw material	$(b = 1, 2, \ldots, B)$
tsu	Supplier relocation options (vehicle)	$(tsu = 1, 2, \ldots, \mathrm{TSU})$
tw	Options for moving between warehouses	$(tw = 1, 2, \ldots, \mathrm{TW})$
tk	Customer transferring options (vehicle)	$(tk = 1, 2, \ldots, \mathrm{TK})$
ti	Displacement options between disassembly centers	$(ti = 1, 2, \ldots, \mathrm{TI})$
tf	Factory transferring options (vehicle)	$(tf = 1, 2, \ldots, \mathrm{TF})$
$d_{c,s,p,t}$	Customer demand in each scenario for each product	
$\mathrm{BC}_{b,su,s}$	Market prices for each supplier in each scenario	
$\mathrm{voff}_{su,b}$	Purchase volume to offer a discount for each supplier	
$\mathrm{CS}_{su,b}$	Part supply capacity for each supplier	
$\mathrm{BO}_{b,p}$	Parts needed to make any product	
$\mathrm{HVM}_{su,s}$	Maximum discount available	
$\mathrm{Risk}_{su,s}$	Material supply risk from the supplier	
$\mathrm{SC}_{s,c}$	Cost of shortage dissatisfaction	
pc_s	Probability of occurrence of scenario s	
$t1_{f,w}^{tf}$	Cost of moving a unit of products from factory f to warehouse w	
$t2_{w,c}^{tw}$	Cost of moving a unit of products from the warehouse w to the customer c	
$t3_{c,i}^{tk}$	Cost of transportation in order to collect products and transfer them from customer c to disassembly center i	
$t4_{i,f}^{ti}$	Cost of moving a unit of products in order to transfer it from the collection dismantling center i to the factory f	
$t5_{su,w}^{tsu}$	Cost of moving a unit of products in order to transfer it from the supplier center su to the warehouse w	
$\varepsilon 1_{f,w}^{tf}$	Rates of transportation of products from factory f to warehouse w	
$\varepsilon 2_{w,c}^{tw}$	Rates of transportation of products from the warehouse w to the customer c	
$\varepsilon 3_{c,i}^{tk}$	Product collection rate and transfer from customer c to disassembly center i	
$\varepsilon 4_{i,f}^{ti}$	Rate of transportation of products from the collection dismantling center i to the factory f	
$\varepsilon 5_{su,w}^{tsu}$	Rates of transportation of products from the supplier su to warehouse w	
$m1_{f,w}$	Distance between factory f and warehouse w	
$m1_{w,c}$	Distance between warehouse w and customer c	
$m3_{c,i}$	Distance between customer c and disassembly center i	
$m4_{i,f}$	Distance between collection dismantling center I and factory f	
$m5_{su,w}$	Distance between supplier and warehouse	
$f_f^{\prime}$	Fixed cost for factory reconstruction f	
$f_{\prime\prime}^{\prime w \prime}$	Fixed cost for warehouse reconstruction w	
$f^{\prime i}$	Fixed cost for reconstruction of the collection dismantling center i	
$v1_{f,p}$	Variable cost of production per unit of product p in factory f	
$v2_{w,p}$	Variable cost of production per unit of product p in stock w	
$v3_{c,p}$	Variable cost of collecting returned products p of customer c	
$v4_{i,p}$	Variable cost of collection center products p	
$v5_{w,b}$	Variable cost of products restoration p	
$Ca_{f,p}$	Maximum factory production capacity f to produce product p	
$Cb_{w,p}$	Maximum warehouse processing capacity w for product warehouse p	
$Cc_{i,p}$	Maximum center i disassembly capacity for product p	
$Cd_{f,p}$	Maximum factory reconstruction capacity f for product p	
$Cm_{w,b}$	Maximum storage capacity w to hold part b	
qr_b	The lowest percentage of each unit of parts returned by a customer (product)	
$qd_{p,t}$	Minimum percentage of product units to be shipped from a disassembly center	
$e1_{f,p}$	The amount of carbon dioxide released per unit of product produced at the plant f	
$e2_{w,p}$	The amount of carbon dioxide released per shipment per unit of stock w	
$e3_{i,p}$	The amount of carbon dioxide released per disassembly of each product unit at the center i	
$e4_{f,p}$	The amount of carbon dioxide released per unit of product regenerated at the factory f	
$e5_{w,b}$	The amount of carbon dioxide released per shipment for per unit b in storage w	

Table 1: Continued.

$et1^{tf}$	The amount of carbon dioxide released to move products between factory f and warehouse w with vehicle tf
$et2^{tw}$	The amount of carbon dioxide released to move products between warehouse w and customer c by a tw-type vehicle
$et3^{tk}$	The amount of carbon dioxide released to move the product between customer c and the disassembly center i with vehicle tk
$t4^{ti}$	The amount of carbon dioxide released to move products between the collection dismantling center i and plant f by vehicle ti
$et5^{tsu}$	The amount of carbon dioxide released to move the part between the warehouses w and the suppliers su with vehicle tsu
k_b	Precautionary storage of parts
$\delta^{\mathbf{tsu}}_{\mathbf{su,w,b,s,t}}$	Number of pieces b purchased from supplier su and transferred to warehouse w by vehicle tsu in scenario s and period t
$\omega^{\mathbf{tw}}_{\mathbf{w,f,b,s,t}}$	The number of pieces b sent from warehouse w to factory using vehicle tw in scenario s and in period t
$\alpha^{\mathbf{tf}}_{\mathbf{f,w,p,s,t}}$	Number of products p produced from factory f and transferred to warehouse w using vehicle tf in scenario s and in period t
$\beta^{\mathbf{tw}}_{\mathbf{w,c,p,s,t}}$	Number of products p sent from warehouse w to customer c using vehicle tw in scenario s and period t
$\gamma^{\mathbf{tk}}_{\mathbf{c,i,p,s,t}}$	The number of products p collected from customer c to the disassembly center i in scenario s and in period t
$\theta^{\mathbf{ti}}_{\mathbf{i,w,b,s,t}}$	The number of products p disassembled that are transferred from center i to factory f using vehicle ti in scenario s and in period t
$\mathbf{MS_{s,b,t,w}}$	Inventory w for each piece b in period t in scenario s
$\mathbf{PS_{s,p,t,w}}$	Inventory w for each product p in period t in scenario s
$\mathbf{sge_{c,p,s,t}}$	Number of products shortages p for each customer c in each period t and for each scenario s
$\mathbf{r1_{s,b,t,su}}$	Cost of parts purchased in different periods from suppliers
$\mathbf{rbb_{s,b,t}}$	Total discounts received from purchases in different periods
$\mathbf{vm_{su,b,s,t}}$	Percentage of discounts offered by suppliers for each type of piece in each period and scenario
$\mathbf{x'_f}$	1 when factory f is active and 0 otherwise
$\mathbf{x''_w}$	1 when warehouse w is active and 0 otherwise
$\mathbf{x'''_i}$	1 when center i is active and 0 otherwise

$$C2 = \sum_{s\in S} p_s \sum_{f\in F}\sum_{p\in P} v1_{f,p} \times \sum_{w\in W}\sum_{tf\in TF} \alpha^{tf}_{f,w,p,s,t} + \sum_{i\in I}\sum_{tk\in \mathrm{TK}} \gamma^{tk}_{c,i,p,s,t} + \sum_{s\in S} p_s \sum_{p\in P}\sum_{i\in I} v4_{i,p} \times \sum_{c\in C}\sum_{tk\in \mathrm{TK}} \gamma^{tk}_{c,i,p,s,t} + \sum_{s\in S} p_s \sum_{p\in P}\sum_{i\in I} v5_{w,b} \times \sum_{i\in I} p_s \sum_{ti\in TI} \theta^{ti}_{i,w,b,s,t} + \sum_{s\in S} p_s \sum_{p\in P}\sum_{w\in W} v2_{w,p} \times \sum_{c\in C}\sum_{tw\in TW} \beta^{tw}_{w,c,p,s,t} + \sum_{s\in S} p_s \sum_{p\in P}\sum_{c\in C} v3_{c,p}, \tag{3}$$

$$C3 = \sum_{s\in S} p_s \sum_{p\in P}\sum_{f\in F}\sum_{w\in W}\sum_{tf\in \mathrm{TF}} t1^{tf}_{f,w} \times \alpha^{tf}_{f,w,p,s,t} + + \sum_{s\in S} p_s \sum_{p\in P}\sum_{c\in C}\sum_{i\in I}\sum_{tk\in \mathrm{TK}} t3^{tk}_{c,i} \times \gamma^{tk}_{c,i,p,s,t} + + \sum_{s\in S} p_s \sum_{b\in B}\sum_{w\in W}\sum_{su\in \mathrm{SU}}\sum_{tsu\in \mathrm{TSU}} t5^{tsu}_{su,w} \times \delta^{tsu}_{su,w,b,s,t} \sum_{s\in S} p_s \sum_{p\in P}\sum_{w\in W}\sum_{c\in C}\sum_{tw\in \mathrm{TW}} t2^{tw}_{w,c,p,s,t} \times \beta^{tw}_{w,c,p,s,t} \sum_{s\in S} p_s \sum_{p\in P}\sum_{i\in I}\sum_{f\in F}\sum_{ti\in \mathrm{TI}} t4^{ti}_{i,f} \times \beta^{ti}_{i,w,b,s,t}, \tag{4}$$

$$C4 = \sum_{s\in S} p_s \sum_{su\in SU}\sum_{b\in B}\sum_{t\in T} r1_{s,b,t,su}, \tag{5}$$

$$\operatorname{Min} f_2 = \mathrm{ERP} + \mathrm{EHA} + \mathrm{EDC} + \mathrm{ERM} + \mathrm{ETR}, \tag{6}$$

$$\mathrm{EPR} = \sum_{f\in F} e1_f \sum_{w\in W}\sum_{tf\in TF} \alpha^{tf}_{f,w,p,s,t}, \tag{7}$$

$$\mathrm{EHA} = \sum_{w\in W} e2_w \sum_{c\in C}\sum_{tw\in \mathrm{TW}} \beta^{tw}_{w,c,p,s,t}, \tag{8}$$

$$\mathrm{EDC} = \sum_{c\in C} e3_i \sum_{i\in I}\sum_{tk\in \mathrm{TK}} \gamma^{tk}_{c,i,p,s,t}, \tag{9}$$

$$\mathrm{ERM} = \sum_{i\in I} e4_f \sum_{i\in I}\sum_{ti\in \mathrm{TI}} \theta^{ti}_{i,w,p,s,t}, \tag{10}$$

$$\begin{aligned}\mathrm{ETR} = {} & \sum_{tf\in \mathrm{TF}} et1^{tf} \sum_{p\in P}\sum_{f\in F}\sum_{w\in W} \varepsilon 1^{tf}_{f,w} \times m1_{f,w} + \sum_{tw\in \mathrm{TW}} et2^{tw} \sum_{p\in P}\sum_{w\in W}\sum_{c\in C} \varepsilon 2^{tw}_{w,c} \times m2_{w,c} \times \beta^{tw}_{w,c,p,s,t} \times m3_{c,i} \times \gamma^{tk}_{c,i,p,s,t} \\ & + \sum_{ti\in TI} et4^{ti} \sum_{p\in P}\sum_{i\in I}\sum_{f\in F} \varepsilon 4^{ti}_{i,f} \times m4_{i,f} \times \theta^{ti}_{i,w,b,s,t} + \sum_{ti\in \mathrm{TI}} et5^{tsu} \sum_{p\in P}\sum_{i\in I}\sum_{f\in F} \varepsilon 5^{tsu}_{su,w} \times m5_{su,w} \times \delta^{tsu}_{su,w,b,s,t} \\ & + \sum_{tf\in TF} et3^{tk} \sum_{p\in P}\sum_{c\in C}\sum_{i\in I} \varepsilon 3^{tk}_{c,i},\end{aligned} \tag{11}$$

$$\min f_3 = \sum_{s\in S} p_s \sum_{c\in C}\sum_{p\in P}\sum_{t\in T} \mathrm{SC}_{s,c} \times \mathrm{SGE}_{c,s,p,t}, \tag{12}$$

$$\min f_4 = \sum_{s\in S} p_s \sum_{su\in \mathrm{SU}}\sum_{t\in T} Wz_{su,s,t} \times \mathrm{Risk}_{su,s}. \tag{13}$$

As mentioned earlier, the total cost in (1)–(5) consists of TotalFixedCost (C1) or fixed costs incurred throughout the chain from supplier to customer; TotalVariableCost (C2), which is the sum of the variable costs of the chain; TotalTransportationCost (C3), costs incurred due to handling and transfers; and TotalBuyingCost (C4), costs of purchasing the parts needed to manufacture the products.

The second objective function in (6)–(11) contains the total cost of carbon dioxide emissions in the raw materials, which is demonstrated with EPR, in production (EHA), in holding and transferring (EDC), and in collecting (ERM). Moreover, the carbon dioxide emissions due to reconstructions and transportation are shown with ETR. In the third objective function (12), the total costs that enter the system due to customer dissatisfaction are minimized. In the fourth objective function (13), the total costs due to the risk of raw material supply are minimized.

$$\sum_{w\in W}\sum_{tf\in TF} \alpha^{tf}_{f,w,p,s,t} \le Ca_{f,p} xa_f \forall f \in F, \quad p\in P,\ s\in S,\ t\in T, \tag{14}$$

$$\sum_{f\in F}\sum_{tf\in \mathrm{TF}} \alpha^{tf}_{f,w,p,s,t} \le Cb_{w,p} xb_w \forall w \in W, \quad p\in P,\ s\in S,\ t\in T, \tag{15}$$

$$\sum_{c\in C}\sum_{tw\in \mathrm{TW}} \beta^{tw}_{w,c,p,s,t} \le \sum_{f\in F}\sum_{tf\in \mathrm{TF}} \alpha^{tf}_{f,w,p,s,t} \forall w \in W, \quad p\in P,\ s\in S,\ t\in T, \tag{16}$$

$$\sum_{w\in W}\sum_{tw\in \mathrm{TW}} \beta^{tw}_{w,c,p,s,t} \le d_{c,s,p,t} \forall c\in C, \quad p\in P,\ s\in S,\ t\in T, \tag{17}$$

$$\sum_{i\in I}\sum_{tk\in \mathrm{TK}} \gamma^{tk}_{c,i,p,s,t} \le d_{c,s,p,t}\ \forall c\in C, \quad t\in T,\ p\in P,\ s\in S,\ t\in T, \tag{18}$$

$$\sum_{c\in C}\sum_{tk\in \mathrm{TK}} \gamma^{tk}_{c,i,p,s,t} \le Cc_{i,p} xd_i \forall i\in I, \quad p\in P,\ s\in S,\ t\in T, \tag{19}$$

$$\sum_{i\in I}\sum_{tk\in \mathrm{TK}} \gamma^{tk}_{c,i,p,s,t} \ge qd_{p,t} \times d_{c,s,p,t} \forall c\in C, \quad p\in P,\ s\in S,\ t\in T, \tag{20}$$

$$\sum_{w\in W}\sum_{ti\in \mathrm{TI}} \theta^{ti}_{i,w,b,s,t} \ge qr_b \times \sum_{tk\in \mathrm{TK}}\sum_{c\in C} \gamma^{tk}_{c,i,p,s,t} \times bo_{b,p} \forall i\in I, \quad p\in P,\ b\in B,\ s\in S,\ t\in T, \tag{21}$$

$$\sum_{i\in I}\sum_{ti\in \mathrm{TI}} \theta^{ti}_{i,w,b,s,t} + \sum_{su\in SU}\sum_{tsu\in TSU} \delta^{tsu}_{su,w,b,s,t} \le Cm_{w,b} \times x''_w \forall w\in W, \quad b\in B,\ s\in S,\ t\in T, \tag{22}$$

$$\sum_{w\in W}\sum_{su\in \mathrm{SU}}\sum_{tsu\in \mathrm{TSU}} \delta^{tsu}_{w,su,b,s,t} \times Wz_{su,s,t} \geq \sum_{w\in W}\sum_{tw\in TW}\sum_{w\in W}\sum_{p\in P} \beta^{tw}_{w,c,p,s,t} \times bo_{b,p} \forall t \in T, \quad b \in B,\ s \in S, \tag{23}$$

$$\begin{gathered}\sum_{tsu\in \mathrm{TSU}}\sum_{su\in \mathrm{SU}}\sum_{w\in W} Xe_{su,b,s,t} \times Vm_{su,b,s,t} \times \delta^{tsu}_{w,su,b,s,t} \times \mathrm{BC}_b = rbb_{s,b,t} \forall b \in B,\\ b \in B,\ t \in T,\ s \in S,\ r1_{s,b,su} \geq 0\, \forall su \in \mathrm{SU},\ t \in T,\ s \in S,\end{gathered} \tag{24}$$

$$\sum_{tw\in \mathrm{TW}} \omega^{tw}_{w,f,b,s,t} \leq \sum_{su\in \mathrm{SU}}\sum_{tsu\in \mathrm{TSU}} \delta^{tsu}_{w,su,b,s,t}, \quad \forall w \in W,\ f \in F,\ t \in T,\ b \in B,\ s \in S, \tag{25}$$

$$\frac{\sum_{b\in B}\sum_{tsu\in \mathrm{TSU}}\sum_{w\in W} \delta^{tsu}_{w,su,b,s,t}}{\mathrm{voff}_{su,b}} \geq Xe_{su,b,s,t}, \quad \forall su \in \mathrm{SU},\ t \in T,\ b \in B,\ s \in S, \tag{26}$$

$$\left(Xe_{su} \times Vm_{su,b,s,t} + 1\right) \times \sum_{tsu\in \mathrm{TSU}}\sum_{w\in W} \delta^{tsu}_{w,su,b,s,t} \times \mathrm{BC}_b = r1_{s,b,ts,u} \forall t \in T, \quad b \in B,\ s \in S, \tag{27}$$

$$\sum_{tsu\in \mathrm{TSU}}\sum_{su\in \mathrm{SU}}\sum_{w\in W} Xe_{su,b,s,t} \times Vm_{su,b,s,t} \times \delta^{tsu}_{w,su,b,s,t} \times \mathrm{BC}_b = rbb_{s,b,t}, \quad \forall b \in B,\ b \in B,\ t \in T,\ s \in S, \tag{28}$$

$$r1_{s,b,su} \geq 0, \quad \forall su \in \mathrm{SU},\ t \in T,\ s \in S, \tag{29}$$

$$Vm_{su,b,s,t} \geq \mathrm{HVM}_{su,s} \times Wz_{su,s,t}, \quad \forall su \in \mathrm{SU},\ t \in T,\ b \in B,\ s \in S, \tag{30}$$

$$Vm_{su,b,s,t} \leq 0, \quad \forall su \in \mathrm{SU},\ t \in T,\ b \in B,\ s \in S, \tag{31}$$

$$\frac{\sum_{b\in B}\sum_{tsu\in \mathrm{TSU}}\sum_{w\in W} \delta^{tsu}_{su,w,b,s,t}}{\mathrm{voff}_{su,b}} - 1 \leq Xe_{su,b,s,t}, \quad \forall su \in \mathrm{SU},\ t \in T,\ b \in B,\ s \in S, \tag{32}$$

$$\mathrm{PS}_{p,w,s,t} - 1 + \sum_{f\in F}\sum_{tf\in \mathrm{TF}} \alpha^{tf}_{f,w,p,s,t} - \sum_{c\in C}\sum_{tw\in \mathrm{TW}} \beta^{tw}_{W,c,p,s,t} = \mathrm{PS}_{p,w,s,t}, \quad \forall w \in W,\ t \in T,\ p \in P,\ s \in S, \tag{33}$$

$$\mathrm{MS}_{b,w,s,t} - 1 + \sum_{su\in \mathrm{SU}}\sum_{tsu\in \mathrm{TSU}} \delta^{tsu}_{su,w,b,s,t} - \sum_{f\in F}\sum_{tw\in \mathrm{TW}} \omega^{tw}_{w,c,p,s,t} = \mathrm{MS}_{b,w,s,t}, \quad \forall w \in W,\ t \in T,\ b \in B,\ s \in S, \tag{34}$$

$$\sum_{tsu\in TSU}\sum_{w\in W} \delta^{tsu}_{w,su,b,s,t} \times \mathrm{Risk}_{su,s} \leq Cs_{su,b,s}, \quad \forall su \in \mathrm{SU},\ t \in T,\ b \in B,\ s \in S, \tag{35}$$

$$Wz_{su,s,t} \times \mathrm{Risk}_{su,s} \leq \mathrm{RF}, \quad \forall su \in \mathrm{SU},\ t \in T,\ s \in S, \tag{36}$$

$$d_{c,s,p,t} - \sum_{w\in W}\sum_{tw\in \mathrm{TW}} \beta^{tw}_{w,c,p,s,t} = \mathrm{SGE}_{c,s,p,t}, \quad \forall c \in C,\ t \in T,\ p \in P,\ s \in S, \tag{37}$$

$$\sum_{w\in W} \mathrm{MS}_{b,w,s,t} \leq k_{b,s}, \quad \forall t \in T,\ b \in B,\ s \in S, \tag{38}$$

$$\alpha^{tf}_{f,w,p,s,t}, \beta^{tw}_{w,c,p,s,t}, \lambda^{tk}_{c,i,p,s,t}, \theta^{ti}_{i,w,b,s,t}, \delta^{tsu}_{w,su,b,s,t} \geq 0, \tag{39}$$

$$x'_f, x''_w, x'''_i \in \{0, 1\}. \tag{40}$$

In (14), any quantity of product p which is considered for transfer from any factory f to any warehouse w through any transport option tf must be less than or equal to the maximum capacity of the relevant factory. In (15), the total number of units of product to be stored in the warehouse through each shipping option must be less than or equal to the maximum warehouse capacity. In (16), the total number of product units from one warehouse to each customer exported through each shipping option must be less than or equal to the total amount of product units that enter the relevant warehouse from each factory through each shipping option.

Moreover, in (17), the total number of product units distributed from each warehouse through shipping options to meet customer demand must be greater than or equal to that customer demand. Equation (18) considers the total number of product units that must be collected from the customer and transported to an assembly center with a shipping option, which must be less than the customers' demand.

Equation (19) calculates the total number of product units that must be collected from the customer and transported to an assembly center with each transportation option, which must be less than the capacity of the relevant center. Equation (20) also limits the total number of product units that must be shipped via each shipping option from one customer to each DC and must be greater than or equal to the minimum percentage of product returns from the total number of relevant customers' requests. In (21), the total number of product units that are sent from each assembly center to each factory through each shipping option must be greater than or equal to the minimum percentage of product units, which must be greater than the total number of product units imported to the assembly center.

In (22), the total number of units of the product that can be produced, which must be sent from each assembly center to a factory by any means of transportation, must be less than or equal to the maximum reproduction capacity of the relevant factory. Equation (23) specifies the minimum raw materials required to manufacture and supply the products required by the market. Equation (24) specifies the parts required to manufacture products according to the list of parts, and according to that, the parts are transferred to the production unit. In (25), the quantity of each type of part sent to the production unit must be less than the amount purchased for that type of part.

Equations (26) and (32) specify which supplier has offered a discount on the purchase of the part. Equation (27) calculates the cost of purchasing parts, considering account discounts. Equation (28) calculates the number of discounts received by the company. Equation (29) states that the cost of purchasing parts must be positive. In (30), each supplier has a limit for offering discounts, which applies to the conditions of suppliers in offering discounts. Equation (31) specifies that the percentage of discounts must be negative.

Equations (32) and (35) calculate the supply risk, and Equation (33) calculates the inventory of products in each period and each scenario. Equation (34) calculates inventory of parts in each period and each scenario. Equation (35) is related to supply risk calculations. Buying a large number is riskier. Since each supplier has the capacity or may supply a certain number of products based on profit and loss, it is necessary to consider some risks for the supply of materials. This equation calculates the supply risk of the component assembly. In (36), it is noted that the risk level of suppliers should not be more than a certain limit. Equation (37) calculates the level of customer dissatisfaction due to nonresponse to needs. Equation (38) keeps the stock of inventory parts above the contingency reserve. This issue is examined in each period and scenario. Equation (39) guarantees the values greater than zero for the variables of transmission volume in the network, and (40) also specifies binary values for the establishment of facilities (factories, warehouses, and collection centers).

2.5. Solution Procedure. The general form of a multiobjective problem is as follows:

$$\begin{aligned} &\operatorname{Max} f_1(x), f_2(x), f_3(x), \ldots, \\ &s.t.\colon x \in S, \end{aligned} \tag{41}$$

where x is the vector of the decision variables; $f_1(x)$, $f_2(x)$, and $f_3(x)$ are the objective functions; and S is the answer space. In the weighting method, the objective functions are usually scaled first, and then each weight is assigned a weight. The general form of the weighting method to solve the problem is as follows:

$$\operatorname{Max} \mathrm{ZW} = \sum_{i=1}^{p} w_i \frac{f_i}{f_i^*}, \tag{42}$$

$$S.T. \begin{cases} 0 \le w_i \le 1, \\ \sum_{i=1}^{p} w_i = 1, \\ \text{model constraints}, \end{cases} \tag{43}$$

where the weight of each of the objective functions is predetermined, and the optimal value of each of the objective functions can be found by using single-objective optimization. In order to better demonstrate the solution procedure, the steps of optimizing the proposed mathematical model are provided in Figure 1.

3. Numerical Results

Based on the amount of customer demand and, in the other dimension, the ability to provide funding or lack of demand, the warehouse and production space are selected, and then production planning and inventory control are specified. According to the model's assumptions, each customer must have received their demand. For example, in the first scenario, the first customer has a demand for the first product, and in the second scenario, there is a demand for the second product. The supply chain is being planned to meet the demand, and the manufactured products are sent from warehouses. Moreover, the number of first type products sent from the first warehouse is equal to the total inputs of this product from the factory to the warehouse, and also according to the list of parts, parts have been purchased. Details of purchasing parts, parts sent to production, products produced, products sent to customers, returned products, and repaired products are as shown in Tables 2–7.

As mentioned earlier, two-stage stochastic programming is applied, and the best solution based on the conditions of the scenarios and their probabilities is obtained. Accordingly, we would decide whether to open or close a facility based on the characteristics of each scenario, but in two-stage programming, a decision is first made on the nature of

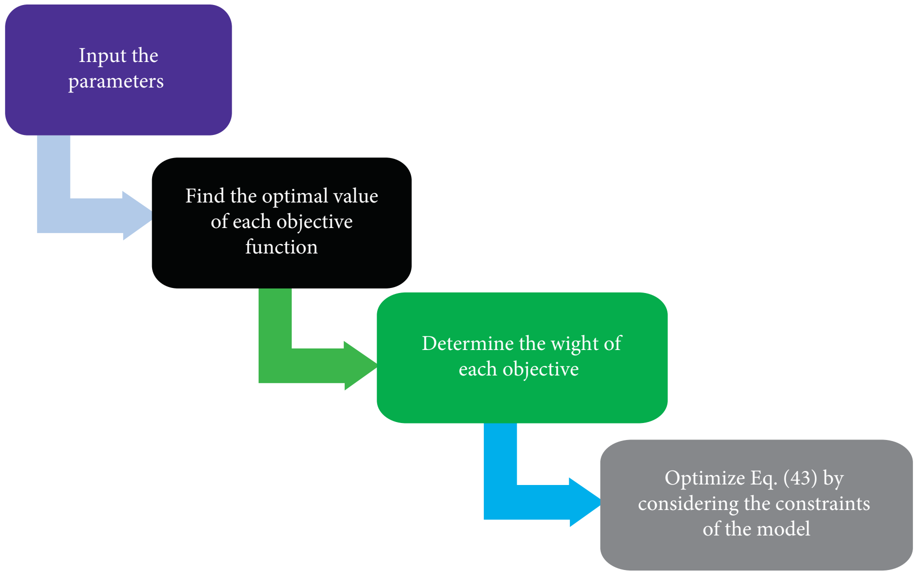

Figure 1: The proposed solution procedure.

Table 2: Values of the parameter $\delta^{tsu}_{su,w,b,s,t}$.

Supplier	Warehouse	Type of transport	Type of piece	Scenario	Periods				
					Period 1	Period 2	Period 3	Period 4	Period 5
su1-RO	First warehouse	Vehicle type 2	b 1-P	1	3	0	6	3	4
su1-RO	First warehouse	Vehicle type 2	b 1-P	2	6	9	2	0	5
su1-RO	First warehouse	Vehicle type 2	b 1-P	1	0	5	9	3	7
su1-RO	First warehouse	Vehicle type 2	b 2-V	2	6	4	5	4	6
su1-RO	First warehouse	Vehicle type 2	b 2-V	1	2	0	1	4	7
su1-RO	First warehouse	Vehicle type 2	b 3-M	2	3	1	8	4	5
su1-RO	First warehouse	Vehicle type 2	b 3-M	1	2	5	2	2	3
su1-RO	Second warehouse	Vehicle type 2	b 1-P	2	7	7	1	2	0
su1-RO	Second warehouse	Vehicle type 2	b 1-P	1	2	4	7	2	8
su1-RO	Second warehouse	Vehicle type 2	b 2-V	2	9	2	1	4	6
su1-RO	Second warehouse	Vehicle type 2	b 2-V	1	6	8	4	2	4
su1-RO	First warehouse	Vehicle type 1	b 3-M	2	9	9	1	6	8
su1-RO	First warehouse	Vehicle type 1	b 3-M	1	4	1	6	3	6
su1-RO	First warehouse	Vehicle type 1	b 3-M	2	1	7	2	2	5
su1-RO	First warehouse	Vehicle type 1	b 3-M	1	2	1	6	5	7
su1-RO	First warehouse	Vehicle type 1	b 3-M	2	10	8	9	2	0

Table 3: Values of the parameter $\omega^{tw}_{w,f,b,s,t}$.

Warehouse	Factory	Type of transport	Type of piece	Scenario	Periods				
					Period 1	Period 2	Period 3	Period 4	Period 5
First warehouse	First factory	Vehicle type 2	b 3-M	1	1	3	3	10	8
First warehouse	First factory	Vehicle type 2	b 1-P	2	3	1	2	10	8
First warehouse	First factory	Vehicle type 2	b 1-P	1	4	10	1	8	4
First warehouse	First factory	Vehicle type 2	b 2-V	2	8	1	6	5	7
First warehouse	First factory	Vehicle type 2	b 2-V	1	1	9	1	0	4
First warehouse	First factory	Vehicle type 2	b 3-M	2	0	6	8	3	6
First warehouse	First factory	Vehicle type 2	b 3-M	1	0	10	5	8	9
First warehouse	First factory	Vehicle type 2	b 1-P	2	2	10	5	1	5
Second warehouse	First factory	Vehicle type 2	b 2-V	1	10	6	8	9	3
Second warehouse	First factory	Vehicle type 2	b 3-M	2	6	8	7	7	3
Second warehouse	First factory	Vehicle type 2	b 1-P	1	1	5	3	4	5
Second warehouse	First factory	Mean type 2	b 1-P	2	5	1	8	4	2
Second warehouse	First factory	Vehicle type 2	b 2-V	1	3	9	6	7	4
Second warehouse	First factory	Vehicle type 2	b 2-V	2	7	7	8	0	4
Second warehouse	First factory	Vehicle type 2	b 3-M	1	6	5	2	0	1
Second warehouse	First factory	Vehicle type 2	b 3-M	2	1	7	0	4	2

Table 4: Values of the parameter $\alpha^{tf}_{f,w,s,t}$.

Factory	Warehouse	Type of transport	Product type	Scenario	Periods				
					Period 1	Period 2	Period 3	Period 4	Period 5
First factory	First warehouse	Vehicle type 1	First product	1	3	3	9	10	5
First factory	First warehouse	Vehicle type 1	First product	2	2	10	1	9	4
First factory	First warehouse	Vehicle type 1	Second product	1	3	8	7	4	4
First factory	First warehouse	Vehicle type 1	Second product	2	1	2	6	7	4
First factory	Second warehouse	Vehicle type 1	First product	1	0	1	7	7	8
First factory	Second warehouse	Vehicle type 1	Second product	2	9	5	8	4	6
First factory	Second warehouse	Vehicle type 1	Second product	1	8	7	5	2	0

Table 5: Values of the parameter $\beta^{tw}_{w,c,p,s,t}$.

Warehouse	Customer	Type of transport	Product type	Scenario	Period				
					First	Second	Third	Fourth	Fifth
First warehouse	First customer	Vehicle type 2	First product	1	9	8	8	5	2
First warehouse	First customer	Vehicle type 2	Second product	2	7	2	3	5	9
First warehouse	second customer	Vehicle type 2	First product	1	3	3	0	10	8
First warehouse	Third customer	Vehicle type 2	First product	2	4	1	8	5	9
First warehouse	Third customer	Vehicle type 2	First product	1	0	9	9	0	5
First warehouse	Third customer	Vehicle type 2	Second product	2	3	10	0	10	10
Second warehouse	Fourth customer	Vehicle type 2	First product	1	9	0	7	2	9
Second warehouse	First customer	Vehicle type 2	First product	2	6	4	1	3	8
Second warehouse	First customer	Vehicle type 2	Second product	1	4	1	3	1	5
Second warehouse	Second customer	Vehicle type 2	First product	2	0	1	8	0	4
Second warehouse	Third customer	Vehicle type 2	First product	1	10	2	6	1	0
Second warehouse	Fourth customer	Vehicle type 2	First product	2	3	5	3	8	5
Second warehouse	Fourth customer	Vehicle type 2	Second product	1	2	0	8	8	0
Second warehouse	Fourth customer	Vehicle type 2	Second product	2	5	2	5	6	0

Table 6: Values of the parameter $\gamma^{tk}_{c,i,p,s,t}$.

Customer	Separation center	Type of transport	Product type	Scenario	Periods				
					Period 1	Period 2	Period 3	Period 4	Period 5
First customer	First capital	Vehicle type 1	Second product	1	4	3	9	6	10
First customer	First capital	Vehicle type 1	Second product	2	5	3	0	2	1
Second customer	First capital	Vehicle type 2	First product	1	8	3	6	1	4
Second customer	First capital	Mean type 2	First product	2	10	4	2	10	8
Fourth customer	First capital	Vehicle type 1	First product	1	4	3	0	1	0
Fourth customer	First capital	Vehicle type 1	First product	2	6	2	5	2	4
Fourth customer	First capital	Vehicle type 1	Second product	1	2	3	4	3	10
Fourth customer	First capital	Vehicle type 1	Second product	2	9	6	10	6	2

Table 7: Values of the parameter $\theta^{ti}_{i,w,b,s,t}$.

Separation center	Warehouse	Type of transport	Type of returned piece	Scenario	Periods				
					Period 1	Period 2	Period 3	Period 4	Period 5
First capital	First warehouse	Vehicle type 1	B1–P	1	0	1	0	0	6
First capital	First warehouse	Vehicle type 1	B1–P	2	0	3	1	0	7
First capital	First warehouse	Vehicle type 1	B2–V	1	0	0	2	0	10
First capital	First warehouse	Vehicle type 1	B2–V	2	0	3	0	4	10
First capital	First warehouse	Vehicle type 1	B3-M	1	0	3	1	0	30
First capital	First warehouse	Vehicle type 1	B3-M	2	2	1	3	0	29

Table 8: Details of the model optimization in multiscenario mode.

Cost	Scenario	Period 1	Period 2	Period 3	Period 4	Period 5	Period 6	Period 7
Fixed cost ($)	Scenario 1	160	155	143	147	159	143	170
	Scenario 2	153	172	265	193	154	116	169
Variable cost ($)	Scenario 1	230	265	293	186	215	168	216
	Scenario 2	242	273	316	189	219	193	221
CO2 emission cost ($)	Scenario 1	2214	2107	2166	1995	2405	2256	2364
	Scenario 2	1949	2303	2151	1955	2091	2271	2015
Total risk ($)	Scenario 1	0.37	0.37	0.39	0.34	0.34	0.38	0.39
	Scenario 2	0.42	0.47	0.53	0.48	0.46	0.47	0.45

Table 9: Solution of different model scenarios and comparison between them.

Weight of objective functions				0.25	0.25	0.3	0.2
Step	State	Scenario	Probability of each scenario	Total fixed and changing costs	Total costs of carbon dioxide	Total deficit costs	Total supply risk costs
1	Uncertain planning step-2	1	0.6	9389	867058	0	1.220
2	Uncertain planning step-2	2	0.4	10481	1221826	0	1.400
3	Certain planning	1	0.6	8669	867195	0	1.310
4	Certain planning	2	0.4	10481	1221826	0	1.400

Table 10: Customer demand in each period and each scenario for each product.

Scenario	First product average	First product variance	Second product average	Second product variance	Possibility
Economic stability	1	0	1.682	0.39	0.6
Irregularities in prices and economic instability	1	0	1.3	0	0.4

Table 11: Customers demand in each period and each scenario for each product.

Customers	Period	Scenario	First product	Second product	Customers	Period	Scenario	First product	Second product
*c*1	1	*s*1	1	0	*c*3	2	*s*1	1	0
*c*1	1	*s*2	1	1	*c*3	2	*s*2	2	0
*c*1	5	*s*1	0	1	*c*3	4	*s*1	1	0
*c*1	5	*s*2	2	1	*c*3	4	*s*2	2	0
*c*2	1	*s*1	1	0	*c*3	5	*s*1	1	0
*c*2	1	*s*2	2	0	*c*3	5	*s*2	1	0
*c*2	2	*s*2	1	0	*c*4	1	*s*2	1	1
*c*2	3	*s*1	1	0	*c*4	2	*s*1	0	1
*c*2	3	*s*2	1	0	*c*4	2	*s*2	1	1
*c*2	4	*s*2	1	0	*c*4	3	*s*1	1	0
*c*2	5	*s*1	1	0	*c*4	3	*s*2	1	0
*c*2	5	*s*2	1	0	*c*4	5	*s*1	0	1
*c*3	1	*s*1	0	1	*c*4	5	*s*2	1	1
*c*3	1	*s*2	0	1	-	-	-	-	-

the facility, and then we respond to the customer's request based on the available facility. The results in 2 different scenarios are shown in Table 8.

In the following, we compare the proposed model in two definite and solid cases (per nominal data) and then examine the sensitivity analysis of the model shown in Table 9.

Both certain and stochastic models have been solved using GAMS optimization software and a computer with Core i7 and 6G RAM. The average and variance of customer demand in both cases are shown in Table 10. Moreover, the demand of customers in each scenario is shown in Table 11.

Given that the model has four objective functions, fixed and variable costs, CO2 emission costs, customer dissatisfaction, and risk of supply, the sensitivity of the scenarios in each period is analyzed. Further information is illustrated in Figures 2–4. The costs of customer dissatisfaction are zero at all times, indicating that it can control a flexible and risky supply chain to minimize customer dissatisfaction.

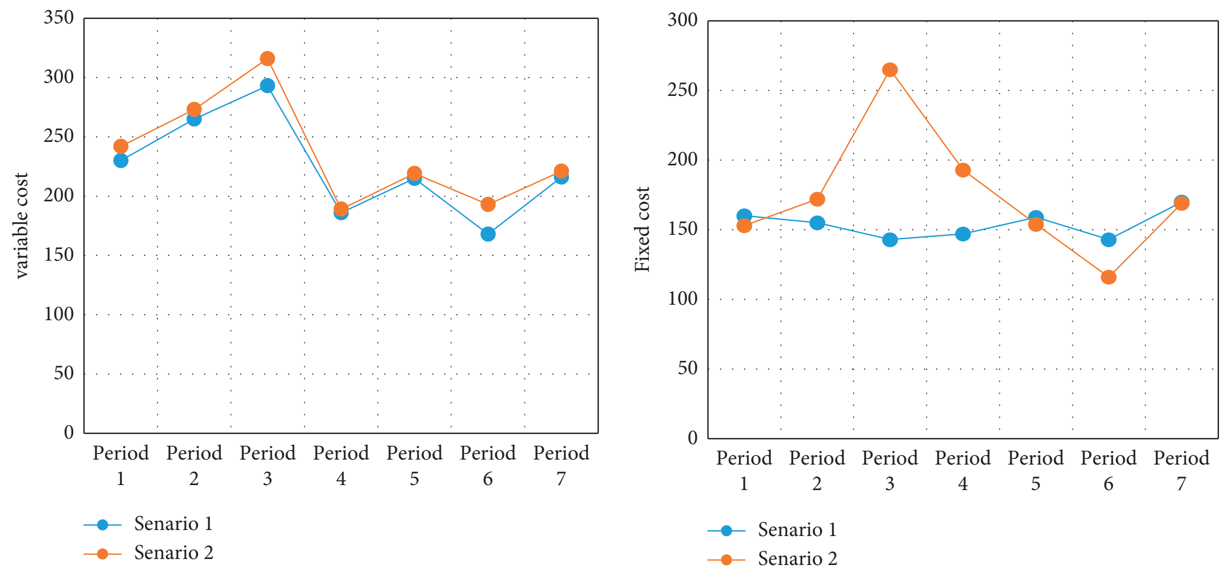

Figure 2: Fixed and variable costs in each scenario.

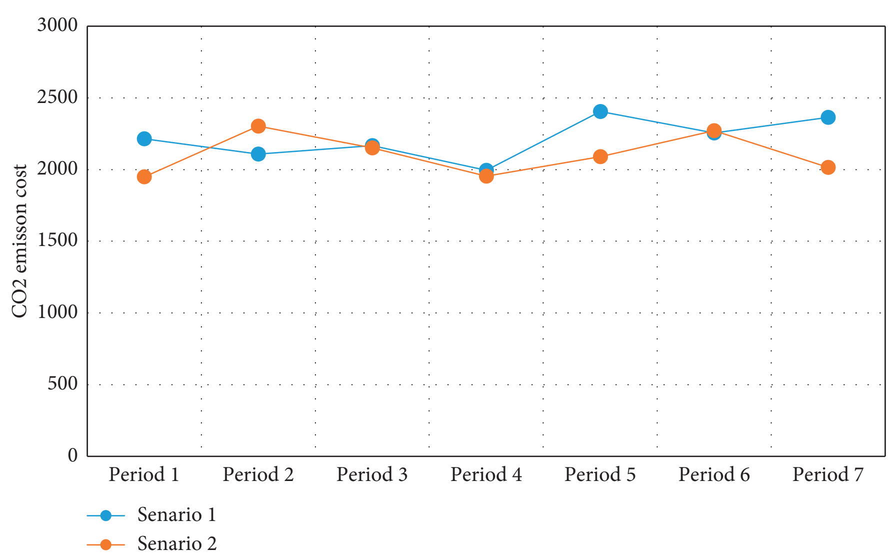

Figure 3: Total CO2 emission costs in each scenario.

According to Figure 4, the increase in the fourth objective function occurs due to occurrence in the supply chain. The fewer suppliers of raw materials, the more purchases of parts for manufacturing and production. Also, supplying more materials from one supplier and reducing costs are more cost-effective than increasing risk due to receiving a discount. Therefore, the risk of material supply increases.

Due to the high risk in supplying materials and selection of and cooperation with suppliers, supply risk and suppliers were examined in the model and selected and optimized as a target function. Table 12 shows the discounts received from suppliers in the optimal solution.

As can be seen in Table 12, the benefit of suppliers discount is more colorful in the first scenario, and for $b3 - M$ part, more discounts have been received from the two related suppliers, which is due to the greater capacity of the supplier. Risk assessment is one of the pillars of risk management, and its purpose is to measure risks based on various indicators, including impacts and probabilities. The more accurate the results at this stage, the more effective it is in risk management.

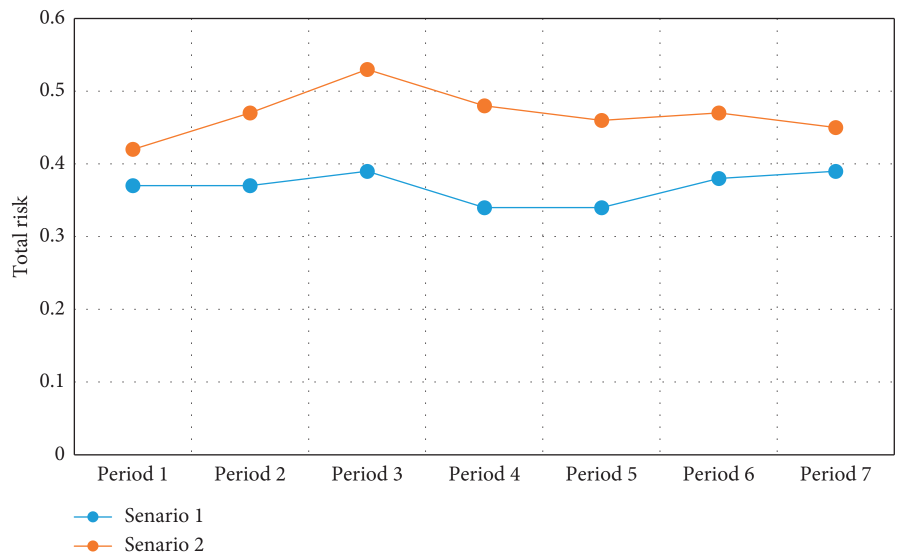

FIGURE 4: Total supply risk in each scenario.

TABLE 12: The amounts of suppliers' discounts offered in different scenarios for different parts.

Supplier	Raw/piece material	Scenario	Period				
			First	second	Third	Fourth	Fifth
$su1-\mathrm{RO}$	$b3-M$	First scenario	−10%	−10%-	0	0	0
$su2-\mathrm{PT}$	$b2-V$	Second scenario	0	0	0	0	−1%
$su2-\mathrm{PT}$	$b3-M$	Second scenario	−1%	−1%	−1%	−1%	−1%
$su9-s-P$	$b3-M$	First scenario	0	0	−1%	0	−5%
$su9-s-p$	$b3-M$	Second scenario	0	0	0	0	−5%

4. Conclusion

In the last decade, supply chain management has moved out of the intangible and has become a strategic element that can have a positive and tangible impact on the activities of organizations. The technology changes in market conditions, transformation of business practices, new expectations of partners in the supply chain, and finally the demand fluctuations are among the factors changing the supply chain.

On the other hand, identifying and managing risks within the supply chain and using coordinated approaches among the supply chain members to reduce the vulnerability of the entire supply chain are defined as supply chain risk management. The purpose of risk management is to identify high-risk situations and develop a strategy to reduce the likelihood of the occurrence and impact of high-risk events.

Accordingly and considering the importance of risk management and control in the supply chain, in this study, a multiobjective mathematical model was presented to design the supply chain network taking into account the risk in production and supply. The objectives of this mathematical model include reducing supply chain costs, adverse environmental impacts, customers' dissatisfaction, and overall supply chain risk. Several different scenarios are defined to formulate different kinds of risks, and for each, a specific probability of occurrence is determined. A two-step stochastic programming method was applied to deal with the uncertainty of scenarios and solve the mathematical model. The results of solving this mathematical model show that by analyzing different scenarios, its impact on fixed and variable costs as well as the amount of production and supply risks in different periods can be evaluated.

After conducting this research, it can be claimed that the approach implemented can help medical product supply chain managers to manage the production and distribution process with the least possible risk. However, this research has some limitations, the most important of which are the high complexity of the mathematical model and the restriction of GAMS software in solving the model in very large dimensions.

In order to develop this research, it is suggested that new metaheuristic algorithms such as the Moth-Flame Optimization, Gray Wolf Optimization, Slap Swarm Optimization, and Sparrow Optimization be used to solve the proposed mathematical model. Uncertainty can also be considered intermittently, and a robust optimization method can be used to deal with uncertainty.

Data Availability

No data were used to support this study.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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Research Article

A Hybrid Mathematical and Decision-Making Model to Determine the Amount of Economic Order considering the Discount

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Suppliers are one of the most important parts of the supply chain, whose performance indirectly has a significant impact on customer satisfaction. Because customer demands are different from organizations, organizations have to consider different criteria for selecting their suppliers. In recent years, many studies in this field have been conducted using various criteria and methods. The main purpose defined in this research is to develop a model for simultaneous item ordering systems in real business conditions. In this research, a model is developed by considering the two objectives of minimizing overall costs and maximizing the amount of products ordered from different suppliers based on their weight value. Weights are calculated based on different criteria using the fuzzy analytic hierarchy process method for each supplier in different periods. Then, due to the multiobjective nature of the model, the proposed model has been solved by using the epsilon constraint in GAMS and nondominated sorting genetic algorithm II in MATLAB software. Considering the simultaneous order of inventory of multiproduct with several suppliers in several periods of time in discrete space with discount is one of the contributions of this research. To validate the proposed model, the results of the exact solution are compared with the meta-heuristic solution. Comparison results and assessment metrics indicate that the results of the proposed solution approach with an error of less than 1% had good performance. The results show that the system cost increases, by increasing the amount of discount, because of the increase in the amount of demand. Therefore, with a 30% increase in the discount, the system costs will increase to 36,496 units. Also, with a 20% reduction, the cost reduction will be reduced to 14,170 units.

1. Introduction

Choosing a set of suppliers is critical to the success of organizations. In recent years, more attention has been paid to the choice of suppliers [1, 2]. Effective selection and evaluation of suppliers is an important responsibility that should always be considered by purchasing managers [3, 4]. The criticality of supplier selection is due to the effects it has on the elements of organizations' end products [5, 6]. According to Mahmoudi et al. [7], the decision to select a supplier involves the following three major decisions: (1) what products to order? Most papers written in this field are for situations where suppliers are selected for only one product. In these cases, different internal dependencies such as reductions in inspection and ordering costs that may exist for a variety of products are not considered. (2) In what quantity and from which supplier should the order be made? (3) In what time periods should the order be made? Determining the optimum quantity of inventory and selecting suppliers are closely related [8]. Making a decision on scheduling orders over time by choosing a supplier can dramatically reduce costs over time [9]. Therefore, one of the most important decisions is to buy, select, and maintain a complete group of suppliers, but recently another concept called supply chain management has emerged [10]. This has led researchers to increasingly realize that the issue of supplier selection is a factor that increases competition throughout the supply chain.

In such issues, the fixed costs of ordering to the supplier and the bid price of that supplier have been considered. On the other hand, the issue of inventory management and control has been studied extensively in the literature [11, 12]. The issue of determining the amount of order is one of the important issues in this area. In these issues, two types of inventory costs and ordering costs have been considered [13]. By reducing the amount of goods in each order and as a result of increasing the number of orders, the inventory of goods in stock and related costs will decrease, but ordering costs will increase, which is not actually cost-effective. On the other hand, the cost of arranging an order from a supplier for a number of different products consists of two components: (1) the total cost of ordering is independent of the number of different products in an order and (2) the ordering cost that depends on the number of different products in an order [14]. The above problem is known as the problem of simultaneous completion of inventory. Due to the overall cost of ordering, using group ordering can lead to significant cost savings [15]. This savings increases significantly when demand between items is closely related [16]. There are two types of strategies for solving inventory completion problems: (1) direct grouping strategy and (2) indirect grouping strategy. In the direct grouping strategy, products are divided into a number of predefined groups and products within each group are ordered with a common cycle time. In the indirect grouping strategy, ordering is performed at regular intervals, which is usually called the base cycle time. Each product has an integer coefficient from the base cycle time and is ordered in custom cycles that is an integer multiple of this coefficient. Research questions include the following: (1) What providers are selected to serve? and (2) How can supply chain supply costs be reduced as much as possible?

2. Literature Review

Most of the decision models proposed for the supplier selection process have focused on the final supplier selection phase. Some of this research has been reviewed in this area. Gaballa [17] was the first researcher to apply mathematical programming to supplier selection in a real case. He has used an integer mixed programming model to formulate this decision in the Australian Post Office. Khalili Nasr et al. [18] proposed a multiobjective fuzzy model to minimize costs in the supply chain. The proposed two-echelon model selects suppliers and assigns them to manufacturers. The main purposes of this study are to minimize environmental costs, operating costs, and lost demand, and maximize employment. Finally, the proposed model is solved by goal programming. Li et al. [19] designed a green supply chain with a single commodity. The most important goals of this research include maximizing the profits of manufacturers, distributors, and collection centers. Another goal is to minimize environmental costs. Considering priority for customers is one of the contributions of this research. The results indicate that with increasing demand, environmental and transportation costs increase sharply. Diabat and Jebali [20] presented a multiperiod, multicommodity model in the supply chain. The intended products have different qualities, and based on this quality, recovery is done. There is also a special penalty for each return. The objectives are to minimize chain costs while minimizing environmental impact. The results of sensitivity analysis indicate that with increasing demand, the amount of shipping costs increases sharply. RezaHoseini et al. [10] have presented a linear programming model with several criteria. In this model, two sets of factors are considered: (1) supplier characteristics including quality, price, and delivery date and (2) characteristics of the buyer company including material requirements and assurance inventory. Shahrokhi et al. [9] proposed an ideal nonlinear mixed nonlinear model for supplier selection. Price, quality, delivery, and service are included in this model, and all criteria are considered in the presented format. Beiki et al. [21] developed a nonlinear mathematical modeling and a heuristic method for selecting suppliers under the terms of multiple goods, multiple suppliers, resource constraints, and discounts based on the number of purchases. Warehouse and investment constraint are considered a limitation in the model. Firouzi and Jadidi [22] used linear and complex number integer programming to select suppliers. In their model, price, delivery, quality, and discount are considered. The quality and time of delivery are considered a limitation. Babbar and Amin [23] used multi-objective linear programming to select suppliers. In this model, total price, quality, and late delivery are considered goals, and two sets of constraints are as follows: (1) system constraints (constraints that are not directly under the control of the purchasing manager) such as supplier capacity, minimum order quantity, and total budget purchasing and (2) policy restrictions including the maximum/minimum amount of purchases from a minimum/maximum number of suppliers to be employed. Baraki and Kianfar [24] proposed a mixed integer model to solve this problem in which buyers need to buy different items from different sellers whose capacity, quality, and quantity of deliveries are limited and the products are categorized. Ahmadi and Amin [25] also proposed a model to examine supplier selection in the presence of several suppliers, multiple criteria, and discounted prices. They have also considered the effects of budget constraints, quality, and capacity of suppliers. In the case of multiproduct issues, the issue is the issue of the simultaneous ordering of products, which occurs in one of the following cases: (1) when multiple products are ordered from one supplier, (2) when multiple products use common transportation equipment, and (3) when a product is packaged in different quantities after mass production or batch. Bektur [26] presented an integrated methodology for the selection of sustainable suppliers and order allocation problem. In their article, first, suppliers are ranked by using integrated the fuzzy analytic hierarchy process. Then, the fuzzy multiobjective optimization (FMOO) model is proposed to find quantities to be purchased from suppliers. The results indicate the proper performance of the proposed model. Kumar and Mahapatra [27] presented a multiwarehouse inventory model for an optimal replenishment policy. They solved their model by the rain optimization algorithm (ROA) considering different parameters such as total cost, total delivery time, and total investment on each item. The results indicate the proper performance of the proposed model. The contributions considered in this research are as follows: (1) considering the discount level in the proposed mathematical model, (2) providing a multiperiod and multicommodity model to control inventory and check the flow of products, and (3) providing a combined approach of nondominated sorting genetic algorithm II (NSGA-II) and fuzzy analytic hierarchy process (FAHP) to select suppliers in the proposed model.

3. Mathematical Modeling

The mathematical model presented in this article is an integer mathematical programming model. The purpose of presenting this model is to select suppliers dynamically in several discrete periods by considering the simultaneous ordering of items and discounts, which causes different suppliers to be selected in each period according to the limitations. Using the simultaneous ordering of items reduces the overall costs of sending products from different suppliers in different periods, and on the other hand, in the competitive market, each supplier tries to apply a discount in exchange for purchasing more of its competitive power. In fact, they have to balance the lower price benefits with more storage and transportation costs to make purchasing decisions, which makes it harder to decide. The assumptions of this issue include the following:

(1) Model parameters (purchase prices, demand, capacity, etc.) in different time periods are definite and known
(2) Shortage is not allowed in any time period
(3) Inventory holding cost has a linear relationship with inventory and is allocated only to the amount of inventory remaining at the end of each period
(4) The amount of inventory at the beginning of the first period and the end of the last period is zero
(5) There are several items of goods, suppliers, and time periods
(6) The buyer can buy the required amount of demand from each product in any time period from one or more suppliers

$$\text{Min} = \sum_{i=1}^{P}\sum_{j=1}^{S}\sum_{k=1}^{K}\sum_{t=1}^{T} X_{ijkt}\text{Pr}_{ijkt} + \sum_{i=1}^{P}\sum_{t=1}^{T} h_{it}I_{it} + \sum_{j=1}^{S}\sum_{t=1}^{T} A_{jt}z_{jt} + \sum_{i=1}^{P}\sum_{j=1}^{S}\sum_{k=1}^{K}\sum_{t=1}^{T} a_{ijt}Y_{ijkt}, \tag{1}$$

$$\text{Max} = \sum_{i=1}^{P}\sum_{j=1}^{S}\sum_{k=1}^{K}\sum_{t=1}^{T} X_{ijkt}W_{jt}, \tag{2}$$

$$\text{St. } I_{it} = I_{i(t-1)} + \sum_{k=1}^{K}\sum_{j=1}^{S} X_{ijkt} - D_{it}, \quad \forall i, t, \tag{3}$$

$$\sum_{i=1}^{P}\sum_{k=1}^{K} Y_{ijkt} \leq MZ_{jt}, \quad \forall j, t, \tag{4}$$

$$\sum_{i=1}^{P}\left[V_i\left(I_{i(t-1)} + \sum_{k=1}^{K}\sum_{j=1}^{S} X_{ijkt}\right)\right] \leq C, \quad \forall t, \tag{5}$$

$$\sum_{i=1}^{P}\sum_{j=1}^{S}\sum_{k=1}^{K} X_{ijkt}\text{Pr}_{ijkt} \leq B_t, \quad \forall t, \tag{6}$$

$$q_{ijkt}Y_{ijkt} \leq X_{ijkt} < q_{ijk+1t}Y_{ijkt}, \quad \forall i, k, j, t, \tag{7}$$

$$\sum_{k=1}^{K} Y_{ijkt} \leq 1, \quad \forall i, j, t, \tag{8}$$

$$I_{i0} = 0, \quad \forall i, \tag{9}$$

$$I_{it} = 0, \quad \forall i, \tag{10}$$

$$X_{ijkt} \,\&\, I_{it} \geq 0, \quad \forall i, j, k, t, \tag{11}$$

$$Z_{jt} \,\&\, Y_{ijkt} = 0 \text{ or } 1, \quad \forall i, j, k, t. \tag{12}$$

Equation (1), the objective function of the model, is to minimize the total costs over the entire time horizon, which consists of 4 components: the first part is related to the total cost of purchasing goods; the second part includes the cost of maintaining inventory at the end of period t; the third part is related to the total cost of ordering from supplier j in period t, which does not depend on the number of goods; and the fourth part deals with the costs of ordering, which depend on the number of goods.

Constraint (2), the second function of the model, represents the sum of goods ordered from suppliers in different time periods based on the weight value of suppliers in different periods. Constraint (3) represents the inventory control between periods. Constraint (4) guarantees the selection of supplier j in time period t. Constraint (5) is related to the maximum storage capacity. Constraint (6) is related to the purchase budget in each time period. Constraint (7) guarantees that the quantity of the ordered goods will be at the discount level offered by the supplier. It is important to note that the upper limit of the last discount level offered by each supplier is equal to the production capacity of each supplier for the product i. Constraint (8) ensures that when ordering goods i, only one discount level is selected from the levels offered by supplier j. Constraints (9) and (10) show that inventory at the beginning and end of the time period for each commodity is zero.

4. Methodology

As stated in this study, a multi-objective model of linear programming integrated integer for supplier selection at different times according to the simultaneous ordering of products is presented. In this section, according to several objectives, considering the objective function, the NSGA-II meta-heuristic algorithm in the MATLAB software space and the epsilon-constraint method in the GAMS software space have been used to specify the part points of the model. The second objective function of the proposed model represents the value of the goods ordered from suppliers based on the criteria of quality, delivery of goods, and flexibility of service level, the weighted value for each supplier in various periods has been calculated using the fuzzy AHP method. In order to show the accuracy of the NSGA-II algorithm presented in this research, a number of problems in different dimensions have been solved using MATLAB software and compared with the results of the model using the epsilon-constraint method in GAMS.

4.1. Epsilon-Constraint Method (ECM). The epsilon-constraint method is one of the well-known methods for dealing with multiobjective problems, which solves this type of problem by transferring all but one of the objective functions to the constraint at each stage. The Pareto boundary can be created by the epsilon-constraint method [12]:

$$\begin{aligned} \min \quad & f_1(x) \\ & x \in X, \\ \text{s.t. } & f_2(x) \leq \varepsilon_2, \\ & f_n(x) \leq \varepsilon_n. \end{aligned} \tag{13}$$

The steps of the epsilon-constraint method are as follows:

(1) Select one of the objective functions as the main objective function
(2) Solve the problem according to one of the objective functions each time and get the optimal values of each objective function
(3) Divide the interval between the two optimal values of the subobjective functions into a predetermined number and obtain a table of values for $\varepsilon_2, \ldots, \varepsilon_n$
(4) Each time obtain the problem with the main objective function with any of the values $\varepsilon_2, \ldots, \varepsilon_n$
(5) Report the Parthian answers obtained

4.2. NSGA-II Algorithm. The NSGA-II method is a common method for solving problems with several objective functions based on genetic algorithms. This algorithm is an efficient method for solving problems with several objective functions, but it also has weaknesses for selecting dominant Pareto and in computational complexity. Therefore, a modified method called NSGA-II has been developed [28]. This method works better than the other methods because it uses the information S_p and N_p, the sum of the members of the population defeated by the P Pareto, and the number of times the P Pareto is defeated by other Pareto. In addition to all the functionality that NSGA-II has, it can be considered a model for the formation of many multi-objective optimization algorithms. This algorithm and its unique approach to multi-objective optimization problems have been used repeatedly by different people to create newer multi-objective optimization algorithms [29]. This algorithm solves the problem as it is defined and its purpose is not to turn the problem into a single objective problem. How to solve a problem with this algorithm requires a number of elements, one of which is the archive or archive of valid answers [30]. Because computer memory is limited, the number of archives cannot be allowed to grow as large as it would like. As a result, an archive size control mechanism is needed to control the number of archived responses.

4.2.1. NSGA-II Algorithm Steps. To implement the NSGA-II algorithm, perform the following steps [31]:

(1) Generate a random initial solution of size $i = 1$, ..., Popsize and set the number of iterations of the NSGA-II algorithm to 1.
(2) At this stage, the Pareto should be arranged on the basis of being defeated and they should be divided into fronts. The lower the number of fronts, the more Pareto the Pareto in them have defeated. To do this, combine the following steps for each of the Pareto, such as P:
    (2.1) Consider s_p the sum of the members of a population defeated by the Pareto P, and consider its value to be zero.
    (2.2) Consider N_p the number of times the P Pareto is defeated by other Pareto and its value is zero.
    (2.3) For each member of the population $n = 1$, ..., Popsize as in q. Follow the steps below:
        (2.3.1) If the Pareto P can defeat the Pareto q, then add q to the set s_p.
        (2.3.2) If the q Pareto can defeat the p Pareto, then add a unit to the set N_p.
(3) If after examining all the Pareto points, $N_p = 0$, then it can be concluded that P is not defeated by any other Pareto points so P is added to the front F_1.
(4) Continue all the following steps until the number of Pareto in front i is equal to zero:
    (4.1) Set the set of Pareto considered on the $i + 1$ front to Q and set it to zero, and then, perform the following steps for each P Pareto in the set f_i:
    (4.2) For each Pareto such as q in the set S_p on the f_i front, perform the following steps:
        (4.2.1) Subtract one unit from N_p. This indicates how many times the q Pareto has been defeated.
        (4.2.2) If N_p equals zero, it indicates that the Pareto q is on the f_{i+1} front. In this case, you have to replace Q with q.
    (4.3) Add a unit to i.
(5) After Pareto fronting, a number of them are selected based on the degree of defeat of other Pareto in order

to create the next generation. The binary method is used to determine the Pareto. For this purpose, at the beginning, two Pareto points are randomly selected and a comparison is made between them, and whichever is better is added to the repository of answers. The criterion for better answers is based on the following two criteria:

(5.1) Rank priority: in this case, the answers that have a lower rank or a lower front are selected because the Pareto points of this front can dominate more Pareto points.

(5.2) In some cases, the two selected Pareto points may be in the same rank; in other words, they may both be in the same order. In this case, a criterion called CD is used, which is described below.

(5.2.1) For each front n_i, consider f_i the number of Pareto points in that front.

(5.2.2) Call the distance between the Pareto points on the fronts f_i, and set the distance between all the Pareto points to zero.

(5.2.3) For each Pareto points such as j on the f_i front, consider each of the objective functions of the problem as m and perform the following steps:

(5.2.3.1) On the f_i front, arrange all the Pareto points based on the objective function m. In other words, we arrange the Pareto points on the f_i front separately based on their objective functions.

(5.2.3.2) After arranging the Pareto points on the f_i front based on the objective function m, set the distance between the first and last Pareto points to infinity. This is because there are no other Pareto points next to the Pareto points to cover it. For Pareto points 2 to n-1, the distance is obtained based on the following equations:

$$CD_k = I(d_k)_1 + \ldots + I(d_k)_m,$$

$$I(d_k)_m = \frac{I(k+1)_m - I(k-1)_m}{f_m^{\max} - f_m^{\min}}. \quad (14)$$

In the above equation, the congestion distance is $I(d_k)_m$ in the objective function m. For the total congestion distance, $I(d_k)$ must be calculated and added for all objective functions, as specified in the above equation.

(5.2.4) After calculating the congestion distance, the Pareto points with the greater congestion distance are selected.

(6) After selecting the Pareto points, in the previous stage, a pond is created, which is called the selected population. Then, genetic operators are used to create the population of the children. The genetic operators used in this study are crossover and mutant operators.

(7) After determining the offspring of P_t, genetic operators, this population merges with the main population of Q_t. Each pool has a capacity of n, and a number of Pareto points that have merged must be removed, so to reach capacity n, we must do the following steps:

(7.1) First, arrange the Pareto points according to the method described in step 2.

(7.2) Determine the distance of each Pareto points on the fronts.

(7.3) Start from front f_1 and select its Pareto points according to CD and pour into the new population pool $(K+1)$. Continue this step until the capacity of the new population pool $(K+1)$ reaches n. Figure 1 indicates the method of selecting a new population, crossover, and mutation.

(8) After creating the population $(K+1)$, go to step 2 and repeat these steps to the specified size.

4.3. Calculate the Weight Importance of Each Supplier. As mentioned, the second objective function of the model includes maximizing purchases from suppliers based on the weight importance of suppliers in different time periods, which the weighted importance for each supplier is calculated using the fuzzy AHP method. Therefore, in this section, the method of calculating the weight of suppliers in different time periods is examined by the fuzzy AHP method.

4.3.1. Fuzzy Analytical Hierarchical Process (FAHP). Although the purpose of using the hierarchical analysis method is to obtain the opinion of experts and specialists, the analytical hierarchical process (AHP) method does not accurately reflect the way of human thinking because in this method, pairwise comparisons are considered numerically. In the fuzzy analytical hierarchical process (FAHP), after preparing the hierarchical diagram, decision-makers are asked to compare the elements of each level and express the relative importance of the elements using fuzzy numbers. The steps of the fuzzy analytical hierarchical process are as follows [32]:

(1) Drawing a hierarchical diagram

(2) Defining fuzzy numbers in order to perform even comparisons

(3) Forming an even comparison matrix using fuzzy numbers

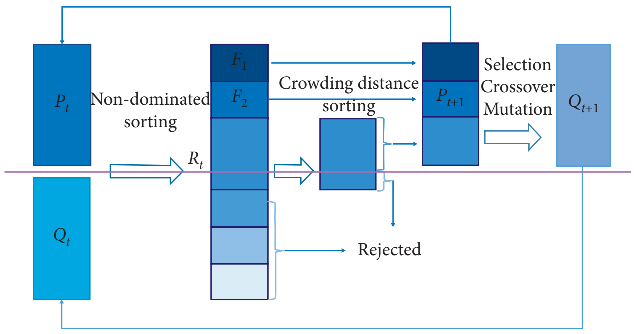

Figure 1: The proposed NSGA-II framework.

The pairwise comparison matrix will be as follows:

$$\tilde{A} = \begin{bmatrix} 1 & \cdots & \widetilde{a_{1n}} \\ \vdots & \ddots & \vdots \\ \widetilde{a_{n1}} & \cdots & 1 \end{bmatrix}. \quad (15)$$

This matrix contains the following fuzzy numbers:

$$\widetilde{a_{ij}} = \begin{cases} 1, & i = j, \\ \tilde{1}, \tilde{3}, \tilde{5}, \tilde{7}, \tilde{9} \text{ or } \widetilde{1^{-1}}, \widetilde{3^{-1}}, \widetilde{5^{-1}}, \widetilde{7^{-1}}, \widetilde{9^{-1}}, & i \neq j. \end{cases} \quad (16)$$

If the decision-making committee has several decision-makers, the components of the comprehensive pairwise comparison matrix used in the fuzzy hierarchical analytical method are a triangular fuzzy number whose first component is the minimum polls, whose second component is the average of the polls, and whose third component is maximum polls.

(4) Calculate S_i for each row of the pairwise comparison matrix, where S_i is a triangular fuzzy number and is calculated from the following equation:

$$S_i = \sum_{j=1}^{m} M_{gj}^{j} * \left[\sum_{i=1}^{n} \sum_{j=1}^{m} M_{gj}^{j} \right]^{-1}. \quad (17)$$

In this regard, i represents the row number and j represents the column number. In this equation M_{gj}^{j} is triangular fuzzy number. Also we can calculate $\sum_{j=1}^{m} M_{gj}^{j}$, $\sum_{i=1}^{n} \sum_{j=1}^{m} M_{gj}^{j}$, and $[\sum_{i=1}^{n} \sum_{j=1}^{m} M_{gj}^{j}]^{-1}$ using the following equations:

$$\sum_{j=1}^{m} M_{gj}^{j} = \left(\sum_{j=1}^{m} I_j, \sum_{j=1}^{m} m_j, \sum_{j=1}^{m} u_j \right),$$

$$\sum_{i=1}^{n} \sum_{j=1}^{m} M_{gj}^{j} = \left(\sum_{i=1}^{n} I_i, \sum_{i=1}^{m} m_i, \sum_{i=1}^{n} u_i \right), \quad (18)$$

$$\left[\sum_{i=1}^{n} \sum_{j=1}^{m} M_{gj}^{j} \right]^{-1} = \left(\frac{1}{\sum_{i=1}^{n} u_i}, \frac{1}{\sum_{i=1}^{n} m_i}, \frac{1}{\sum_{i=1}^{n} I_i} \right).$$

In the above relations, I_i, m_i, u_i are the first to third components of fuzzy numbers.

(5) Calculate the S_i relative to each other as follows:

$$V(M_2 \geq M_1) = \begin{cases} 1, & \text{if } m_2 \geq m_1, \\ 0, & \text{if } I_1 \geq u_2, \\ \dfrac{I_1 - u_2}{(m_2 - u_2) - (m_1 - I_1)}, & \text{otherwise.} \end{cases} \quad (19)$$

(6) Calculation of the weight of criteria and alternative in even comparison matrices is given as follows:

$$d'(A_j) = \operatorname{Min} V(S_i \geq S_k). \quad (20)$$

Therefore, the non-normalized vector is as follows:

$$W' = (d'(A_1), d'(A_2), \ldots, d'(A_n))^T. \quad (21)$$

(7) Calculating the final weight vector as follows:

$$W = (d(A_1), d(A_2), \ldots, d(A_n))^T. \quad (22)$$

5. Computational Results

In this section, the computational results obtained from solving the model in small, medium, and large scales will be shown. To demonstrate the efficiency of the NSGA-II algorithm, five small-scale problems are generated and the results are compared with the results of the ε – constraint method. Table 1 shows the range of considered parameters. The parameter values follow a uniform distribution function. For example, ordering costs can be between 100 and 600 units.

Table 2 shows the number of products, suppliers, discount levels, and periods. As it is known, with increasing the scale of the problem, the number of products, suppliers, quality levels, and periods increase.

Tables 3 and 4 show the results of the FAHP approach. As it is known, Table 3 calculates the incompatibility rate in pairs. This rate is calculated to be 0.78. Also, the weight of the first objective function is calculated according to experts 0.488 and the weight of the second objective function is equal to 0.512.

Table 5 shows a comparison of the results of the epsilon-constraint and NSGA-II approaches. As it turns out, the results of the first and second objective functions are reported by both methods. The results show that the calculated error rate for all problems was less than 1%. Solution time also increases exponentially in the epsilon-constraint method, whereas it increases at a much slower rate in the NSGA-II method. Therefore, the solution results of the proposed NSGA-II approach can be trusted.

Figure 2 shows the Pareto solutions resulting from model solving. The blue points show the exact solution results, and the red points show the Meta-heuristic solution results. As can be seen, the results of exact solution and

Table 1: Data ranges of parameters used in the model

Parameters	Range of values
$\mathbf{Pr_{ijkt}}$	$\sim U\,(150000, 300000)$
$\mathbf{V_i}$	$\sim U\,(100000, 200000)$
$\mathbf{B_t}$	$\sim U\,(100000, 250000)$
$\mathbf{q_{ijkt}}$	$\sim U\,(200000, 800000)$
L_{ijt}	$\sim U\,(100000, 300000)$
a_{ijt}	$\sim U\,(50, 100)$
H_{it}	$\sim U\,(50, 100)$
A_{jt}	$\sim U\,(100, 600)$

Table 2: Dimensions of problem instances and sizes.

Problem size	Size	**i**	**j**	**k**	Period
Small	SS1	2	3	2	3
	SS2	3	4	3	3
	SS3	4	6	4	3
	SS4	5	8	8	4
	SS5	6	8	9	4
Medium	MS1	11	11	9	4
	MS2	12	13	10	5
	MS3	14	14	12	5
	MS4	15	15	12	6
	MS5	17	16	13	6
Large	LS1	20	25	20	5
	LS2	22	27	30	6
	LS3	25	29	40	8
	LS4	28	30	50	8
	LS5	30	35	60	9

Table 3: Incompatibility rate in pairs.

$V\,(S_{c21} \geq S_{cij})$	$V\,(S_{c22} \geq S_{ci})$
—	1
0.78	—

Table 4: Weight of objective functions.

FAHP	OBJ1	OBJ2
Final weight	0.488	0.512
Rank	2	1

Table 5: The results of calculation for small, medium, and large size test problems.

No	Epsilon constraint			NSGA-II			Error %	
	f_1	f_2	Time (s)	f_1	f_2	Time (s)	f_1	f_2
1	35473.2	1260.6	2	35473.2	1260.6	2	0	0
2	35498.6	1340.7	26	35498.6	1340.7	6	0	0
3	35532.0	1489.9	52	35541.5	1484.4	7	0.02	1
4	35546.9	1553.8	93	35560.3	1549.9	9	0.03	0.5
5	35551.7	1675.5	142	35576.2	1671.4	14	0.06	1
6	56788.8	2466.0	1364	56799.9	2462.6	23	0.01	1
7	56798.4	2583.9	2897	56823.2	2579.1	26	0.04	0.07
8	56836.2	2700.7	3742	56849.5	2695.3	32	0.02	0.9
9	56864.4	2839.3	4981	56891.1	2832.0	38	0.04	0.9
10	56892.7	2898.6	6429	56938.7	2984.1	41	0.08	1
11	73963.2	6783.2	—	73967.2	6780.0	—	0.005	0.0471
12	74556.2	6932.1	—	74559.9	6928.2	—	0.004	0.056
13	75125.5	8988.0	—	75128.6	8984.4	—	0.004	0.040
14	77068.5	9538.7	—	77074.8	9532.5	—	0.008	0.064
15	79862.0	10725.0	—	79868.2	10720.0	—	0.007	0.046

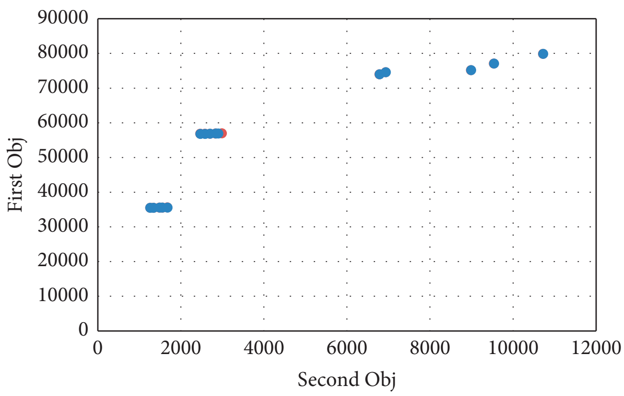

Figure 2: Pareto solutions.

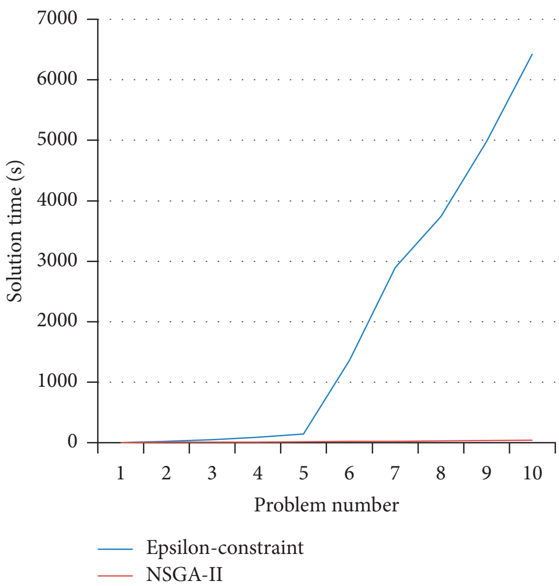

Figure 3: CPU time.

meta-heuristic are very close to each other, so the results of the meta-heuristic approach can be trusted.

Figure 3 shows a comparison of the solution times of the two approaches. As it is known, the solution time of epsilon-constraint approach increases exponentially, whereas the solution time of the NSGA-II approach is reasonable.

Table 6 shows the assessment metrics results for the NSGA-II approach and the epsilon constraint. As can be seen, the average mean ideal distance for the epsilon-constraint and NSGA-II approaches is 6.491 and 6.552, respectively. Also, the average spacing metric for the epsilon-constraint and NSGA-II approaches is 0.401 and 0.404, respectively.

Figure 4 shows the MID and SM metrics results. The blue points show the epsilon-constraint results, and the red points show the NSGA-II results. As can be seen, the results of exact solution and meta-heuristic are very close to each other, so the results of the meta-heuristic approach can be trusted.

Table 7 shows the results the one of the Pareto points. As can be seen in Table 7 in period 1, suppliers 1, 3, 4, and 5 are active. Also in period 2, suppliers 1, 2, 3, 4, and 6 are active.

Table 6: Multi-objective metrics obtained for each algorithm.

No	Mid		SM	
	Epsilon constraint	NSGA-II	Epsilon constraint	NSGA-II
1	6.23	6.25	0.365	0.365
2	6.26	6.28	0.369	0.371
3	6.33	6.35	0.371	0.374
4	6.36	6.38	0.375	0.377
5	6.42	6.46	0.380	0.386
6	6.60	6.65	0.424	0.428
7	6.63	6.67	0.427	0.430
8	6.65	6.69	0.430	0.435
9	6.69	6.71	0.436	0.438
10	6.74	6.78	0.439	0.442

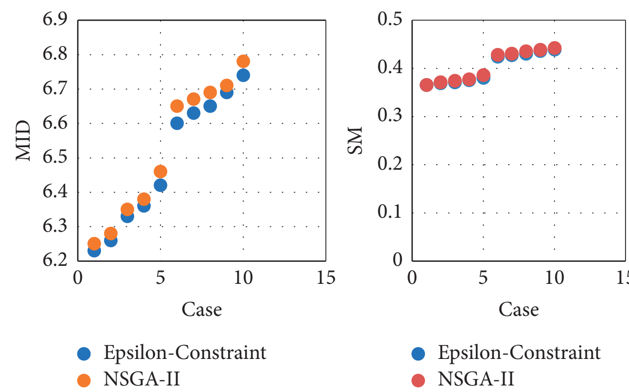

Figure 4: MID and SM metrics.

Table 7: Supplier selection outputs.

	Period 1	Period 2
Supplier 1	1	1
Supplier 2	0	1
Supplier 3	1	1
Supplier 4	1	1
Supplier 5	1	0
Supplier 6	0	1

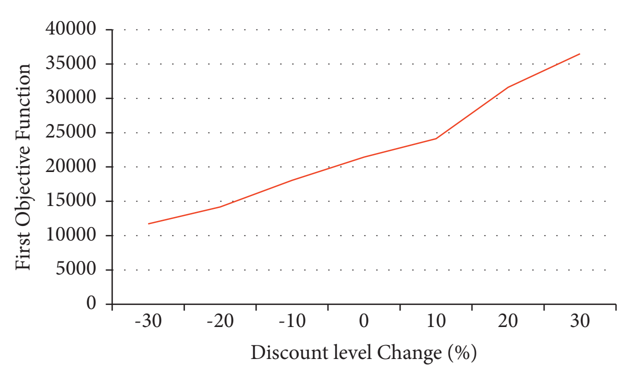

Figure 5: Effect of the change in discount on the cost.

Figure 5 shows the effect of the change in discount on the cost of the proposed systems. As it has been determined, the system cost increases, by increasing the amount of discount, because of the increase in the amount of demand. Therefore, with a 30% increase in the discount, the system costs will increase to 36,496 units. Also, with a 20% reduction, the cost reduction will be reduced to 14,170 units.

6. Conclusion

One of the important factors for survival in today's highly competitive environment is the reduction of production costs. Choosing the right suppliers can significantly reduce purchasing costs and increase an organization's competitiveness. The reason for this is that in most industries, the cost of raw materials and components of the product accounts for a large part of the cost of the product. According to the obtained results, the average error rate between the proposed NSGA-II algorithm and the epsilon-constraint method is acceptable. It is less and more acceptable. The incompatibility rate in pairs is calculated to be 0.78 using FAHP. Also, the weight of the first objective function is calculated according to experts 0.488 and the weight of the second objective function is equal to 0.512. The average mean ideal distance for the epsilon-constraint and NSGA-II approaches is 6.491 and 6.552, respectively. Also, the average spacing metric for the epsilon-constraint and NSGA-II approaches is 0.401 and 0.404, respectively. The results show that the system cost increases, by increasing the amount of discount, because of the increase in the amount of demand. Therefore, with a 30% increase in the discount, the system costs will increase to 36,496 units. Also, with a 20% reduction, the cost reduction will be reduced to 14,170 units. Among the research limitations is the lack of access to accurate information on transportation costs. Therefore, transportation costs are based on the estimates of transportation specialists. To develop the proposed model, the following future suggestions can be considered:

(1) Considering the policy of shortage of products in different time periods

(2) Considering probability or fuzzy uncertainty for capacity and demand parameters

(3) Considering the time value of money in the issue of choosing a supplier and ordering items at the same time

(4) Considering the maintenance cost of each unit of products as decreasing or increasing over time (dynamic nature of maintenance cost)

Notations

i: Products
j: Supplier
k: Discount
t: Time periods
C: Total storage capacity
V_i: The volume of space used by the product i
B_t: Purchase budget for time period t
q_{ijkt}: Discount level offered by supplier j for product i in period t
L_{ijt}: Production capacity of product i by supplier j in period t
a_{ijt}: Cost of ordering product i from supplier j in period t
H_{it}: The cost of maintaining product i during the period t
A_{jt}: Total cost of ordering from supplier j in time period t
Pr_{ijkt}: The price offered by supplier j at the discount level k for item i in period t
Y_{ijkt}: If the purchase order of item i from supplier j at the discount level k in period t, it is equal to 1; otherwise, it is equal to 0
X_{ijkt}: Order amount of products i from supplier j at discount level k in period t
z_{jt}: If supplier j is selected in time period t, it is equal to 1; otherwise, it is equal to 0
I_{it}: Inventory i at the end of period t.

Data Availability

No data were used to support this study.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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Research Article

Applying Sustainable Development to Economic Challenges of Small and Medium Enterprises after Implementation of Targeted Subsidies in Iran

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Although small and medium enterprises are important in the production and employment, these firms have structural limitation in terms of human and material resources. These limitations are highlighted after implementation of targeted subsidies in Iran, release prices of energy carriers, and simultaneity of political and economic situation. The main challenge in the current path of sustainable development is addressed to all sectors of society such as engineering and production. Manufactured products must consider the impact of three aspects of sustainability over their life cycle. The three aspects of sustainability as an integral part of sustainability issues are economic, environmental, and social factors. Therefore, in this study, for achieve sustainable economic development in Iran, consider only economic aspect. Because, it will greatly benefit from the transfer of advanced production technologies in industry through international agreements such as the clean development mechanism (CDM). However, the highly competitive environment is critical because of more cost-effective projects, which is why Iran needs to strike a balance between sustainable development and profitability for projects. In this study, identifying and ranking of major challenges of leading small and medium industries have been studied. It also uses the failures mode and effect analysis (FMEA) technique and survey experts and managers of small and medium industries in the province recognized and decision model using several branches. VIKOR was ranked as the most important challenge. The results show that exchange rate volatility has been the highest priority, so the first challenge has been identified. Similarly, the political boycott and the rise in the cost of production and cost of product manufacturing enterprises were identified as the next challenges.

1. Introduction

Today, small and medium enterprises are considered as major factors in the growth of the industrial structure of the country, and they are very important in a lot of developing countries' industries that sought to revive their economic structure. These countries have understood that in order to speed up the process of industrialization, priority should be given to the development of small and medium industries and not big industries. For this reason, we have an unprecedented enthusiasm of the small industries in many different countries [1]. The most important advantages that make economic policies to focus on small and medium industries are as follows: first, training of capable managers in the competitive environment [2]; second, making an effective role in entrepreneurship and job creation, resulting in increased exports and high functionality, and at the same time, adapting to the policies of downsizing, outsourcing, and reengineering [3]. Developing has been futile [4, 5]. In our country, in despite of the huge number of small industries, there are failures in their industrial structures, as they are not able to do effective roles as small industries in developed and developing countries. [4–6]. High cost of production in Iran, the weakness of the banking system, problems in taxation and customs issues, and inadequate financial support are things that undermine these firms, decline production, and take them of the production system [4].

The law of subsidies is one of the most important components of the economic development plan that has significant impacts on the industrial sector. Hence, this study aims to identify the main challenges that concerns recognizing challenges of subsidy for small and medium-sized manufacturing enterprises in relation to the development of their activity. The article focuses on subsidy and economic firms and 30 important challenges and their priorities that firm encounter. In the last part, the major findings and recommendations are presented.

Therefore, main contributions of this study are as follows:

(i) Identify the challenges facing industries after government subsidies

(ii) Ranking and determining the most important challenge facing industries after government subsidies using multiple criteria decision making (MCDM)

The rest of this study is organized as follows. In Section 2, basic issues such as the concept of subsidies, types of subsidies, subsidy goals, sustainable development literature review, and motivation and contribution are presented. In Section 3, methodology and the VIKOR decision-making method are explained. In Section 4, the results are presented. In Section 5, the managerial insights and main limitations of the research are presented, and finally, in Section 6, an overall conclusion is presented.

2. Literature Review

In this section, the impact of successful implementation of targeted government subsidies for sustainable development is reviewed. Sustainable development can be defined as the practice of maintaining the productivity by replacing resources used with resources of equal or greater value without degrading or endangering natural biotic systems [7]. Sustainable development binds together concern for the carrying capacity of natural systems with the social, political, and economic challenges faced by humanity. Sustainability science is the study of the concepts of sustainable development and environmental science. There is an additional focus on the present generations' responsibility to regenerate, maintain, and improve planetary resources for use by future generations [8, 9]. For this purpose, Liu et al. [10] presented the evolutionary dynamics in China's electric vehicle industry for taxes and subsidies. In this study, the production fluctuation in electric vehicle (EV) industry is explained by evolutionary game. The optimal decision of two players and Nash equilibrium is derived in three decision scenarios. Also, the influence of government intervening in consumer demand and vehicle supply on EV industry development path is examined. Finally, results show that the policy of dynamic emission taxations and static subsidies is more effective in the EV industry development. Kumar et al. [11] evaluated the effectiveness of fisheries subsidies as a trade policy tool to achieving sustainable development goals at the WTO. To this end, this study provides possible implications of the fisheries subsidies as a trade policy tool for market access and its effectiveness in achieving the overall sustainable development goals. To examine the effectiveness of subsidies in fisheries negotiations, the study focuses on the global supply and demand side of the fisheries resources from the perspective of the fish resource holders and the fishing resource capacity. Using both the market demand and supply for fisheries resource extraction, the study examines the effectiveness of subsidies as a trade policy tool to attain the overall sustainable development goals. Based on the analysis, certain policy strategies follow, which are important for countries to consider before the elimination of fisheries subsidies at the WTO. Moghaddam and Wirl [12] determined the oil price subsidies in oil and gas exporting countries. According to the political policy, it is easy to grant subsidies but much more difficult to remove them. High oil revenues tend to raise subsidies and make abolishing them more difficult. Therefore, without proper policies, domestic demand will explode. Grilli and Murtinu [13] considered selective subsidies, entrepreneurial founders' human capital, and access to R&D alliances. Because, selective subsidies help new technology-based firms (NTBFs) access R&D alliances and also apply both R&D alliances with other firms and R&D alliances with public research organizations/universities. Founders' technical education is a key determinant for NTBFs to get the first selective subsidy. Findings show that founders' previous industry-specific work experience positively moderates the impact of subsidies on the likelihood to form a corporate R&D alliance. Thorne and Hughes [14] evaluated the effectiveness of electric vehicle subsidies in Canada. In this study, the cost-effectiveness of achieving emissions reductions through EV subsidy programs is evaluated with respect to each provincial electricity system in Canada. These results were then used to compare the cost-efficiency of EV subsidies to other investments in climate change mitigation initiatives, and ultimately decide whether EV subsidies are feasible to implement in any of Canada's provinces. Solarin [15] examined the factors affecting energy intensity to sustainable development and its components such as electricity intensity, oil intensity, gas intensity, and coal intensity. In this study, special attention is paid to the roles of the fossil fuel subsidies, which include total fossil fuel, fossil-fueled electricity, oil, gas, and coal subsidies in developing countries. Using a generalized method of moments approach, it is shown that increase in fossil fuel, electricity, oil, gas, and coal subsidies promote energy intensity or its component elements. The results further suggest that urbanization, industrialization, and foreign direct investment also promote energy intensity. Also, it is noted that real gross domestic product per capita and human capital development have negative impact on energy intensity and its components. Moreover, the countries are clustered according to their income level, and the relationship in the variables is reexamined in each of the clusters. The results are not substantially different to those obtained for the total sample. The implications of these empirical findings are analyzed in the study. The priority development of public transport cannot be achieved without the support of the government's fiscal and taxation policies, while the implementation of the subsidy policy is the joint effect of multiple stakeholders. For this purpose, Zhang et al. [16] analyzed the implementation mechanism of public transport subsidy policy from the perspective of carbon emission to discuss the evolutionary stability strategy of tripartite game under different situations, thereby, clarifying the key factors affecting the evolutionary path of the stability strategy through simulation. The main conclusions achieved are as follows. (1) When the subsidy and sunk cost are greater than the improper profit brought by the false report and the travel cost (time and economy) of public transport is greater than that of the individual motorized travel combined, the three will eventually arrive at the state in which government chooses no-audit, the enterprise chooses true report, and the resident choose public transport. (2) More government supervision can help reduce the false reporting behavior of public transport enterprises in the implementation of public transport subsidy policy. (3) The punishment and the improper profit brought by the false report are also the key factors that influence the behavior decision-making of the government and the enterprises. (4) The economic cost of travel plays an important role in the evolution path of residents' stabilization strategy, yet is of little significance on the behavior decision of enterprises and governments. From the perspective of sustainable transportation development, it is necessary for the government to control or even reduce the ticket price of public transport and to increase the economic cost of individual motorized travel. Increased stress on environmental pollution, resource consumption, and public health resulting from the rapid growth of kitchen waste (KW) necessitated a disposal way of recycling and reuse. Therefore, Shi et al. [17], in their study, considered three disposal lines to convert KW into clean and renewable energy products, during which a Stackelberg equilibrium-based model is developed to achieve a balance between cost savings, carbon emissions reduction, and profit making by considering the interests of the local government and KW disposal plants. Recently, the outbreak of the COVID-19 pandemic poses great challenges to the current government subsidy models in the renewable energy sector for recovering in the post-pandemic economy. Although, many subsidy models have been applied to accelerate renewable energy investment decisions. However, it is important to develop a new model to ensure the sustainability of the renewable energy supply network under disruptions on both the supply and demand sides due to hazardous events. For this purpose, Tsao et al. [18], in their study, investigated different subsidy models (renewable credit, supplier subsidy, and retailer subsidy) to find a win-win subsidy model for sustainable energy supply under disruption risks. The objective is to determine the optimal capacity of renewable energy added to the grid, the optimal wholesale price of the power plant, and the optimal retail price of the aggregator under different subsidy models to maximize the economic, social, and environmental benefits of the whole network. A novel scenario-based robust fuzzy optimization approach is proposed to capture the uncertainties of business-as-usual operations (e.g., some relevant costs and demand) and hazardous events (e.g., COVID-19 pandemic). The proposed model is tested in a case study of the Vietnamese energy market. The results show that for a high negative impact level of hazardous events on the supply side, the renewable credit and supplier subsidy models should be considered to recover the renewable energy market. Furthermore, the proposed approach has a better performance in improving the power plant's robust profit for most of the hazard scenarios than the robust optimization model. Song et al. [19] evaluated the effects of government subsidies on the sustainable innovation of university-industry collaboration. This research shows that members in the university-industry collaboration who receive the government subsidy will produce more profit and also concluded that the government subsidy rate is negatively related to the consumer demand impact coefficient. Therefore, with the same level of effort, enterprises receiving government subsidies will generate greater social welfare. Finally, these study results can help governments to define sustainable innovation subsidy policy. Table 1 provides the research literature by the method, industry, and considered characteristics.

2.1. Motivation and Contribution. According to the abovementioned, studies have generally focused on identifying economic challenges and their impact on subsidies in each industry. Based on the knowledge gained, there are few studies that pay attention to both identification and ranking challenges. Therefore, the valuable contributions of this study are as follows:

(i) Identify the challenges facing industries after government subsidies

(ii) Ranking and determining the most important challenge facing industries after government subsidies

Based on main contribution of this study abovementioned, the main research questions are as follows:

(i) What are the main challenges facing small and medium enterprises after the implementation of targeted subsidies from an economic perspective?

Table 1: Literature categorized.

Author	Year	Method	Industry	Attribute
Liu et al.	2017	Evolutionary dynamics game	Electric vehicle	(i) Government intervening in consumer demand (ii) Vehicle supply
Kumar et al.	2018	Evaluated effectiveness of fisheries subsidies	Fisheries subsidies	(i) Global supply (ii) Demand side of fisher
Moghaddam and Wirl	2018	Determined oil price subsidies	Oil and gas	(i) Oil revenue (ii) Domestic demand
Thone and Hughes	2019	Evaluate effectiveness of electric vehicles	Electric vehicle	(i) Cost-effectiveness
Tsao et al.	2020	Investigated different subsidy models	Energy	(i) Renewable credit (ii) Supplier subsidy (iii) Retailer subsidy
Song et al.	2022	Evaluated government subsidies	University-industry	(i) Consumer demand
This study	Current year	Identifying and ranking using MCDM	Small and medium industries	(i) Possibility to happen (ii) Amount of risk (iii) Possibility to control

(ii) What are the priorities the small and medium enterprises subsidies challenges?

3. Methodology

Figure 1 shows the proposed framework of the research. This study is a descriptive and exploratory research based on surveys of experts. It is an applied research and uses the descriptive study, with the data field of the library from two ways: (i) libraries (search, study, and use of documents, texts, magazines, and newspapers economy) and (ii) other than libraries (preliminary interviews and questionnaires) to extract the indicators of population, and then with surveys of experts and specialists authorities, it weighs and ranks the challenges done. To do the research, a list of experts has been made to conduct research in Hamedan province with the help of industrial estates in connection with managers of government agencies and the private sector on the other hand. Totally, 25 experts declared their readiness to respond to the questionnaire. Most of the questionnaires have been spread among managers and experts who are fully informed about problems of production in Hamedan (in Iran) and who were aware of policies in the field or who were the supervisors or executors of governmental plans. The experts enjoy the following major features:

(i) They have no formal training and were less than undergraduate level, so half of them had bachelor, other half at the graduate level, and one at the PhD level.

(ii) People in the group of measuring the value had at least 14 years' experience in different and associated fields. So in one hand, they were informed about documents, rules, and policies of states in the field of production, and on the other hand, they were related to the managers of production companies, and sometimes, they had some collaboration and management in production.

(iii) Having diversity of work experience in various fields

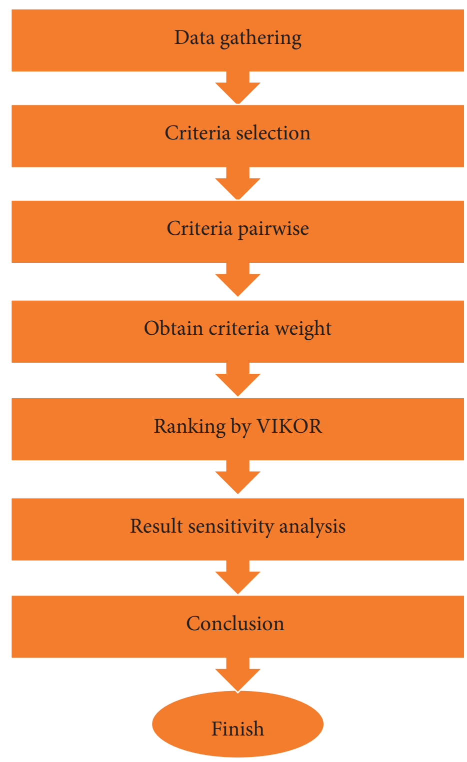

Figure 1: Proposed research framework.

The method used in this research is VIKOR. VIKOR, a compromised MADM method, was developed in 1998 based on LPG. This multicriteria decision-making method is created for solving a discrete decision problem with disproportionate measures (different measurement units). This method focuses on ranking and selecting an alternative category and determines compatible solutions to the problem even with conflicting criteria. It can help decision makers to reach to a final decision. Compliant solution is a feasible solution that is the closest to the ideal solution. Compatibility means the answer which is made by the mutual compromise. VIKOR advantages can be mentioned as follows:

(i) Necessarily, in the model, we do not require using expert' opinions to evaluate options based on criteria, and we can use raw data. For example, in the criteria of "connection way" to evaluate which village has a suitable condition, we can measure the connection way to the village and put it in the model, without using the experts' opinion. This evaluation can be based on raw data or based on expert opinion. The aim of this model is to determine the weight and value of each option and rank them. There is no need to complex software, and considering that in all the parts, the mathematical formulas have been used, and we can use Excel software to realize the goal [20].

(ii) The VIKOR method uses linear normalization and the TOPSIS method uses vector normalization. In VIKOR method, the normalized amount does not depend on the criteria measure unit. However, in the TOPSIS method, the normalized amount depends on the criteria measure unit.

To evaluate the risk in most of the resources, only two criteria, "probability" and "effect" of risk, have been used, while some other resources use "risk control criteria" or "eliminate risk criteria." In this study, all three criteria are considered for ranking the challenges as risks. There are several methods for risk assessment, including FMEA (failure modes analysis and its effects), FMECA (analysis of critical scenarios and consequences of it), HAZOP (analysis of the associated risks with the process), and FTA (tree hazard analysis). But the most valid method is FMEA which is first used by America's military to decrease the risk management as well as the risks of natural disasters' damages [21]. This method is used to predict and prevent errors [22]. The prediction is done by experts who have enough knowledge and experience about the design process or service. According to [23], the advantages of this method are as follows:

(i) Assessing the current situation (possible risk control)

(ii) A more accurate and realistic risk assessment methods than the traditional methods

(iii) A reliable method for predicting risk and managing preventive solutions

3.1. VIKOR Method. The VIKOR is a method developed by Opricovic in 1998. It is based on the definition of the vector of weights for the established criteria based on expert knowledge [24]. This approach obtains in the next steps, after certain transformations, the closeness of the solution to the ideal solution. Based on this distance, the final ranking is determined, assessing the quality of the alternatives tested. The result obtained may largely depend on the weights for the criteria defined at the beginning [25]. The vector of the weights specified by the expert should meet the following condition:

$$\sum_{i=1}^{N} w_i = 1. \tag{1}$$

Each of the criteria is initially defined as a cost or profit type of criteria (2). The cost type shows that we want it to achieve the lowest possible values, while the profit type should achieve the highest possible values.

$$f_i^* = \max_j f_{ij}, f_i^- = \min_j f_{ij}, \quad \text{if } i^{\text{th}} \text{ criterion is the profit,}$$
$$f_i^* = \min_i f_{ij}, f_i^- = \max_j f_{ij}, \quad \text{if } i^{\text{th}} \text{ criterion is the cost,} \tag{2}$$

$$w_j \cdot \frac{f_j^* - f_{ij}}{f_j^* - f_i^-}. \tag{3}$$

For each of the criteria, the best f_i^* and the worst f_i^* values are defined. Then, using equation (3), preference values for each criterion are calculated, taking into account the weights for criteria defined at the beginning. On this basis, the closeness to the ideal solution is calculated, considered in three different rankings calculated from the following formulas (4)–(6) for S, R, and Q, respectively.

$$S_i = \sum_{j=1}^{N} w_j \cdot \frac{f_j^* - f_{ij}}{f_j^* - f_i^-}, \tag{4}$$

$$R_i = \max_j \left[w_j \cdot \frac{f_j^* - f_{ij}}{f_j^* - f_i^-} \right], \tag{5}$$

$$Q_i = v \cdot \frac{s_i - s^*}{s^- - s^*} + (1 - v) \cdot \frac{R_i - R^*}{R^- - R^*}. \tag{6}$$

The VIKOR method is useful, especially in situations when a decision maker cannot express his/her preference. Even if the achieved ranking is not as accurate as the decision maker expects it to be, the weights for each criterion could be redefined. All processes could be performed once more to check if the obtained results are closer to the expected ranking. Moreover, this method provides results that depend on the ideal solution, which stands only for the given set of alternatives. It means that changing the group of alternatives and their values for specified criteria would affect receiving an utterly new preference ranking in which position for each option can differ in comparison with the one received in the previous attempt.

3.2. Criteria Identifying. In this study, three criteria are considered for ranking choices. All three criteria are selected from literature, as given in Table 2.

Table 2: Criteria selection.

Criteria	Resource
Possibility to happen	Izadyar and Pride [20]; Ghasemi [5]; Dicle and Dicle [26]
Amount of risk	Cant et al. [27]; Lin and Zhang [28]
Possibility to control	Zoogah et al. [29]; Solarin [15]; Zhang et al. [16]

Table 3: Pairwise, normalized, and criteria weight.

Pairwise	Possibility to happen	Amount of risk	Possibility to control
Possibility to happen	1	3	5
Amount of risk	0.33	1	5
Possibility to control	0.20	0.20	1
Normalized	Possibility to happen	Amount of risk	Possibility to control
Possibility to happen	0.65	0.71	0.45
Amount of risk	0.21	0.24	0.45
Possibility to control	0.13	0.05	0.10
Weight	0.60	0.30	0.10

Table 4: Decision matrix.

	Criteria	Possibility to happen	Amount of risk	Possibility to control
	Criteria's weight	0.60	0.30	0.09
Choices	Lack of liquidity	6	5.92	5.62
	High production costs	7.23	6.92	6.31
	Reduced profit margins	6.31	5.92	6.46
	Low quality of national production	4.54	5.77	5.15
	Lack of innovation and creativity atmosphere	4.92	6.15	4.54
	Prolongation of profitability	5.15	6.31	5.54
	Lack of agility in operations	4.46	5.62	5.62
	Lack of the marketing mechanism	5.85	6.38	5.15
	Unfavorable business atmosphere	5.69	6.54	5.08
	Lack of information and knowledge	4.38	6.08	5.15
	Existence of insecure investment environment	6.15	6.46	6.15
	Inflation	7.15	6.23	6.62
	Economic downturn	5.62	5.77	6.38
	Price gap	6.38	6.08	6.15
	Growing instability	6.77	6.46	6.00
	Rising energy prices	6.23	5.92	6.31
	Unpredictability of economic variables	5.92	5.77	5.92
	Lack of local buyers	4.92	5.23	5.54
	Lack of implementation of the government's commitment in the support package	6.23	5.69	6.69
	Lack of coordination between the financial institutions and the executive	5.77	5.92	6.00
	Existence of exclusive production firms	4.00	5.00	6.15
	Lack of cooperatives	4.62	5.00	5.92
	The lack of a systematic strategy	6.23	6.00	5.85
	Diversity policies	6.31	6.31	5.62
	Cumbersome rules	5.69	6.69	6.00
	Payment with high profit	5.46	6.31	5.85
	Dependence on foreign technology	5.08	6.15	6.00
	Lack of classified and frequent monitoring	6.69	6.92	6.46
	Political sanctions	7.00	7.08	6.62
	Exchange rate volatility	7.23	7.62	6.69
	f_i^*	7.23	7.62	6.69
	f_j^*	4.00	5.00	4.54

Table 5: Calculation of S_i value.

	Criteria	Possibility to happen	Amount of risk	Possibility to control
Choices	Lack of liquidity	0.23	0.11	0.04
	High production costs	0.00	0.22	0.02
	Reduced profit margins	0.17	0.11	0.01
	Low quality of national production	0.50	0.09	0.06
	Lack of innovation and creativity atmosphere	0.43	0.13	0.09
	Prolongation of profitability	0.39	0.15	0.05
	Lack of agility in operations	0.51	0.07	0.04
	Lack of the marketing mechanism	0.26	0.16	0.06
	Unfavorable business atmosphere	0.29	0.18	0.07
	Lack of information and knowledge	0.53	0.12	0.06
	Existence of insecure investment environment	0.20	0.17	0.02
	Inflation	0.01	0.14	0.00
	Economic downturn	0.30	0.09	0.01
	Price gap	0.16	0.12	0.02
	Growing instability	0.09	0.17	0.03
	Rising energy prices	0.19	0.11	0.02
	Unpredictability of economic variables	0.24	0.09	0.03
	Lack of local buyers	0.43	0.03	0.05
	Lack of implementation of the government's commitment in the support package	0.19	0.08	0.00
	Lack of coordination between the financial institutions and the executive	0.27	0.11	0.03
	Existence of exclusive production firms	0.60	0.00	0.02
	Lack of cooperatives	0.48	0.00	0.03
	The lack of a systematic strategy	0.19	0.11	0.04
	Diversity policies	0.17	0.15	0.04
	Cumbersome rules	0.29	0.19	0.03
	Payment with high profit	0.33	0.15	0.04
	Dependence on foreign technology	0.40	0.13	0.03
	Lack of classified and frequent monitoring	0.10	0.22	0.01
	Political sanctions	0.04	0.24	0.00
	Exchange rate volatility	0.00	0.30	0.00
	S_i	7.97	3.92	0.97
	R_i		7.97	

Table 6: VIKOR index value and ranking.

Criteria	Possibility to happen	Amount of risk	Possibility to control
Q	0.873	0.958	0.071
Rank	2	1	3

Table 7: Changing importance weight.

Δw	W_{new}		
	Possibility to happen	Amount of risk	Possibility to control
+0.05	0.65	0.35	0.14
−0.05	0.55	0.25	0.04

4. Results

The data were collected from questionnaires; first, we calculate the weight of normalized criteria through arithmetic mean. Table 3 provides the pairwise, normalized, and weight of the criteria, possibility to happen, amount of risk, and possibility to control. According to Table 3, the normalized values are between zero and one, and the sum of the weights obtained is equal to one. Second, the decision matrix is given in Table 4. Also, the results of the calculations made to VIKOR are given in Table 4; then, the challenges in order of priority of importance criteria are determined.

According to Table 4, value of f_i^* and f_j^* is calculated. Use f_i^* and f_j^* based on the VIKOR method $w_j \cdot ((f_j^* - f_{ij})/(f_j^* - f_i^-))$ for each choice and $S_i = \sum_{j=1}^{N} w_j \cdot ((f_j^* - f_{ij})/(f_j^* - f_i^-))$ for each criteria calculated, as given in Table 5, respectively.

According to Table 5, the calculated values of S are given. Based on the results, the value of S depends on the weight of the criteria. When criteria weight is greater than each other, value of S is greater. Finally, Q as the VIKOR index is calculated for each criterion, as given in Table 6.

According to the indicators obtained from the VIKOR method, the option with the highest value is chosen as the most important option [30], based on the output obtained from Table 6, it can be concluded that amount of risk has the highest priority rank; therefore, it has been identified as the first challenge. Similarly, the possibility to happen and possibility to control in manufacturing firms were identified as the next challenges.

Table 8: Changing value of S and Q.

Index	Δw	Criteria		
		Possibility to happen	Amount of risk	Possibility to control
S	+0.05	8.64	4.57	1.51
Q		0.985	0.944	0.352
S	−0.05	7.31	3.27	0.43
Q		0.783	0.882	0.031

4.1. Sensitivity Analysis. In this section, by changing the importance weight value to $\Delta w = \pm 0.05$, we examine the modified results. Table 7 provides the value of new weight according to $\Delta w = w_{\text{old}} - w_{\text{new}} = \pm 0.05$. Also, Table 8 provides the value changed for the new weights. Based on the calculated results, if the weight increases, the S values will increase. Consequently, in such condition, the value of the VIKOR index (Q) also increases.

5. Managerial Insights

According to the results, study findings can add valuable knowledge to managers. Based on the results, in addition to identifying the challenges facing small and medium industries in granting government subsidies, ranking and selection of important choices has been done. In addition to the valuable results of this study, there are limitations that include the following:

(i) In this study, a questionnaire was used to find the background; as a result, some people may refuse to provide a real answer and give an unreal answer.

(ii) This research has been done cross-sectionally. Because of this, it makes it difficult to draw conclusions about causality.

(iii) The large number of questions in the questionnaire led to the prolongation of its implementation time, which did not affect the accuracy of the participants' answers

6. Conclusion

Currently, industry faces many problems such as production expense that increases raw material expense, payments, and the price of energy transporter. Generally speaking, different sectors experience different effects, but virtually, all sectors will be affected. If a firm is not a big energy user, it may be affected by an energy user firm or the high payment of its human resource, as they need more money to work. The increased costs will reduce profit margins, unless permission is given to raise prices in relation to increased costs. The results showed that the most important challenge small and medium enterprises face is exchange rate volatility after the targeted subsidy and lack of space in between the challenges of innovation and creativity. Consider that removing subsidies and later increased price of energy transporter causes increasing production expense and decreases margin profit of small and medium firms.

(i) Using empty firm's production capacity more

(ii) Facilitating investors' access to finance resources based on rates approved by the central bank and central bank supervision on the cost of financing in various alternatives

(iii) Reducing tariffs on raw materials and intermediate irreplaceable internal production requirements

(iv) Prioritizing the payment of credit facilities for the purchase of new technologies

(v) Reducing transportation costs by optimizing transportation capacity

(vi) Changes in the product portfolio and consumption patterns

(vii) Raising the level of continuing education and new skills and proficiency of workforce

(viii) Shortening the supply chain

(ix) Promotion and improvement of quality management systems standards

(x) Reducing duplication and reducing tails

(xi) Reducing of production cycles/increasing the volume of production of goods and services

(xii) Reducing sleep time of machinery and equipment

Data Availability

No data were used to support this study.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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Research Article

Vehicle Routing Problem in Relief Supply under a Crisis Condition considering Blood Types

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Despite the advances achieved in Medical Sciences, no substitute has been found for blood as a vital factor. Therefore, preparing sufficient and healthy blood in crisis conditions is a challenge that health systems encounter. Along with examining the conducted investigations in this field, the main contribution of current research is to develop a biobjective Mixed-Integer Linear Programming (MILP) model for relief supply under crisis condition. For this purpose, this paper proposes a model for routing of bus blood receiver under crisis conditions considering different blood groups. Besides, hours of unnecessary travel by bloodmobiles (buses) between each blood station (BS) and the crisis-stricken city for dispatching the collected blood is prevented thanks to considering a helicopter. The mentioned model has two objectives: maximizing the amount of blood collected by bloodmobiles and minimizing the arrival time of the blood receiver buses and a helicopter to a crisis-stricken city after the collected blood is used up. The model is coded by CPLEX software, and the results obtained from solving the model indicate that, without considering a helicopter, the demand is not supplied within the critical period after crisis. Given that blood cannot be artificially produced, its primary resource is blood donors. Concerning the importance of this issue under crisis conditions, this research investigates the relief vehicles' routing problem, including bus and helicopter, in a crisis considering supply and transfer of different blood groups to a crisis-stricken city for maximum relief supply and blood transfer within the shortest period.

1. Introduction

Today, supply chain network design has been a demanding question and attracted great interest in a wide range of fields, such as medical industry. The important aspect of the entire discipline of the medical industry is the concept of blood management which recently brought striking attention among managers and decision-makers [1]. Blood transfusion is one of the most vital medical actions and interventions. However, blood is a highly scarce resource. Since blood cannot artificially be produced, the only blood resource is blood donors. It is reported that the demand for blood is 92 million units per year worldwide, while regular blood donors merely account for 5% of the world population [2]. Generally, the blood network consists of main centers, temporary facilities, bloodmobiles, and laboratory centers. The schematic of the blood supply chain is indicated in Figure 1. The main centers with preservation capacity and equipped with high technologies are responsible for collecting blood. Creating these centers requires very high investment. However, temporary facilities with a limited level of facilities for supplying demand and increasing the

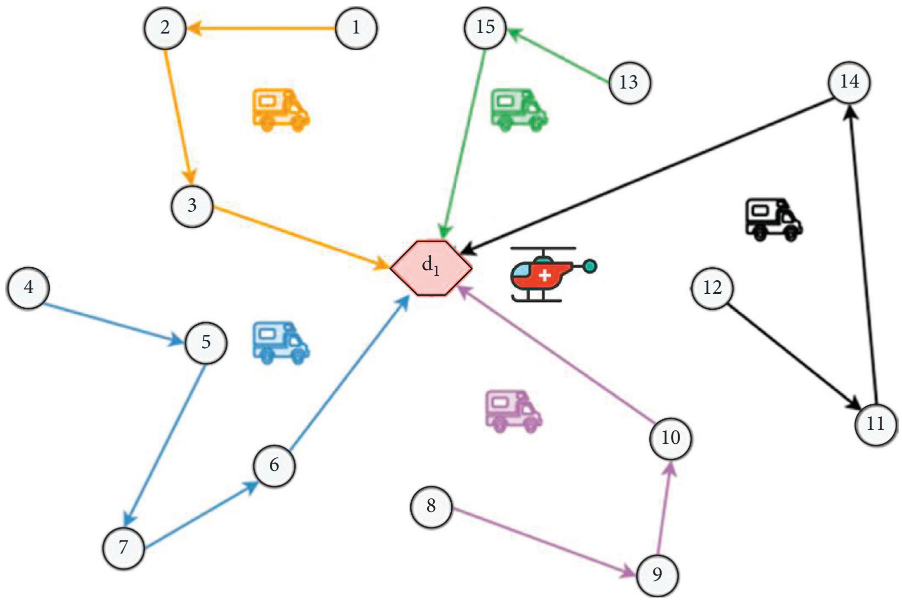

Figure 1: Routing-inventory of the bloodmobiles and the helicopter in blood supply chain.

number of donors are highly flexible. Effective use of the bloodmobiles may be helpful and increase the number of donors. The bloodmobiles are vehicles equipped with essential equipment for processing the received transfusion blood from donors. Compared to fixed blood donation centers, these vehicles can attract more donors by staying in crowded regions. Besides, employing this system prevents blood scarcity in blood transfusion centers and hospitals in a crisis and reduces blood wastes and system costs [3]. Blood donation starts when an individual visits a blood transfusion center or a service-provider bus. Bloodmobiles start their route from a particular location. Afterward, they follow their route to more centers in each city or even neighboring cities to collect more blood. It may take them several days to continue their routes. In order to prevent the blood collected by bloodmobiles from spoilage during their routes or deliver the collected blood to the patients on time, a helicopter visits bloodmobiles at the end of a day and dispatches the blood collected by bloodmobiles to the crisis-stricken city so that the bloodmobiles do not have to return to the crisis-stricken city at the end of the day. In the blood collecting centers, the blood units are processed and its components are separated. Ultimately, it is transferred to a hospital or a clinic according to the demand [4]. Even though blood units as a product may not be highly subject to spoilage, their separated components can be completely spoiled and destructed within a particular time [4]. Blood units are broken down into blood products, including white blood cells, platelets, and plasma. Red blood cells and platelets can be stored for 42 and 5 days, respectively. Each parameter can be divided into four groups of O, B, A, and AB, which can also be classified into other groups with positive or negative RH depending on the existence of special antigens [4]. Thereby, eight blood groups must be controlled simultaneously. Also, there are recipients (as chain customers) who are in dire need of various blood units and will suffer serious injury and death if they do not receive blood in the time of need. Therefore, not only are the different levels in such networks of a greater importance than those in other supply networks, but also the availability of network flow can determine the recipients' life at lower levels of the chain [1]. Consequently, for making better use of available resources, advanced approaches for decision-making are needed. Also, better planning for receiving and collecting leads to better handling in times of scarcity such as crisis, i.e., COVID-19 pandemic, earthquake, etc. [5]. Therefore, one of important decisions in blood transfusion is the substitution of blood groups. Ideally, the transfused blood group must be identical to the patient's blood type, while this is not always possible. When a blood group is not available at the time of the request, a compatible blood group with the desired blood group must be provided [6]. According to Table 1, the donated blood types are categorized based on the blood receiver and donor [3].

In general, the term "crisis" refers to any situation that temporarily limits the capability of services to preserve, store, and supply blood more than usual or creates a situation that increases the sudden demand for blood more than usual [6]. Disasters often lead to many problems, such as damage, financial losses, fatalities, and transportation problems in the damaged regions. Eighty-three thousand disasters have occurred from 2000 to 2012 worldwide [2]; for instance, demand is usually more than supply during the first 24 hours after the earthquake. Another concern regarding the design of blood supply chain networks is the limitation in the storage and transportation of blood products [7]. Compared to normal conditions, there is more demand for water, food, shelter, medical equipment, and other vital requirements, such as blood as a vital product after a disaster [2]. In order to tackle the challenges mentioned above, a novel and effective collecting system is proposed in this research for the vehicle routing problem, such as bloodmobiles and relief supplier helicopters after a

Table 1: Blood groups that are compatible with each other.

Receptor blood type	Donor blood type							
	+AB	−AB	+B	−B	+A	−A	+O	−O
−O								*
+O							*	*
−A						*		*
+A					*	*	*	*
−B				*				*
+B			*	*			*	*
−AB		*		*		*		*
+AB	*	*	*	*	*	*	*	*

crisis employing the concept of routing and using mathematical modeling. Besides, it is assumed that crises happened in a city, and the blood receiving bloodmobiles collect blood from certain cities. Accordingly, in the mathematical model, a bloodmobile is allowed to stop at each visited city in order for the collected blood to be maximized. In addition, given that a crisis has taken place, the arrival time of the bloodmobiles and helicopters to the crisis-stricken city is minimized. Besides, the relief helicopters collect and dispatch the blood left in the bloodmobiles in the cities to the crisis-stricken city. Indeed, this investigation carries out the routing of blood receiving bloodmobiles and relief helicopters in the crisis-stricken location such that the maximum amount of blood is collected within the shortest period. Since the number of injured individuals suddenly increases in a crisis, patients wait to receive blood when the blood is being collected. Thus, the earlier each donation vehicle arrives at the blood bank, the more patients receive blood and are healed. Hence, this research accords a high priority to the minimum arrival time of the blood receiving bloodmobile and helicopter to the crisis-stricken city. The following suppositions are the main objectives of the paper:

(i) Developing a blood network to consider both amount of collected blood and arrival time to service

(ii) Maximizing the amount of collected blood and minimizing the arrival time of service provider into the crisis-stricken city

(iii) Utilizing deterministic programming to evaluate the model behavior in the real-world case study

The following of this article is arranged as follows: In Section 2, a historical review of the issue is presented. In Section 3, along with introducing the methodology, the problem assumptions and mathematical model are presented. The problem-solving results are indicated in Section 4. Finally, in Section 5, a conclusion and some suggestion for future researches are presented.

2. Literature Review

The investigations into the management of spoilable products' supply chain and blood products specifically started in 1960 and culminated in the early 1980s [8]. During these years, various studies have been conducted on the blood supply chain, addressing different problems, such as the location of regional centers, blood banks, inventory, and routing problems of vehicles for blood collection and distribution. In recent years, some investigations into blood supply chain management have been conducted, which are introduced in the following. For instance, considering the location and allocation of them to the closest blood bank, Prastacos [9] proposed a mathematical model. This model aimed to minimize the total costs of the supply chain. In 2017, Haghjoo et al. [10] proposed a random bistage mathematical model for the design of a blood supply chain network and inventory management. Sha and Huang [11] proposed a multiperiod location-allocation mathematical model for the design of a blood supply chain network under emergency circumstances. They employed the Lagrange Relaxation method to solve the proposed mathematical model. Jabbarzadeh et al. [7] proposed a robust optimization mathematical model for the design of the blood supply chain network in an earthquake. They aimed to design a blood supply chain network with costs of three levels, including blood donors, blood centers, and blood collecting centers. The blood centers aimed to minimize the total costs of the supply chain. Zahiri and Pishvaee [12] proposed a biobjective mathematical model aiming to minimize the total costs of the supply chain and the unsupplied demands. This article designs a supply chain network by considering the compatibility of blood groups. For this purpose, a biobjective mathematical model is developed that minimizes the total costs and addresses the maximum undesired demand. Gunpinar and Centeno [13] modeled a vehicle routing problem employing an integer programming approach to simultaneously identify the number of blood transfusion buses and minimize the traveled distance. Besides, this model is developed to consider the uncertainty in the blood donation potential and the variable length in the visitors of the bloodmobiles. Rodríguez-Espíndola et al. [14] proposed a collaborative humanitarian approach for disaster preparedness for logistic resource management when a natural disaster happens. In this model, the multiobjective optimization model is employed for making emergency logistic management decisions. Paul and Wang [15] proposed a robust network of allocation of relief supply pieces of equipment for earthquake preparedness. This robust network can optimize the number of equipment, capacities, and distribution centers and reduce social costs. Parameters with uncertainty in this model are listed as follows: Damaged facilities, casualties because of the intensity of an incidence, and the travel time of the relief supplier vehicles. In a recent study, Adarang et al. [16] proposed a temporary robust biobjective location-routing model for providing emergency medical services. This model aimed to minimize the relief supplying time and total cost. Total costs are the sum of spatial costs and the cost of covering the route by vehicle (ambulance and helicopter). Arani et al. [17] presented a novel mixed-integer programming model for designing a sustainable lateral resupply blood supply chain network. In this paper, we addressed a blood inventory-routing problem with supply and demand uncertainties. Also, we developed a scenario-based stochastic optimization model and revised multichoice goal programming approach to solve.

Goodarzian et al. [18] considered an economic green medicine supply chain network under uncertainty. In this study, we developed multiperiod, three-echelon, multiproduct, and multimodal transportation based fuzzy biobjective Mixed-Integer Linear Programming. Davoodi and Goli [19] presented an integrated model for location, allocation, and routing in disaster relief response. In this paper, minimizing last visit time is used as a suitable objective function in rural areas disasters. For faster convergence Benders decomposition was developed using metaheuristics. Finally, we analyzed a real case to demonstrate the applicability of the research methodology. Samani and Hosseini-Motlagh [20] presented a novel capacity sharing mechanism to collaborative activities in the blood collection process during the COVID-19 outbreak. According to this research, a two-stage optimization tool for coordinating activities to mitigate the shortage in this urgent situation is considered. In the first stage, a blood collection plan considering disruption risk in supply to minimize the unmet demand will be solved. Then, in the second stage, the collected units will be shared between regions by applying the capacity sharing concept to avoid the blood shortage in health centers. Tirkolaee et al. [21] presented a robust biobjective mathematical model for disaster rescue unit's allocation and scheduling with learning effect. For this purpose, the effect of learning in the disaster management problem is considered. Then, a biobjective robust MILP model for rescue units allocation and scheduling is designed. Finally, a multichoice goal programming (MCGP) with utility functions to cope with the biobjectiveness of the model is applied. Wang et al. [22] presented a framework for optimization of warehouse location and resources distribution for emergency rescue under uncertainty. For this purpose in this paper, a mixed-integer programming (MIP) model based on time cost under uncertainty is proposed, which helps solve the emergency warehouse location and distribution problem. Mamashli et al. [23] presented a heuristic-based multichoice goal programming for the stochastic sustainable-resilient routing-allocation problem in relief logistics. The proposed model aims at minimizing total traveling time, total environmental impacts, and total demand loss. The fuzzy robust stochastic optimization approach is utilized to cope with uncertain data arising in disaster conditions. Then, due to the complexity of the research problem, a hybrid approach based on the multichoice goal programming method and a heuristic algorithm is developed to solve the problem in a reasonable time. Mousavi et al. [1] evaluated an integrated sustainable medical supply chain network during the COVID-19 pandemic. Three hybrid metaheuristic algorithms, namely, ant colony optimization, fish swarm algorithm, and firefly algorithm, are suggested, hybridized with variable neighborhood search used to solve the sustainable medical supply chain network model.

Although several studies on vehicle routing under crisis conditions have been introduced in the literature review, a study that addresses the defined condition mentioned in this study has not been found despite the carried-out examinations. Therefore, in this research, the routing of the blood receiver bus and relief supplier helicopter in the crisis-stricken area is carried out such that the maximum amount of blood is collected within the shortest possible period. In this case, the arrival time of the blood receiver bus and the relief supplier helicopter from the defined cities to the crisis-stricken city is minimized.

3. Methodology

3.1. Problem Statement. This study aims to determine which of the equipped buses visit which stations. Also, it determines in what order and how much time the stations should be visited. Besides, it specifies in what order the helicopter visits the stations to take delivery of the collected blood. With such a case, the collected blood by the bloodmobiles (buses and helicopters) is maximized until the end of the day. Since the condition is critical, the lower the blood collection time is, the more the individuals are saved. Accordingly, this is a problem with two objective functions. The first objective is to maximize the collected blood by considering the blood type. The second objective is to minimize the longest time for arrival of the equipped buses and the helicopter to the crisis-stricken city. Since the amount of collected blood is inversely proportional to the blood collection time, our objective is to determine the variables such that a balance is struck between the blood collection time and collected blood amount.

3.2. Model Structure. Generally, proposed blood supply chain consists of main centers, mobile centers, and laboratory centers. Mobile centers are a few numbers of equipped bloodmobiles (bus). Blood buses are equipped with several beds, the pieces of equipment required for receiving blood from a donor, and a lab for monitoring the blood accuracy, a few nurses, and one physician. Shuttle, which is indeed a helicopter, prevents unnecessary hourly bus travels for receiving the collected blood between each BS and the crisis-stricken city. In this case, the buses are not required to transfer the collected blood to the crisis area, and a helicopter will take this responsibility. Thus, we assume that a crisis has happened in a city. This problem consists of a blood bank located in the crisis-stricken city and several nodes that are the cities and the defined villages of the city. The blood bank is equipped with a specific number of bloodmobiles (a number of buses) and a relief helicopter. The equipped buses (bloodmobiles) start moving from the blood bank and visit the blood stations (BS) for blood collection; they should return to the blood bank until the end of the day. Concerning the proposed model, the buses decide for how much time (hours) they make a stop in each BS to maximize the collected blood. Besides, an excessive stop in a city confines the opportunity of visiting other cities. Therefore, making more stops in a city does not necessarily mean more blood collection. Since a shortage would be at the cost of more human lives, it is not allowed in the problem, and all of the demands should be satisfied. The buses can provide the collected blood from each BS to that station by considering the blood preservation condition until the helicopter reaches that point. The main objective of the helicopter is to visit the buses leaving or that have left the stations each hour, taking delivery of their collected blood. In this case, they can deliver the collected blood to the crisis-stricken city. This approach enables the buses to continue the predefined routes and make complete use of the other blood stations without having to return to each station of the crisis-stricken city at the end of being in service time. However, at the end of each route, the buses deliver the remaining collected blood to the blood bank. Therefore, the helicopter does not visit every blood station (BS).

3.3. Model Assumption and Notation. In this section, all elements of the assumption are presented in Table 2.

3.4. Model Notation and Formulation. In current section, objectives and constraints of the mentioned problem are modeled as follows. The objective function includes two sections:

$$\text{Max } Z1 = \sum_{b=1}^{4} Q_b. \quad (1)$$

Equation (1) formulates the first objective. This objective firstly maximizes the amount of collected blood.

$$\text{Min } Z2 = \max(\text{TB}, \text{TM}), \quad (2)$$

$$\text{TB} = \max\left(T_{n+1k} * Y_{n+1k}\right), \quad \forall k \in (1, \ldots, K), \quad (3)$$

$$\text{TS} = \max\left(\text{TT}_{n+1} * W_{n+1}\right). \quad (4)$$

Equation (2) indicates second objective, that is, minimizing the arrival time of the service-provider bus and helicopter to a crisis-stricken city that separate under assumptions intended for TB and TS in equations (3) and (4), respectively. Thus, the objective of the model is to minimize the arrival time of the service-provider bus and the helicopter to the crisis-stricken city if the collected blood is maximized by considering the blood type.

$$X_{iik} = 0, \quad \forall i \in (1, \ldots, n+1),\ k \in K. \quad (5)$$

Constraint (5) indicates that bloodmobile k (buses) cannot travel from city i to city i (loop is not allowed).

$$X_{1n+1k} = 0, \quad \forall k \in K. \quad (6)$$

Constraint (6) indicates that bloodmobiles k (buses) cannot travel directly from the starting city to the crisis-stricken city.

$$\sum_{i=0}^{n} X_{ijk} = \sum_{i=1}^{n+1} X_{jik} = Y_{jk}, \quad \forall j \in (1, \ldots, n), K \in (1, \ldots, k). \quad (7)$$

Constraint (7) is the flow balance; based on this constraint, if bloodmobile k (buses) enters the BS of city j from each point, it should drive to other stations merely from the BS of city j only if the mentioned bus (bus k) has visited city i. In order words, for each input, one output should exist.

$$Y_{ik} \le \sum_{j=2}^{n} X_{1jk}, \quad \forall i \in (1, \ldots, n+1), k \in (1, \ldots, k). \quad (8)$$

Constraint (8): bloodmobile k (buses) should start visiting from starting city.

$$Y_{ik} \le \sum_{j=2}^{n} X_{jn+1k}, \quad \forall i \in (1, \ldots, n+1), k \in (1, \ldots, k). \quad (9)$$

Constraint (9) confines the bloodmobile k (buses) at the end of their route to return to the crisis-stricken city.

$$X_{ijk} \le Y_{ik}, \quad \forall i, j \in (1, \ldots, n+1), k \in (1, \ldots, k). \quad (10)$$

$$X_{ijk} \le Y_{jk}, \quad \forall i, j \in (1, \ldots, n+1), k \in (1, \ldots, k). \quad (11)$$

Constraints (10) and (11) guarantee that when bloodmobile k (buses) travels from city i to city j, it should visit city i at first and then visit city j.

$$\sum_{k=1}^{K} Y_{ik} \le 1, \quad \forall i \in (2, \ldots, n). \quad (12)$$

Constraint (12) guarantees that the maximum number of buses visiting a city is 1.

$$\sum_{i=2}^{n+1} X_{1ik} \le 1, \quad \forall k \in (1, \ldots, k). \quad (13)$$

Constraint (13) indicates that, at the time of operation start, each bloodmobile k (buses) can either be used or not. It is obvious that each blood mobile k (bus) travels to merely one city at first.

$$YD_{ik} \le Y_{ik}, \quad \forall i \in (2, \ldots, n),\ k \in (1, \ldots, k). \quad (14)$$

Constraint (14) indicates that if bloodmobile k (buses) visits city i, bus k can either transport the collected blood from city i or leave it there to be transported by the helicopter to the same point.

$$T_{iK} + S_{iK} + t_{ij} \le T_{jk} + \left(1 - X_{ijk}\right)M, \quad \forall i \in (1, \ldots, n),\ j \in (2, \ldots, n+1), K \in (1, \ldots, k). \quad (15)$$

Table 2: Detail of the proposed model.

Assumption

(i) The start time of the blood donation operations is 8:00, and the end time is at most 20:00.
(ii) The stop time has a constraint with a minimum and maximum limit.
(iii) The collected blood in each BS depends on the city population and the stop time in that station.
(iv) There is a specific demand for blood that should be satisfied; the shortage is not allowed. Therefore, it is a vital constraint.
(v) Each equipped bus and the helicopter start their operations from the crisis-stricken city; after visiting various areas, it returns to the crisis-stricken city. The number of equipped buses is limited and specified.

Parameters

Notation	Description
N	Maximum number of points chosen as the station
K	The number of bloodmobiles (buses)
D	The donors' population
α	The blood type percentage in that population (the normality of universal blood type)
R_b	The demand of blood types
t_{ij}	The interval (time) that a bus travels from city i to city j
tt_{ij}	The interval (time) a helicopter travels from city i to city j
Beta	The population of donors frequently donating blood

Binary variable

$$X_{ijk} = \begin{cases} 1, & \text{bus } k \text{ travels from city } i \text{ to } j, \\ 0, & \text{otherwise.} \end{cases}$$

$$Z_{ij} = \begin{cases} 1, & \text{the helicopter travels from city } i \text{ to } j, \\ 0, & \text{otherwise.} \end{cases}$$

$$Y_{ik} = \begin{cases} 1, & \text{bus } k \text{ visits city } i, \\ 0, & \text{otherwise.} \end{cases}$$

$$YD_{ik} = \begin{cases} 1, & \text{after receiving the collected blood, if bus } k \text{ leaves them at city } i, \\ 0, & \text{otherwise.} \end{cases}$$

$$w_j = \begin{cases} 1, & \text{the helicopter visits city } j, \\ 0, & \text{otherwise.} \end{cases}$$

Nonnegative variable

Notation	Description
TT_i	The required time for arriving city i
S_{ik}	The stop time (hours) of bus at city k
SS_i	The stop time (hours) of the helicopter at city
$Q1_{kb}$	The amount of collected blood of blood types by bloodmobiles (buses)
$Q2_b$	The amount of collected blood of blood types by the helicopter
Q_b	The total amount of collected blood by the bloodmobiles (buses) and the helicopter per blood type
$F_b(S_{ik}) = S_{ik}.\, D_i.\, \alpha.$ beta	Function of the amount of collected blood type b by bus k at city i, when it stopped S_{ik} hours

Constraint (15) is related to the schedule of each bloodmobile (buses). Indeed, it strikes a balance between the entrance and exit time of bloodmobile (buses) from cities.

$$Z_{ii} = 0, \quad \forall i \in (1, \ldots, n+1),\ k \epsilon (1, \ldots, k). \tag{16}$$

Similar to constraint (5), constraint (16) guarantees that the helicopter cannot travel from city i to i (loop is not allowed).

$$Z_{1n+m} = 0, \quad \forall k \epsilon (1, \ldots, k). \tag{17}$$

Similar to constraint (6), constraint (17) indicates that the helicopter cannot travel directly from starting city to the crisis-stricken city.

$$\sum_{i=0}^{n} Z_{ij} = \sum_{i=1}^{n+1} Z_{ji} = W_j, \quad \forall j \in (1, \ldots, n). \tag{18}$$

Constraint (18) is the flow balance constraint of the helicopter, such that if the helicopter enters from each city to city j, it should travel to other cities only from city j (only if it has visited city j).

$$W_i \le \sum_{j=2}^{n} Z_{1j}, \quad \forall i \in (1, \ldots, n+1). \tag{19}$$

Constraint (19) guarantees that the helicopter starts routing from the starting city.

$$W_i \le \sum_{j=2}^{n} Z_{jn+1}, \quad \forall i \in (1, \ldots, n+1). \tag{20}$$

Constraint (20) guarantees that the helicopter visits the crisis-stricken city at the end of the route.

$$Z_{ij} \le W_i, \quad \forall i, j \in (1, \ldots, n+1), \tag{21}$$

$$Z_{ij} \le W_j, \quad \forall i, j \in (1, \ldots, n+1). \tag{22}$$

Constraints (21) and (22) guarantee that when the helicopter is going to travel from city i to city j, it should visit city j; afterward, it visits city j.

$$\sum_{j=2}^{n=1} Z_{1j} \leq 1. \quad (23)$$

Constraint (23) guarantees that when the operation starts, the helicopter can either be used or not. It is clear that the helicopter can travel to only one city at first.

$$W_i = \sum_k YD_{ik}, \quad \forall i \in (1, \ldots, n+1). \quad (24)$$

Constraint (24) indicates that if the bloodmobiles (buses) left the collected blood in a city, the helicopter would visit that city.

$$TT_i + SS_i + tt_{ij} \leq TT_j + \left(1 - Z_{ij}\right)M, \quad \forall i \in (1, \ldots, n), j \in (2, \ldots, n+1), K \in (1, \ldots, k). \quad (25)$$

Constraint (25) is related to the helicopter's schedule. Indeed, it strikes a balance between the entrance and exit of the helicopter from cities.

$$\left(S_{ik} + T_{ik}\right). YD_{ik} \leq TT_i.W_i, \quad k \in (1, \ldots, K), i \in (1, \ldots, N). \quad (26)$$

Constraint (26) is about the helicopter's schedule for collecting blood, such that the helicopter should arrive at that location after delivering the collected blood to city i by bus if city i is not the final station of the route.

$$Q1_{kb} = \sum_{i=1}^{n} F_b\left(S_{ik}\right).\left(1 - YD_{ik}\right), \quad \forall b \in (1, \ldots, 4), k \in (1, \ldots, K). \quad (27)$$

Constraint (27) is the total blood type b delivered to the crisis-stricken city by bloodmobile k (buses).

$$Q2_b = \sum_{k=1}^{K} \sum_{i=0}^{n} F_b\left(S_{ik}\right). YD_{ik}. W_i, \quad \forall b \in (1, \ldots, 4). \quad (28)$$

Constraint (28) is the total blood type b delivered to the crisis-stricken city by the helicopter.

$$Q_b = \sum_{k=1}^{K} Q1_{kb} + Q2_b, \quad \forall b \in (1, \ldots, 4). \quad (29)$$

Constraint (29) is the buses' total collected blood and the helicopter per blood type.

$$Q_1 \geq R_1, \quad (30)$$

$$Q_1 + Q_2 \geq R_2, \quad (31)$$

$$Q_1 + Q_3 \geq R_3, \quad (32)$$

$$Q_1 + Q_3 + Q_2 + Q_4 \geq R_4. \quad (33)$$

Constraints (30) to (33): the collected blood by the blood mobiles (buses) and the helicopter should be equal or greater than the demand of each group. In fact, constraints emphasize that shortage is not allowed.

$$X_{ijk}, Y_{ik}, YD_{ik}, W_i, Z_{ij} \in \{0, 1\}, \quad \forall i, j \in (1, \ldots, n), \forall K \in (1, \ldots, k). \quad (34)$$

In the end, constraint (34) specifies the limits of variables.

3.5. Solution Method. In this paper, weighted sum method (WSM) is used for solution method to find the optimal solution. WSM is a multiobjective optimization method in which there will be multiobjective and we have to determine the best solution. WSM combines all multiobjective functions into single scalar, composite objective function using weighted sum according to the following equation:

$$F(x) = w_1 f_1 + \cdots + w_n f_n. \quad (35)$$

An important issue there is in assigning the weighting coefficients vector $(w_1, \ldots, w_n)$ in the WSM because the optimal solution strongly depends on the chosen weighting coefficients. Also, these weights have be positive and should be according to the following equation:

$$\sum_{i=1}^{n} w_i = 1, \quad w_i \in (0, 1). \quad (36)$$

4. Numerical Results

In order to solve the developed mathematical model, it is assumed that there has been an earthquake in Avaj, located in Qazvin Province in Iran. There are several injured individuals in need of receiving blood. Blood collection should be carried out from a number of neighboring cities to save their lives. In order to solve the model, IBM ILOG CPLEX Optimization Studio software is used. Some cities are considered for blood collection, such as Qazvin, Alvand, Takestan, Abyek, Buin Zahra, Danesfahan, Lak, and Avaj. The considered interval (time) for the cities is indicated in Table 3, and the arrival time is considered to be 30% of that of buses.

In order to execute the model, the input parameters of the problem are determined as follows. The number of bloodmobiles (buses) is considered 3, and the helicopter 1. The demand for each blood type is considered [31895, 22865, 25965, and 21156]. After executing the model, almost 102000 blood units were collected during 11.84 hours, and all demands were satisfied. The optimum results of the model are depicted in Table 4. Also, in Table 5 routing results are shown. The route of the first bus is demonstrated in Table 5 from Qazvin to Alvand, then to Buin Zahra, and at the end to Avaj. The second bus route is from Qazvin to Lak and Danesfahan and, in the end, to Avaj. Finally, the third bus route is from Qazvin to Takestan and then to Abyek and

Table 3: The distance between cities (hours).

	Qazvin	Alvand	Takestan	Abyek	Buin Zahra	Danesfahan	Lak	Avaj
Qazvin	0	0.26	0.37	0.48	0.54	1.10	1.41	1.31
Alvand	0.26	0	0.47	0.45	0.45	1.08	1.57	1.47
Takestan	0.37	0.47	0	1.10	0.58	0.38	1.14	1.05
Abyek	0.48	0.45	1.10	0	1.19	1.42	2.13	2.04
Buin Zahra	0.54	0.45	0.58	1.19	0	0.29	2.33	1.24
Danesfahan	1.10	1.08	0.38	1.42	0.29	0	1.14	1.05
Lak	1.41	1.56	1.14	2.13	1.33	1.14	0	0.54
Avaj	1.31	1.47	1.05	2.04	1.24	1.05	0.54	0

Table 4: Optimum result.

Blood quantity (blood units)	Time collection (hours)	Number of vehicles	
		Bus	Helicopter
102000	11.84	3	1

Table 5: Routing results.

Vehicle	Quantity	Assigned route to vehicle		Time (hours)
		Vehicle	Route	
Bus	3	Bus 1	Qazvin > Alvand > Buin Zahra > Avaj	1.95
		Bus 2	Qazvin > Lak > Danesfahan > Avaj	3.60
		Bus 3	Qazvin > Takestan > Abyek > Avaj	3.51
Helicopter	1	Helicopter 1	Qazvin > Danesfahan > Lak > Avaj	2.78

Table 6: Changing the key parameters.

Scenarios	Parameters		Time (hours)	Blood (blood units)
	Blood mobiles	Helicopter		
1	2	1	13.65	82000
2	2	0	14.23	92000
3	1	1	17.68	75000
4	1	0	18.20	62000
5	3	0	12.95	98000

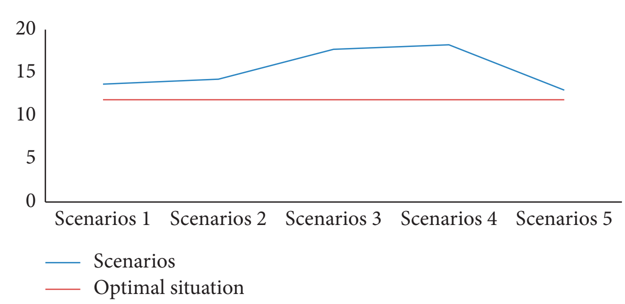

Figure 2: Time comparison between optimal and each scenario.

Avaj. Also, the route of the helicopter has been from Qazvin to Danesfahan, Lak, and Avaj.

4.1. Sensitivity Analysis. In this section, the effect of changing the key parameters including the blood mobiles and helicopter quantity on the decisions of proposed model is examined. In Table 6 all considered changing is shown. As depicted in Table 6, changing blood mobiles and helicopter quantity have the remarkable effect on time and collected blood quantity.

Figures 2 and 3 show a comparison of the optimal situation with each of the scenarios considered for sensitivity analysis. According to Figure 2, it is shown that, based on

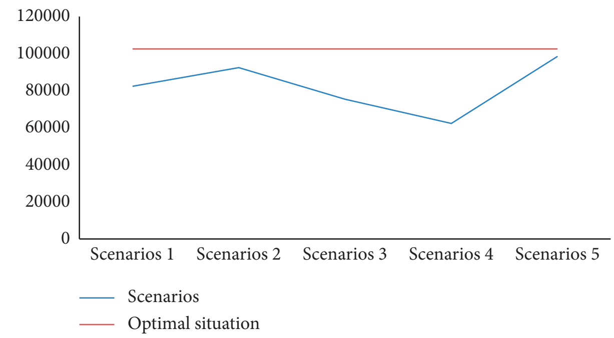

Figure 3: Blood collected comparison between optimal and each scenario.

each of the scenarios, the collection time of blood by the considered vehicles is always longer than the optimal time. Also, Figure 3 shows the amount of blood collected. According to Figure 3, the amount of blood collected based on the considered scenarios is always less than the optimal amount of blood. Therefore, it is impossible to improve the situation if the parameters are manipulated. The favorable condition is the optimal solution.

5. Conclusion

When a crisis strikes, blood transfusion is one of the most vital actions and medical interventions. Despite its importance and vital role, there is a significantly limited resource of blood. Concerning the fact that it cannot be produced artificially, the donors are the only blood source. Concerning the importance of the issue at the time of a crisis, to provide relief operations and transfer maximum blood level during a shorter period to a crisis-stricken city, this study has provided a routing problem for relief vehicles, including a number of buses and a helicopter. Therefore, the main contribution of current research is to develop a biobjective Mixed-Integer Linear Programming (MILP) model for relief supply under crisis condition. In this study, the MILP problem is examined at the time of a crisis strike by considering the supply and transportation of various kinds of blood types to a crisis-stricken city. Given that the routing problem of relief vehicles to provide services under a crisis is an active research area, the contributing factors to it can be investigated from different aspects. Accordingly, concerning the existing research gaps in the former studies, a Mixed-Integer Linear Programming (MILP) model is provided for bloodmobile routing under a crisis and by considering blood types. In the provided model, the stop time duration of each bloodmobile in blood donation stations varies. The amount of collected blood is considered a function of stop time duration. The blood delivery can be carried out by both buses and the helicopter. Also, the blood type compatibility is considered, getting the model closer to the real-life blood supply chain. In the end, the model is solved by using CPLEX software and close data to real life. By using the provided model, the optimal route of each bloodmobile and their stop time in each station are determined such that the total collected blood is maximized. In contrast, the arrival time of the bloodmobiles (the buses) to the crisis-stricken city is minimized. By changing the models' assumptions, such as lowering the number of bloodmobiles, the blood collection time increases, reaching 44 hours. In addition, we considered a model without any helicopter, observing that the required blood in the crisis-stricken area cannot be transported and supplied on time. The main limitations of this work can be described as follows:

(i) Some limitations to access operational data that must be obtained from indirect sources

(ii) Challenges to determine demand for each blood type

Data Availability

No data were used to support this study.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

Authors' Contributions

Mahsa Rezaei Kallaj contributed to software, investigation, and writing of the original draft. Milad Abolghasemian participated in conceptualization, resources, reviewing, and editing. Samaneh Moradi contributed to software, reviewing, and editing. Majid Sabkara contributed to methodology and native editing. Adel Pourghader Chobar contributed to translation to English and formal analysis.

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Research Article

Soft Computing Methodology to Optimize the Integrated Dynamic Models of Cellular Manufacturing Systems in a Robust Environment

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Machine learning, neural networks, and metaheuristic algorithms are relatively new subjects, closely related to each other: learning is somehow an intrinsic part of all of them. On the other hand, cell formation (CF) and facility layout design are the two fundamental steps in the CMS implementation. To get a successful CMS design, addressing the interrelated decisions simultaneously is important. In this article, a new nonlinear mixed-integer programming model is presented which comprehensively considers solving the integrated dynamic cell formation and inter/intracell layouts in continuous space. In the proposed model, cells are configured in flexible shapes during the planning horizon considering cell capacity in each period. This study considers the exact information about facility layout design and material handling cost. The proposed model is an NP-hard mixed-integer nonlinear programming model. To optimize the proposed problem, first, three metaheuristic algorithms, that is, Genetic Algorithm (GA), Keshtel Algorithm (KA), and Red Deer Algorithm (RDA), are employed. Then, to further improve the quality of the solutions, using machine learning approaches and combining the results of the aforementioned algorithms, a new metaheuristic algorithm is proposed. Numerical examples, sensitivity analyses, and comparisons of the performances of the algorithms are conducted.

1. Introduction

Facility layout (FL) considers the layout of machines within cells (Intracell layout) and the layout of cells (Intercell Layout) on the shop floor which can be counted as an essential element to plan a CMS. The cutdown in material handling cost, work-in-process, and throughput rate is the result of an efficient FL [1]. The system's performance would have the capacity to be boosted by designing a capable layout and the expense of the production also would fall around 40% to 50% on average [2]. In the FL problem, the actual parameters in the flow of some objectives might be ignored. The objectives which might diminish the intercellular circulation but none of them would certainly cause the charge of material handling to be minimized could be the minimization of the number of exceptional elements (EEs) or another common one can be referred to as the cost reduction of intercell movement. Although layout design has been somehow neglected in the CMS as many of the related researches have only investigated the CF, the vital point in this design could be using the FL problem [3, 4]. As stated, the decisions that are made in the FL and CF problem are interrelated, and tellingly to have a favored CMS design inscribing these two concurrently is of high importance [5]. Nevertheless, it has been asserted a complicated issue to make any of these kinds of decisions [6, 7]. Therefore the simultaneous addressing of these decisions is a difficult issue.

In most studies, some of the mentioned decisions have been handled and sometimes all of them consecutively [8]. On the other hand, most approaches in the area of facility layout and CF problem, for simplicity, usually consider minimizing the number of intercell movements or intracell movements or both [9]. To make a minimum material handling cost in FL design, it is an important matter to inspect the exact details of this design like the concept of distance. On the other hand, these types of approaches might make some illusive presumptions being machine location or fixed cells in the FL problem which might lead to an incompetent outcome. Also, in earlier investigations, the machines existing in a cell space were placed only in one type of location which was a line-formed one. There is another way to locate the machines other than line-form as well which is a U-form but the problem would be the expenses add up to the system.

Roughly speaking, many models in the field of CMS can be classified as NP-hard problems. Thus, employing and proposing exact mathematical approaches to tackle the models of CMS is usually ineffective. To this end, different heuristic, metaheuristic, and machine learning approaches have been applied, which can effectively handle the NP-hard models of CMS.

Machine learning, neural networks, and metaheuristic algorithms are relatively new subjects employed broadly in different fields of industrial engineering and management studies. They are also closely related to each other: learning is somehow an intrinsic part of all of them [10, 11]. Computer science, probability and statistic rules, and information and decision theory play a major role in the development of machine learning and other algorithms of metaheuristics. Machine learning methods find applications in different fields of industrial engineering, vehicle routing problem, and lot sizing, and maintenance optimization models are among others [12].

As the proposed mixed-integer nonlinear model in this paper is NP-hard, four metaheuristic algorithms are employed to tackle the problem. In the first step, the Genetic Algorithm (GA), Keshtel Algorithm (KA), and Red Deer Algorithm (RDA) are designed to optimize the model. To further improve the solutions of the algorithms, using machine learning approaches, a novel metaheuristic algorithm, which benefits from the merits of the aforementioned technique, is proposed. Accordingly, using soft computing methodology to optimize the integrated dynamic cell formation problem in a robust environment is the main contribution of the current study.

The rest of the paper is organized as follows: In Section 2, the mathematical model for the problem is presented. Section 3 presents the metaheuristic algorithms for optimizing the model. Section 4 discusses how the algorithms are tuned and reports the results of computations and calculations. Finally, Section 5 concludes the paper.

2. Proposed Mathematical Model

2.1. Notations

2.1.1. Sets

$i, i' = \{1, 2, \ldots, m\}$: machines group symbol

$j = \{1, 2, \ldots, n\}$: parts symbol

$l, k, k' = \{1, 2, \ldots, c\}$: cells group symbol

$h = \{1, 2, \ldots, H\}$: periods group symbol

2.1.2. Parameters

D_{jh}: parts demand for type j in period h

B_j: batch size for parts transportation type j

C^j_{intra}: the expense of intracell material handling for the transportation of part j per unit distance ($/unit)

C^j_{inter}: the expense of intercell material handling for the transportation of part j per unit distance ($/unit)

C_i: the expense of relocating machine i ($/unit)

R_{ij}: the number of operations done on part j using machine i

E: shop floor horizontal length (the length of the shop floor)

F: job shop vertical length (the width of the shop floor)

SP: the pairs group (i, j) such that $a_{ij} \geq 1$ (the group of elements that are not zero of a part-machine matrix)

NM: every cell's maximum figure of relocated machines per period

α_j: the expense coefficient (or penalty) caused by existence of any special part type j per period

N: an appropriate big positive figure

$A_{kl}, B_{kl'}$: a random variable and a zero

$A_{ii'h}, B_{ii'h}$: a random variable and a zero

$f^j_{ii'h}$: trips number for changing the location of part type j between machines i and i' in period h:

$$f^j_{ii'h} = \begin{cases} \left\lceil \dfrac{D_{jh}}{B_j} \right\rceil, & \text{if } R_{i'j} - R_{ij} = 1, \\ 0, & \text{if } R_{i'j} - R_{ij} \neq 1. \end{cases} \quad (1)$$

2.1.3. Decision Variables

$$X_{ikh} = \begin{cases} 1, & \text{If machine } i \text{ is allocated to cell } k \text{ in period } h, \\ 0, & \text{Otherwise} \end{cases}$$

$$Y_{jkh} = \begin{cases} 1, & \text{If part } j \text{ is allocated to cell } k \text{ in period } h, \\ 0, & \text{Otherwise} \end{cases}$$

$Z_{ih} = \{1,$ If machine i displaces through periods h and $(h+1)$, 0, Otherwise

$$U_{ijkh} = \begin{cases} 1, & \text{if } Y_{jkh} = 0 \text{ and } X_{ikh} = 1, \\ 0, & \text{Otherwise} \end{cases}$$

$$V_{ijkh} = \begin{cases} 1, & \text{if } Y_{jkh} = 1 \text{ and } X_{ikh} = 0, \\ 0, & \text{Otherwise} \end{cases}$$

x_{ih}: the center of machine i in period h in horizontal coordinate

y_{ih}: the center of machine i in period h in vertical coordinate

p^1_{kh}: the left side of cell k in period h in horizontal coordinate

p^2_{kh}: the right side of cell k in period h in horizontal coordinate

q^1_{kh}: the bottom side of cell k in period h in vertical coordinate

q^2_{kh}: the top side of cell k in period h in vertical coordinate

Thus, the expense of displacing part j between machines i and i' in period h concerning the movement of the intercell or intracell could be determined as follows.

If $X_{ikh}, X_{i'kh} > 0$ this cost is equal to the following equation:

$$C^j_{ii'h} = \left(\left|x_{ih} - x_{i'h}\right| + \left|y_{ih} - y_{i'h}\right|\right) C^j_{\text{intra}}. \quad (2)$$

If $X_{ikh} X_{i'kh} = 0$ and $X_{ikh} X_{i'k'h} > 0$ this cost is equal to the following equation:

$$C^j_{ii'h} = \left(\left|x_{ih} - x_{i'h}\right| + \left|y_{ih} - y_{i'h}\right|\right) C^j_{\text{inter}}. \quad (3)$$

The way cells are configured, the machines plot inside them, and also their layout on the shop floor are the goals of this model to be defined simultaneously in kinetic situations somehow that some expenses such as cells redesigning, parts total transportation cost, and EES number are reduced. In the given model, the job shop figure is considered for the intracellular layout. Some mixed-integer nonlinear programming models are discussed below along with multiple presumptions, parameters, and decision variables.

2.2. Model Assumption. The following presumptions are taken into account to simulate the model:

(i) In every period, the flow between machines is defined. The demand for parts, operational paths of parts, and also the parts transportation batch size are how this figure is gained from.

(ii) If each product's batch size is in all periods constant and determined, the parts can move within the batches. For both inter- and intracell displacements, the parts batch largeness is considered the same.

(iii) By applying rectilinear distance, the expense of material handling is assessed regarding the center-to-center distance between machines.

(iv) The expense of material handling for inter- and intracell relocations for machines and parts pertains to the distance traveled.

(v) The unit expense of intercell and intracell relocations for every part type is predestined and stays constant in the planning horizon.

(vi) During the periods, the unit expense of machine displacement remains the same and is predestined for every kind of machine. The expense contains the opening, transferring, and resetting of the machine.

(vii) In every period, by using the expected workload in every cell, the number of cells to be shaped can be ascertained beforehand. Nevertheless, during the planning horizon, since the cells are malleable, they can be shaped easily; hence, their configuration would not be predetermined.

(viii) Only one number of each machine kind exists.

(ix) During the planning horizon, the maximum capacity of cells is determined and stays constant.

(x) The machines are supposed to have a unit dimension, since they are squares of equal area. No extra inventory should exist between the periods; each demand must be supplied in the related period and no delayed orders are permitted.

(xi) 100% is assumed for machines and production efficiency.

2.3. Mathematical Formulation. Concerning input parameters and variables, the presented nonlinear model for this problem is as follows:

$$\text{minimize} \sum_{h=1}^{H}\sum_{j=1}^{n}\sum_{i=1}^{m}\sum_{i'=1}^{m} f^j_{ii'h} C^j_{ii'h} + \sum_{h=2}^{H}\sum_{i=1}^{m} C_i Z_{ih} + \sum_{h=1}^{H}\sum_{k=1}^{C}\sum_{(i,j)\in sp} \alpha_j . \frac{\left(U_{ijkh} + V_{ijkh}\right)}{2}. \quad (4)$$

It is subject to

$$\sum_{k=1}^{C} X_{ikh} = 1, \quad i = 1, 2, \ldots, m, \forall h, \tag{5}$$

$$\sum_{k=1}^{C} Y_{jkh} = 1, j = 1, 2, \ldots, n, \forall h, \tag{6}$$

$$1 \le \sum_{i=1}^{m} X_{ikh} \le NM, k = 1, 2, \ldots, C, \forall h, \tag{7}$$

$$NZ_{ih} \ge \left|x_{ih} - x_{i(h+1)}\right| + \left|y_{ih} - y_{i(h+1)}\right|, \quad \forall i, h < H, \tag{8}$$

$$\left|x_{ih} - x_{i'h}\right| + \left|y_{ih} - y_{i'h}\right| \ge 1, \tag{9}$$

$$\begin{cases} x_{ih} \ge p_{kh}^{1} - N\left(1 - X_{ikh}\right), \\ x_{ih} \le p_{kh}^{2} + N\left(1 - X_{ikh}\right), \\ y_{ih} \ge q_{kh}^{1} - N\left(1 - X_{ikh}\right), \\ y_{ih} \le q_{kh}^{2} + N\left(1 - X_{ikh}\right) \end{cases}, \quad \forall i, k, h, \tag{10}$$

$$\begin{cases} p_{kh}^{1} \ge 0, \\ q_{kh}^{1} \ge 0, \\ p_{kh}^{2} \le E, \\ q_{kh}^{2} \le F \end{cases}, \quad \forall k, h, \tag{11}$$

$$\begin{cases} p_{kh}^{1} - p_{lh}^{2} + NA_{kl} + NB_{kl} \ge 0, \\ p_{kh}^{2} - p_{lh}^{1} - NA_{kl} - N\left(1 - B_{kl}\right) \le 0, \\ q_{kh}^{1} - q_{lh}^{2} + N\left(1 - A_{kl}\right) + NB_{kl} \ge 0, \\ q_{kh}^{2} - q_{lh}^{1} - N\left(1 - A_{kl}\right) - N\left(1 - B_{kl}\right) \le 0, \\ 0 \le k < l \le C, \end{cases} \tag{12}$$

$$\begin{cases} x_{ih} - x_{i'h} + NA_{ii'h} + NB_{ii'h} \ge 1, \\ x_{i'h} - x_{ih} - NA_{ii'h} - N\left(1 - B_{ii'h}\right) \ge 1, \\ y_{ih} - y_{i'h} + N\left(1 - A_{ii'h}\right) + NB_{ii'h} \ge 1, \\ y_{i'h} - y_{ih} - N\left(1 - A_{ii'h}\right) - N\left(1 - B_{ii'h}\right) \ge 1 \end{cases}, \quad \forall 1 \le i < i' \le M. \tag{13}$$

The intracellular and intercellular material transferring costs are represented by the first term of the objective function. The expense of cell reshaping which might alter from period to period is defined in the following term. The decreasing number of exceptional parts is in connection with the third term. The double calculation of decision variables when they are 1 in this relationship is the reason behind the coefficient of 1/2. The first set of constraints (Equation (5)) guarantees that every machine is allocated to just one cell. Every part that has been allocated to one part family only is ensured by the second constraint (Equation (6)). Constraint (7) is the limitation for the number of machines in one cell. Variable Z_{ih} equals 1 when machine type i is displaced during periods h and $(1 + h)$, which is ensured by the fourth constraint (Equation (8)). The fifth constraint (Equation (9)) which is replaced with Equation (13) prevents machines from being overlapped. As mentioned, the machines are considered squares with a unit dimension. Each machine that has to displace in space of its corresponding cell is indicated in the set of relationships (10). The next constraint (Equation (11)) is developed to control the cells which are in space of the job shop. Preventing cells from being overlapped is shown in the set of relationships in (12).

2.4. Proposed Robust Model. Robust optimization is used when there is uncertainty in the parameters. In this case, with a slight change in the value of one of the parameters, the optimality and justification of the answer may be compromised. Therefore, to control the situation, it is necessary to use an optimization model that, considering the existing uncertainties, obtains an optimal answer that remains an optimal and justified answer to the problem under investigation in the face of changes in uncertain parameters.

In this paper, to face the uncertainty of the parameters, set-induced robust optimization is used. In this optimization, it is assumed that uncertain data belongs to an uncertainty set, and the aim is to choose the best solution among those "immunized" against data uncertainty, that is, candidate solutions that remain feasible for all realizations of the data from the uncertainty set.

According to the above, a symmetric interval for the range of parameter changes is considered as follows.

The objective coefficients and the constraint coefficients possibly change with an unknown distribution but they are symmetrical and independent in the following intervals:

$$\widetilde{C}_{\text{intra}}^{j} \in \left(C_{\text{intra}}^{j} - \widehat{C}_{\text{intra}}^{j}, C_{\text{intra}}^{j} + \widehat{C}_{\text{intra}}^{j}\right),$$

$$\widetilde{C}_{\text{inter}}^{j} \in \left(C_{\text{inter}}^{j} - \widehat{C}_{\text{inter}}^{j}, C_{\text{inter}}^{j} + \widehat{C}_{\text{inter}}^{j}\right),$$

$$\widetilde{C}_{i} \in \left(C_{i} - \widehat{C}_{i}, C_{i} + \widehat{C}_{i}\right),$$

$$\widetilde{D}_{jh} \in \left(D_{jh} - \widehat{D}_{jh}, D_{jh} + \widehat{D}_{jh}\right),$$

$$\begin{aligned}
&\widetilde{C}^{j}_{ii'h} \in \left(\left(\left|x_{ih}-x_{i'h}\right|+\left|y_{ih}-y_{i'h}\right|\right)\left(C^{j}_{\text{intra}}-\widehat{C}^{j}_{\text{intra}}\left(\left|x_{ih}-x_{i'h}\right|+\left|y_{ih}-y_{i'h}\right|\right)\left(C^{j}_{\text{intra}}+\widehat{C}^{j}_{\text{intra}}\right)\right)\right),\\
&\widetilde{C}^{j}_{ii'h} \in \left(\left(\left|x_{ih}-x_{i'h}\right|+\left|y_{ih}-y_{i'h}\right|\right)\left(C^{j}_{\text{inter}}-\widehat{C}^{j}_{\text{inter}}\right)\left(\left|x_{ih}-x_{i'h}\right|+\left|y_{ih}-y_{i'h}\right|\right)\left(C^{j}_{\text{inter}}+\widehat{C}^{j}_{\text{inter}}\right)\right),\\
&\widetilde{f}^{j}_{ii'h} \in \begin{cases} \left[\dfrac{D_{jh}-\widehat{D}_{jh}}{B_j}, \dfrac{D_{jh}+\widehat{D}_{jh}}{B_j}\right], & \text{if } R_{i'j}-R_{ij}=1,\\ 0, & \text{if } R_{i'j}-R_{ij}\neq 1. \end{cases}
\end{aligned} \tag{14}$$

For each parameter $\widetilde{a}_{ij}$ which is subject to uncertainty, a_{ij} represents the nominal value of the parameters and $\widehat{a}_{ij}$ represents constant perturbation (which are positive).

In this paper, a robust approach developed by Bertsimas and Sim is used to face the uncertainty of the parameters. Therefore, the robust counterpart of the original problem is obtained by replacing the original constraint with its robust counterpart constraint:

$$\begin{aligned}
&F \geq \sum_{h=1}^{H}\sum_{j=1}^{n}\sum_{i=1}^{m}\sum_{i'=1}^{m} f^{j}_{ii'h}C^{j}_{ii'h} + \sum_{h=2}^{H}\sum_{i=1}^{m} C_i Z_{ih} + \Gamma_0 Z_0 + \sum_{h=1}^{H}\sum_{j=1}^{n}\sum_{i=1}^{m}\sum_{i'=1}^{m} q^{j}_{ii'h} + \sum_{h=2}^{H}\sum_{i=1}^{m} s_{ih}\\
&\quad + \sum_{h=1}^{H}\sum_{k=1}^{C}\sum_{(i,j)\in sp} \alpha_j.\frac{\left(U_{ijkh}+V_{ijkh}\right)}{2},\\
&Z_0 + q^{j}_{ii'h} \geq \frac{\widehat{D}_{jh}}{B_j}\left(\left|xx_{ih}-xx_{i'h}\right|+\left|yy_{ih}-yy_{i'h}\right|\right)\widehat{C}^{j}_{\text{intra}}, \quad \forall i,h,j,i',\\
&Z_0 + q^{j}_{ii'h} \geq \frac{\widehat{D}_{jh}}{B_j}\left(\left|xx_{ih}-xx_{i'h}\right|+\left|yy_{ih}-yy_{i'h}\right|\right)\widehat{C}^{j}_{\text{inter}}, \quad \forall i,h,j,i',\\
&Z_0 + s_{ih} \geq \widehat{C}_i\, ZZ_{ih}, \quad \forall i,h,\\
&-xx_{ih} \leq x_{ih} \leq xx_{ih}, \quad \forall i,h,\\
&-xx_{i'h} \leq x_{i'h} \leq xx_{i'h}, \quad \forall i',h,\\
&-yy_{ih} \leq y_{ih} \leq yy_{ih}, \quad \forall i,h,\\
&-yy_{i'h} \leq y_{i'h} \leq yy_{i'h}, \quad \forall i',h,\\
&-ZZ_{ih} \leq Z_{ih} \leq ZZ_{ih}, \quad \forall i,h,\\
&\sum_{k=1}^{C} X_{ikh} = 1, \quad i=1,2,\ldots,m, \forall h,\\
&\sum_{k=1}^{C} Y_{jkh} = 1, \quad j=1,2,\ldots,n, \forall h,\\
&1 \leq \sum_{i=1}^{m} X_{ikh} \leq NM, \quad k=1,2,\ldots,C, \forall h,\\
&NZ_{ih} \geq \left|x_{ih}-x_{i(h+1)}\right| + \left|y_{ih}-y_{i(h+1)}\right|, \quad \forall i, h<H,
\end{aligned}$$

$$
\begin{aligned}
&\left|x_{ih}-x_{i'h}\right|+\left|y_{ih}-y_{i'h}\right|\geq 1,\\
&\begin{cases} x_{ih}\geq p_{kh}^{1}-N\left(1-X_{ikh}\right)\\ x_{ih}\leq p_{kh}^{2}+N\left(1-X_{ikh}\right)\\ y_{ih}\geq q_{kh}^{1}-N\left(1-X_{ikh}\right)\\ y_{ih}\leq q_{kh}^{2}+N\left(1-X_{ikh}\right)\end{cases},\ \forall i,k,h,\\
&\begin{cases} p_{kh}^{1}\geq 0\\ q_{kh}^{1}\geq 0\\ p_{kh}^{2}\leq E\\ q_{kh}^{2}\leq F\end{cases},\quad \forall k,h,\\
&\begin{cases} p_{kh}^{1}-p_{lh}^{2}+NA_{kl}+NB_{kl}\geq 0,\\ p_{kh}^{2}-p_{lh}^{1}-NA_{kl}-N\left(1-B_{kl}\right)\leq 0,\\ q_{kh}^{1}-q_{lh}^{2}+N\left(1-A_{kl}\right)+NB_{kl}\geq 0,\\ q_{kh}^{2}-q_{lh}^{1}-N\left(1-A_{kl}\right)-N\left(1-B_{kl}\right)\leq 0,\\ 0\leq k<l\leq C,\end{cases}\\
&\begin{cases} x_{ih}-x_{i'h}+NA_{ii'h}+NB_{ii'h}\geq 1\\ x_{i'h}-x_{ih}-NA_{ii'h}-N\left(1-B_{ii'h}\right)\geq 1\\ y_{ih}-y_{i'h}+N\left(1-A_{ii'h}\right)+NB_{ii'h}\geq 1\\ y_{i'h}-y_{ih}-N\left(1-A_{ii'h}\right)-N\left(1-B_{ii'h}\right)\geq 1\end{cases},\quad \forall 1\leq i<i'\leq M,\\
&xx_{ih},xx_{i'h},yy_{ih},yy_{i'h},q_{ii'h}^{j},s_{ih}\geq 0,
\end{aligned}
\tag{15}
$$

where Γ is the adjustable parameter controlling the size of the uncertainty set.

3. Proposed Solution Algorithm

The literature approved that the CMS models are classified as NP-hard problems [13–19]. The high complexity of CMS in large-scale instances motivates several researchers to propose novel metaheuristics [20]. This study in addition to the Genetic Algorithm (GA) applies two recent nature-inspired metaheuristics: Keshtel Algorithm (KA) and Red Deer Algorithm (RDA). To improve the benefits of these recent and old metaheuristics, a novel hybrid algorithm is also developed to better address the proposed problem and to provide a comparison among these algorithms based on the solution time and quality. Next, the encoding plan to run the initial population of the metaheuristics is explained. Then, the proposed optimizers are introduced.

3.1. Solution Representation. Since all stochastic optimizers such as GA, KA, and RDA use a continuous search space, an encoding plan to transform it into a discrete area to confirm that the algorithm can address the constraints of our model is highly needed [21–23]. A general view of the encoding scheme is depicted in Figure 1. Then, the assignment of machines and details of the cell manufacturing to generate a feasible solution are given in Figure 2.

Finally, to compute the objective functions (the fitness functions), a matrix with H rows and N columns is generated regarding the matrixes in Figure 2. The structure of the final matrix for the alignment is given in Figure 3.

3.2. Keshtel Algorithm (KA). Swarm intelligence is one of the main inspirations for metaheuristics. Considering that the swarm behavior of birds, bees, and ants is a hot topic for metaheuristics studies, the Keshtel Algorithm (KA) is another swarm intelligence-based metaheuristic. This algorithm was firstly developed by Hajiaghaei-Keshteli and Aminnayeri [24]. With regard to inspiration from a dabbling dock, this metaheuristic studies the feeding behavior of *Anas* docks.

According to behaviors of this type of birds, they live in Asia and normally in northern countries like Russia, Azerbaijan, and Iran. They always migrate from northern lands in Russia to the northern parts of Iran and Azerbaijan near the Caspian sea. The Keshtels have amazing behavior in their feeding. When they find a source of food in the lake, other Keshtels approach this lucky Keshtel who firstly found a portion of good food and they swirl together in a circle. Other Keshtels who cannot find a good source of food move to other parts of the lake or fly to another lake [24].

To model these behaviors of Keshtels, Hajiaghaei-Keshteli and Aminnayeri [24] proposed a nature-inspired metaheuristic for solving optimization problems. They generated the initial Keshtels as a set of random solutions in the lake. They divided this population into three groups (i.e., N_1, N_2, and N_3) with regard to the fitness or the cost of the objective function. N_1 is the group of the lucky Keshtels who

[[Z] [X] [Y]]

Figure 1: General view of the solution representation.

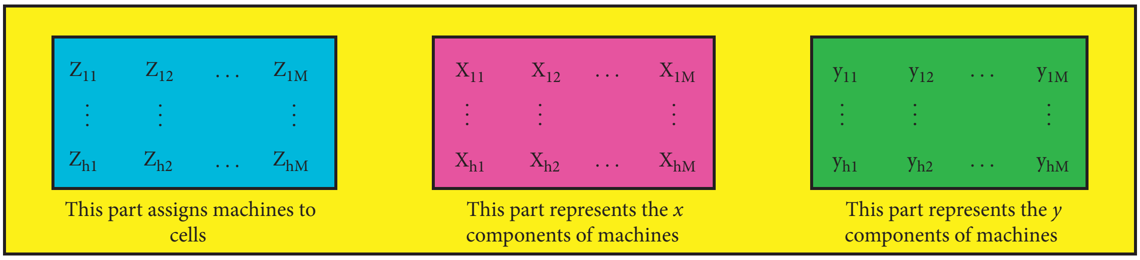

Figure 2: Generation of a feasible solution.

$$\begin{bmatrix} z'_{11} & z'_{12} & & z'_{1N} \\ \vdots & \vdots & \cdots & \vdots \\ z'_{h1} & z'_{h1} & & z'_{HN} \end{bmatrix}$$

Figure 3: Final matrix to compute the fitness function.

have found a good source of food in the lake. N_2 moves fast between the lucky Keshtels to search for source of food . The best source of food is the global solution and each Keshtel finding it is the best solution in all iterations. Finally, the last group, that is, N_3 population, is generated randomly in each iteration. They are new Keshtels that may land in the lake.

As a metaheuristic, it is very important to find an interaction between two main search phases, that is, intensification and diversification. In this metaheuristic, this classification of three groups is very useful to explore the new search areas. The first group (N_1) does the exploitation or intensification phase. Other groups help the algorithm to perform the diversification phase. Most importantly, the N_3 group finds a way for the algorithm to escape from the local solutions. To the best of our knowledge, no paper contributes the KA in this research area. To have a conclusion about the steps of KA, a pseudocode is presented in Figure 4.

3.3. Red Deer Algorithm (RDA). Evolutionary algorithms are another well-known classification of metaheuristics. These algorithms are also nature-inspired. However, from the current to the next generation, only a group of animals who are probably stronger than other ones will remain and other agents will be removed. As another evolutionary metaheuristic, Fathollahi-Fard et al. [25] recently proposed the Red Deer Algorithm (RDA) inspired by an amazing behavior of males and females in a breeding season.

This algorithm studies the behavior of red deer with regard to roaring, fighting, and mating behaviors. These animals are naturally living in the British Isles, mainly in Scotland. In this regard, the scientists called them Scottish Red Deer (*Cervus elaphus scoticus*). In a breeding season, the males that are also known as stags roar loudly and repeatedly to attract the females, so-called hinds. Based on this feature of the males, the hinds select their preferable stag, and he will create his territory and harem. A harem is a group of hinds and a commander as the head of this group manages and controls them. The fighting action always exists among males. Stags and commanders fight, and the winner will achieve the territory and harem. This competition among males is the main activity. The last part of this season is the mating behaviors among males and hinds and, as a result, the new red deer will have born for the next breeding season. Among all roaring, fighting, and mating processes, the evolutionary concept confirms that only the strongest will always remain in nature and this rule has existed among red deer.

Fathollahi-Fard et al. [25] modeled these facts as another evolutionary algorithm. They generated the first population of red deer as the random solutions. This population is divided into males and hinds. Then, males roar, and, based on their power, a group of them will be selected as the commanders and the others are stags. Next, a fight between commanders and stags occurs. After that, for each commander, a harem will be generated by some random hinds. The number of hinds in a harem is directly related to the power of the commander. After that, the commoner has this ability to mate with a number of his hinds in the harem and a few hinds in another harem. The stag that does not have a chance to be a commander can mate with one hind that is closest to him geographically. After the mating, offspring is created for each mating. Finally, for the next generation, the males will be selected as the best solutions among all available solutions and the hinds will be selected by an evolutionary mechanism like the roulette wheel selection method.

With these features, the authors developed an interesting and successful metaheuristic and called it RDA. To have a brief illustration of RDA, its pseudocode is presented in Figure 5.

3.4. Proposed Novel Hybrid Metaheuristic (H-RDKGA). Based on the aforementioned description, it is approved that the KA uses a high exploitive behavior. The RDA is good at the exploration phase. The GA has also a classical crossover operator to do the explorative behavior. The proposed novel hybrid metaheuristic called H-RDKAGA uses the aforementioned benefits.

```
Initialize Keshtels population.
Calculate the fitness and sort them into three types: N1, N2, and N3
X*=the best solution.
while (t< maximum number of iterations)
    for each N1
        Calculate the distance between this lucky Keshtel and all Keshtels.
        Select the closest neighbor.
        S=0;
        while (S< maximum number of swirling)
            Do the swirling.
            if the fitness (at least, one of the objective functions has been improved) of this new position is better
than prior
                Update this lucky Keshtel.
                    break
            endif
            S=S+1
        end while
    endfor
    for each N2
        Move the Keshtel between the two Keshtels, randomly.
    endfor
    for each N3
        Create a random solution.
    endfor
    Merge the N1, N2, and N3.
    Sort the Keshtels and form N1, N2, and N3 for the next iteration.
    Update the X* if there is a better solution.
    t=t+1;
end while
return X*
```

Figure 4: The pseudocode of KA.

In the proposed hybrid algorithm, the RDA acts as the main loop and two other algorithms improve the subloop of this algorithm. This hybrid metaheuristic uses the swirling process instead of roaring and fighting operators in the RDA. In this regard, each male performs the swirling process with his closest neighbor. The proposed hybrid algorithm also considers the crossover of the GA instead of the mating operator. Other steps are similar to the main RDA. Finally, the pseudocode of H-RDKGA is provided in Figure 6. The evaluation metrics for the performance of the algorithms are shown in Table 1.

Then, the acquired results for every problem are converted to the Relative Percentage Deviation (RPD) computed by

$$\mathrm{RPD} = \frac{\left|\mathrm{Alg}_{\mathrm{sol}} - \mathrm{Best}_{\mathrm{sol}}\right|}{\mathrm{Best}_{\mathrm{sol}}}, \quad (16)$$

where $\mathrm{Alg}_{\mathrm{sol}}$ is the output of the algorithm and $\mathrm{Best}_{\mathrm{sol}}$ is the best value ever found in the problem size. It should be noted that the lower value for the RPD is preferred.

4. Tuning of Algorithms and Comparison Studies

In this section, first, using the design of the experimental approach, the parameters of the aforementioned algorithms are tuned. Then, a comprehensive study is done to evaluate the performances of the algorithms.

4.1. Tuning of Metaheuristics. As all metaheuristics have some controlling parameters, tuning is needed satisfactorily. Here, based on the concept of the Design of Experiment (DOE), all algorithms have been calibrated. This method can analyze the impact of different candidate values on the parameters of the algorithms and evaluate the behavior of the algorithms. Without a good calibration of the parameters, the behavior of the metaheuristics is not reliable.

To do the tuning, the parameters of the given metaheuristics are considered. With regard to the DOE method, a full factorial method to analyze all possible experiments with regard to the levels is done. The levels and tuned values for each parameter are given in Table 2. It should be noted that all candidate level values are taken from similar studies in the literature [18, 21, 26].

4.2. Comparison among Employed Metaheuristics. To do the comparison among the employed metaheuristics, nine test studies are benchmarked from the literature [15]. These tests are selected from small-scale to large-scale instances. As the model of our work is novel and differs from previous works, no comparison between our results and previous studies is

```
Initialize the Red Deers population.
Calculate the fitness and sort them and form the hinds (N_hind) and male RDs (N_male).
X*=the best solution.
while (t< maximum number of iterations)
  for each male RD
    A local search near his position.
    Update the position if better than the prior ones (at least, one of objectives among all has been improved).
  end for
  Sort the males and also form the stags and the commanders.
  for each male commander
    Fight between male commander and stag.
    Update the position of male commander and stag.
  end for
  Form harems.
  for each male commander
    Mate male commander with the selected hinds of his harem randomly.
    Select a harem randomly and name it k.
    Mate male commander with some of the selected hinds of the harem.
  end for
  for each stag
    Calculate the distance between the stag and all hinds and select the nearest hind.
    Mate stag with the selected hind.
  end for
  Select the next generation with roulette wheel selection.
  Update the X* if there is better solution.
  t=t+1;
end while
return X*
```

Figure 5: The pseudocode of RDA.

```
Initialize the Red Deers population.
Calculate the fitness and sort them and form the hinds (N_hind) and male RDs (N_male).
X* = the best solution.
  while (t< maximum number of iterations)
    for each male RD
      Calculate the distance between this male and all males.
      Select the closest neighbor.
      S=0;
      while (S< maximum number of swirling)
      Do the swirling.
    if the fitness of this new position is better than prior
      Update this lucky male.
       break
      end if
      S=S+1
      end while
      end for
      Sort the males and also form the stags and the commanders.
      for each male commander
      Select a hind by roulette wheel selection.
      Mate (Crossover) male commander with the selected hind.
       end for
      for each stag
      Select a hind randomly.
      Mate (Crossover) stag with the selected hind.
      end for
      Select the next generation via roulette wheel selection.
      Update the X* if there is better solution.
      t=t+1;
    end while
    return X*
```

Figure 6: The pseudocode of H-RDKGA.

Table 1: Evaluation metrics to the performance of the algorithms (i.e., DM, SNS, DEA, and POD).

Instances		DM		
M × P	GA	KA	RDA	H-RDKGA
3 ∗ 5	15861	14389	16452	14015
4 ∗ 6	18753	17275	19743	16527
5 ∗ 8	20213	19833	21872	18817
6 ∗ 9	22916	21806	33112	20763
7 ∗ 11	25817	24319	39671	23917
8 ∗ 13	27918	26518	43749	24008
10 ∗ 12	32650	31997	55761	29879
11 ∗ 13	38650	36521	57144	34699
12 ∗ 15	47840	47003	60195	45810
Instances		SNS		
M × P	GA	KA	RDA	H-RDKGA
3 ∗ 5	2498	2267	1748	2699
4 ∗ 6	6122	7210	5426	7495
5 ∗ 8	7445	7296	6948	8155
6 ∗ 9	3485	3105	2915	4039
7 ∗ 11	2143	1834	7501	2867
8 ∗ 13	1077	1282	675	2049
10 ∗ 12	5482	4912	4466	4288
11 ∗ 13	6388	5187	5514	6382
12 ∗ 15	6237	5853	6432	7528
Instances		DEA		
M × P	GA	KA	RDA	H-RDKGA
3 ∗ 5	0.18	0.16	0.12	0.15
4 ∗ 6	0.20	0.12	0.18	0.12
5 ∗ 8	0.24	0.22	0.26	0.18
6 ∗ 9	0.28	0.14	0.22	0.14
7 ∗ 11	0.16	0.26	0.18	0.16
8 ∗ 13	0.24	0.12	0.12	0.19
10 ∗ 12	0.18	0.14	0.20	0.22
11 ∗ 13	0.26	0.18	0.14	0.18
12 ∗ 15	0.14	0.22	0.20	0.35
Instances		POD		
M × P	GA	KA	RDA	H-RDKGA
3 ∗ 5	0.16	0.22	0.14	0.22
4 ∗ 6	0.18	0.18	0.19	0.21
5 ∗ 8	0.22	0.20	0.10	0.18
6 ∗ 9	0.15	0.14	0.11	0.16
7 ∗ 11	0.17	0.18	0.16	0.12
8 ∗ 13	0.19	0.14	0.12	0.18
10 ∗ 12	0.22	0.16	0.14	0.12
11 ∗ 13	0.22	0.18	0.14	0.16
12 ∗ 15	0.20	0.16	0.08	0.22

done. Accordingly, we compare our metaheuristics with each other, as well as the results of the exact solver.

As the metaheuristics are naturally random, we run each algorithm 10 times and the best, the worst, the average, and the standard deviation of solutions among runs are reported. An average of the computational time of the algorithms is noted. To check the validation of the results, an exact solver implemented by GAMS software is used. Table 3 provides all the results. It should be noted that the exact solver is not able to find a solution for the large-scale instances after one hour. But all the metaheuristics can solve the problem in a few minutes.

Generally, the behavior of the algorithms in the criterion of the solution time is very close. Both hybrid algorithms and KA have a neck-and-neck competition. However, the KA is slightly better than all the metaheuristics. Without a doubt, the proposed H-RDKGA outperforms other algorithms and its solution is very close to the global solution based on the results.

Finally, the results indicate that, based on the average of the standard deviation of the results and the gaps of the algorithm in the interval plot, the proposed hybrid algorithm, that is, H-RDKAGA, is highly better than other algorithms and outperforms the best. After this algorithm, a

Table 2: Tuning of metaheuristics.

Metaheuristic	Parameters	Levels −1	Levels 0	Levels +1	Tuned value
GA	Population size	100	150	200	**200**
	Maximum number of iterations	300	500	700	**500**
	Rate of mutation	0.05	0.15	0.25	**0.15**
	Rate of crossover	0.6	0.7	0.8	**0.8**
KA	Population size	100	150	200	**100**
	Maximum number of iterations	300	500	700	**300**
	Percentage of N_1	0.1	0.2	0.3	**0.1**
	Percentage of N_2	0.4	0.5	0.6	**0.6**
	Maximum number of swirlings	5	10	15	**10**
RDA	Population size	100	150	200	**150**
	Maximum number of iterations	300	500	700	**700**
	Number of males	15	25	30	**25**
	Alpha	0.5	0.6	0.7	**0.6**
	Beta	0.7	0.8	0.9	**0.7**
	Gamma	0.8	0.9	1	**0.8**
H-RDKGA	Population size	100	150	200	**150**
	Maximum number of iterations	300	500	700	**500**
	Number of males	15	25	30	**30**
	Maximum number of swirlings	5	10	15	**15**

Table 3: Comparison of algorithms.

Algorithm		*P*1	*P*2	*P*3	*P*4	*P*5	*P*6	*P*7	*P*8	*P*9
EX	B	24283	28641	84180	119046	218907	476036	—	—	—
	CPU	18	64	201	836	1872	3315	3600	3600	3600
GA	B	24283	28641	84180	119046	221470	476124	694902	952906	120094
	W	27925	32937	98482	139038	257709	572564	812835	1118365	138304
	A	24283	28641	85637	120903	224095	497882	706813	972491	120265
	SD	4205	4960	15740	22090	40414	101164	129847	180812	20929
	CPU	22	17	22	32	42	65	79	96	102
KA	B	24283	28641	84180	119046	219968	480789	701712	962243	121270
	W	24525	28927	85021	123807	228766	504828	736797	1010355	127333
	A	24428	28812	84684	121902	225246	495212	722763	991110	124907
	SD	194	230	677	3834	7085	19358	28254	38745	4882
	CPU	18	15	20	28	38	58	72	88	92
RDA	B	24283	28641	84180	119046	219850	476362	687953	943376	118893
	W	24524	28926	85021	122617	226445	490652	708591	971677	122459
	A	24451	28840	84768	121545	224466	486365	702399	963186	121389
	SD	160	190	560	2382	4399	9532	13767	18879	2378
	CPU	24	18	26	33	43	66	78	95	106
H-RDKGA	B	24283	28641	84180	119046	218907	476101	681004	933847	117692
	W	24283	29213	85863	121426	223285	485623	694624	952523	120045
	A	24283	28927	85021	120236	221096	480862	687814	943185	118868
	SD	0	286	841	1190	2189	4761	6810	9338	1176
	CPU	22	16	20	26	40	62	72	90	94

B = best, W = worst, A = average, SD = standard deviation, EX = exact solver, and CPU = run time (seconds).

slight difference exists between the KA and the RDA, but the RDA is better. The last algorithm is the GA, as it has the weakest performance in this comparison.

5. Conclusion

Inter/intracell layouts and dynamic cell formation in a steady space were investigated concurrently in this paper by a novel mixed-integer nonlinear programming model. This model was performed somehow to minimize the cost of the number of exceptional elements (EEs), parts total transportation expense, and cell redesigning. As the model was an NP-Hard problem, first, three metaheuristic algorithms are proposed for optimization. In the next step, to further improve the solutions, a new hybrid metaheuristic algorithm combining the results of the three metaheuristics is proposed. To combine and improve the solutions of the algorithms, machine learning approaches are employed. More precisely, combining the merits of the aforementioned algorithms, the new metaheuristic algorithm is proposed.

Several recommendations can be proposed for better orientations in this study. Merging the proposed model for instance with a scheduling problem would be interesting. Also, to overcome the uncertainty, a two-stage or multistage stochastic programming method could be used. Applying more in-depth analyses by other large-scale optimization problems could be another approach from the aspect of the new suggested hybrid algorithm. Lastly, to evaluate the outcomes of the offered algorithms, new metaheuristics can be proposed.

Data Availability

The data and MATLAB codes used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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Research Article

Viable Supply Chain Network Design by considering Blockchain Technology and Cryptocurrency

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Nowadays, using Blockchain Technology (BCT) is growing faster in each country. It is essential to apply BCT in Supply Chain Network Design (SCND) and is considered by the designer and manager of SC. This research indicates Viable Supply Chain Network Design (VSCND) by applying BCT. A new form of two-stage robust optimization is suggested. Facility locations and activation BCT for VSCND is the first stage of decisions; finally, we determine flow transshipment between components in the next stage. The GAMS-CPLEX is used for solving the model. The results show that running BCT will decrease 0.99% in costs. There is an economic justification for using BCT when demand is high. A fix-and-optimize and Lagrange relaxation (LR) generate lower and upper bound to estimate large scale in minimum time. The gap between the main model and fix-and-optimize is better than the LR algorithm. Finally, this research suggests equipping VSCND by BCT that becomes more resilient against demand fluctuation, sustainable, and agile.

1. Introduction

One of the new discussions in the present age is the Viability of Supply Chain (VSC) in postpandemic adaptation. Ivanov and Dolgui [1] proposed the viability of SC that includes resiliency, sustainability, and agility. They suggested that organizational, informational, technological, financial, and process-functional structure should improve and change as follows:

(1) Organizational (subcontractor and backup supplier, workplace resilience, facility fortification)
(2) Informational (data analytics, visibility, digital twins, supplier portals, blockchain)
(3) Technological (robotics, additive manufacturing, smart manufacturing and warehousing, industry 4.0)
(4) Financial (business-government, revenue management, liquidity reserves)
(5) Process-functional (flexible capacity and sourcing, inventory and capacity buffers, Omnichannel, product diversification, and substitution) [2]

Therefore, using BCT is clearly toward VSC. The BCT can help in the clarity and agility of SC [3]. Smart contract executes contract automatically between layers of SC. After every event happens, such as transactions by customers in retailers, instant settlement and checkout processes are done in all SC layers. This technology runs information sharing, and all components of SC are aware of demands until the end of chain.

Smart contract in BCT runs contracts well between nodes, and financial transaction runs without human intervention. However, establishing BCT in SC needs programming and receiving correct input until giving the correct output. Therefore, it can mitigate risks and transaction costs [4]. Smart contract reduces costs compared to traditional contract and when it runs, tractable and irreversible transactions are established [5]. In the blockchain industry, Ethereum environments can implement smart contracts for SC as well. When a smart contract starts, there is no way to stop it. Thus, this procedure decreases demand fluctuation, raises awareness of demand variation in all SC layers, and decreases bullwhip effects [3]. This subject increases SC's resiliency and sustainability through SC's flexibility by sharing information on transactions and demands, decreasing flow quantity in SC and CO_2 emission, and increasing satisfaction and welfare. Walmart for food supply ecosystem, Ford for supplying cobalt, De Beers for tracking diamond, UPS for tracking logistics, FedEx for tracking shipments are companies that used BCT to add transparency in SC. We should use this technology to manage SC clearly, be resilient against demand, and be sustainable for the future [6, 7]. In Figure 1, we can see the trend of using BCT and the market size of BCT in USA from 2016 to 2028 and the market share of Europe in 2020; it can show that the growth rate is 82.4% from 2021 to 2028. Therefore, we should consider this trend, and every SC that uses this technology can be successful in the future.

The main contribution and motivation of this study are as follows:

(1) Applying BCT to increase viability and agility of SCND
(2) Using a new mathematical model for showing the effects of BCT on SCND
(3) Adding resiliency, sustainability, and robustness to VSCND by considering BCT

We organized this paper as follows. In Section 2, we study on related work and show gap research in scope SCND. In Section 3, we determine VSCND mathematical model. In Section 4, the findings and results of the proposed model with sensitivity analysis are explained. In Sections 5 and 6, the managerial insights and conclusion and outlook are determined.

2. Related Work about SCND

Increasing the presence of investors in the cryptocurrency industry has caused other people in the community to be attracted to this industry. This subject has led many researchers to focus on this area, which is described below. Nayak and Dhaigude [9] reviewed and evaluated 178 articles that employed BCT in SCs. They presented that the benefits of BCT include data management, improving transparency, improving response time smart contract management, operational efficiency, disintermediation, immutability, and intellectual property management. Moreover, one of the most important advantages of BCT is increasing SC resiliency, reducing disruptions, helping risk management, and establishing multilayer protection [10].

We surveyed SC by applying BCT with considering the mathematical model and other tools presented below.

Choi [11] proposed global SC operations with air logistics with a mean-variance (MV) approach for risk analysis by applying the BCT era. They utilized their model by helping with the newsvendor problem. Choi and Luo [12] surveyed data quality problems for emerging markets in sustainable fashion SC. Their model includes decentralized SC and implementing BCT to enhance the profit and transparency of SC and increase welfare. They used newsvendor to the model problem and compared the decentralized SCM model with BCT and centralized model. In other works of Choi [11], he proposed BCT for diamond SC. He used BCT for exploring diamonds and compared the traditional model with the BCT platform. He found that using BCT platform can reduce cost and is beneficial to all parties in the luxury SC.

Nayak and Dhaigude [9] suggested a conceptual model for sustainable SC management (SCM) using BCT. They used Interpretive Structural Modeling (ISM) and Matrice d'Impacts Croise's Multiplication Appliquée a UN Classement (MICMAC) to draw a conceptual model, identify factors, and show effects of BCT on SCM. Rahmanzadeh et al. [13] designed a tactical SC planning model with open innovation consideration within a BCT. They proposed using BCT for registering, collecting, and refining ideas in open innovation. They used a fuzzy mathematical model to tackle uncertainty in the home appliances domain. They found that, by spending 1% of the total cost of SC, they can receive good ideas and decrease 41% of the total cost. Dolgui et al. [3] developed multiple logistics service providers by considering a smart contract for flexible flow shop scheduling. They used dynamic control theory for a running model.

Manupati et al. [14] proposed a multiechelon green SC for the production allocation problem by implementing a blockchain approach. They suggested a Mixed Integer Nonlinear Programming (MINLP) for a carbon taxation policy for the greenness of the model. They showed that the distributed ledger-based blockchain approach enables minimizing total cost and carbon emissions. Liu et al. [15] surveyed a green agrifood SC by applying information service based on blockchain and big data (ISBD). They applied Stackelberg's game theory to draw the model and solve investment decision problems. They compared four models, surveyed the freshness of agrifood by BCT, and used BCT for information sharing between producer and retailer. De Giovanni [4] explained that BCT could manage risks and transaction costs. He drew a situation that suppliers and retailers can activate by a traditional online platform or BCT. They removed transaction costs by BCT. Finally, they determined a smart wholesale price and revenue sharing contract to increase coordination between layers. They utilized game theory to solve the model.

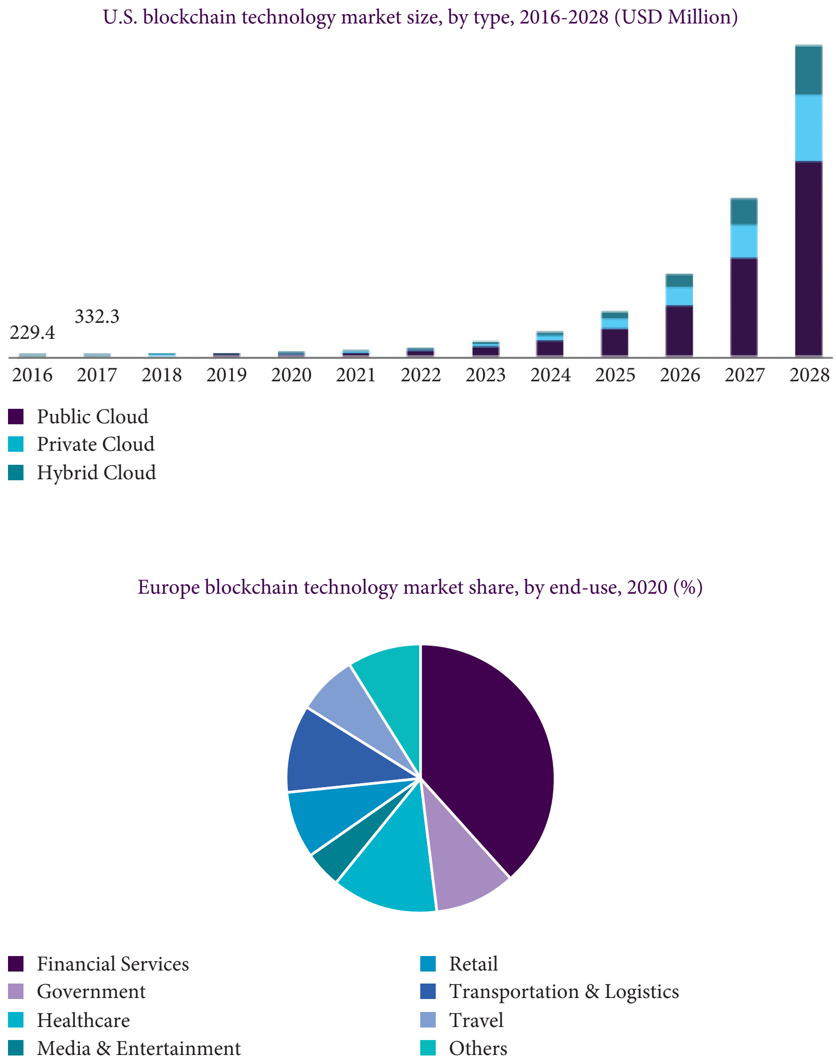

Figure 1: The market size of BCT in the USA and the market share of Europe [8].

Alkahtani et al. [16] considered an e-agricultural SCM with BCT equipment in a cooperative situation. They applied the BCT into the agricultural SCM. Further, a Fuzzy Inference System (FIS) and Analytical Hierarchy Process (AHP) are embedded to show uncertainties in the model. They wanted to maximize profit with advertisement costs constraints and space constraints. As this model was NLP, they employed Karush–Kuhn–Tucker (KKT) to solve the model. They found that the effect of BCT can reduce the costs of SCM. Zhong et al. [17] implemented a Stackelberg game for container shipping lines and surveyed it using blockchain. Their model uses two stages to define the freight rate. They found that entering BCT can regulate the freight rate and improve the price in the container shipping market. The first stage is entering the blockchain or not, and the next step is assigning container shipping lines. They used the Stackelberg game and Cournot game for the second stage to show BCT effects.

We classified the literature review in Table 1 and the application of BCT in SCND. It can be seen that we want to design VSCND by BCT platform, which are not studied yet. We present VSCND through (flexible capacity (resilience strategy), sustainability constraints, and agility (by considering BCT)) for SCND. Finally, we add uncertainty through the robust scenario by defining a new form of the objective function.

3. Problem Description

In this research, we try to design VSCND with considering BCT. The previous section shows a lack of research in resilience and sustainable SC considering BCT. In the present study, we have customers, retailers, manufacturers, suppliers that transact in the BCT environment. The current SC uses BCT and smart contracts and executes contracts automatically between layers of SC. After customers transact in retailers, all payments automatically expand in SC layers, each component withdraws its share at once, and no charge remains in the retailers' accounts. Eventually, we present VSCND through the flexible capacity facility (resilience strategy), sustainability constraints, and agility (by considering BCT) for SCND.

Table 1: Survey of SCND with considering BCT.

Ref.	Problem	Platform	Objectives					Uncertainty	Method	Industry
			Economic	Environmental	Energy	Social	Others			
[11]	SC operations	BCT	✓	—	—	—	—	Probably	Scenario newsvendor + risk	—
[12]	Data quality problems	BCT	✓	—	—	—	—	Probably	Newsvendor	Fashion
[11]	Diamond SC	BCT	✓	—	—	—	—	Probably	Stackelberg game	Diamond
[9]	Sustainable SC	BCT	—	—	—	—	✓	—	ISM + MICMAC	Numerical example (NE)
[13]	Tactical with open innovation	BCT	✓	—	—	—	—	Fuzzy	*MILP	Home appliances
[3]	Flexible flow shop scheduling	BCT	—	—	—	—	✓	—	Dynamic optimal control	NE
[14]	Production allocation problem	BCT	✓	—	—	—	—	—	MINLP + NSGA-II	NE
[15]	ISBD green in agrifood SC	Big data + BCT	✓	—	—	—	—	Probably	Stackelberg game	NE
[4]	SCM	BCT	✓	—	—	—	—	Stochastic	Stackelberg game	NE
[1]	VSC	Digital concept	✓	—	—	—	—	—	Dynamics control approach	—
[2]	VSC	Digital concept	✓	—	—	—	—	—	Dynamic game-theoretic	—
[18]	Sustainable SC	—	✓	✓	—	✓	—	—	MILP, *MOGWO, MORDA, AEC	Aluminum
[19]	Open-CLSC	—	✓	—	—	✓	✓	Robust	MILP + AWT	NE
[16]	E-agricultural SCM	BCT	✓	—	—	—	—	FIS + AHP	NLP + KKT	E-agriculture
[17]	Container shipping lines	BCT	✓	—	—	—	—	—	Stackelberg and Cournot game	NE
[20]	Waste VSC	—	✓	—	—	—	—	Robust	Scenario + risk	Iran
This research	VSCND	BCT	✓	—	—	—	—	New robust stochastic	MILP	Computer

* MILP: Mixed Integer Linear Programming; MOGW: Multiobjective Gray Wolf Optimizer; MORDA: Multiobjective Red Deer Algorithm; AEC: Augmented Epsilon Constraint; AWT: Augmented Weighted Tchebycheff.

In Figure 2, we used Ethereum smart contract technology that pays at once after payment of customers. We want to consider BCT instead of a traditional transaction. Therefore, using BCT enables reducing variable costs. We draw a model that can select applying traditional transactions with higher variable costs or select BCT with lower variable costs. Still, there are fix and maintenance costs for establishing BCT.

Hence, we need this assumption is as follows.

Assumption 1

(i) All demands should be prepared, and the shortage is not permitted (agility)

(ii) Flow and capacity constraints are active in forwarding SC (agility)

(iii) A BCT is used for payment in layers of SC decreasing variable cost (agility)

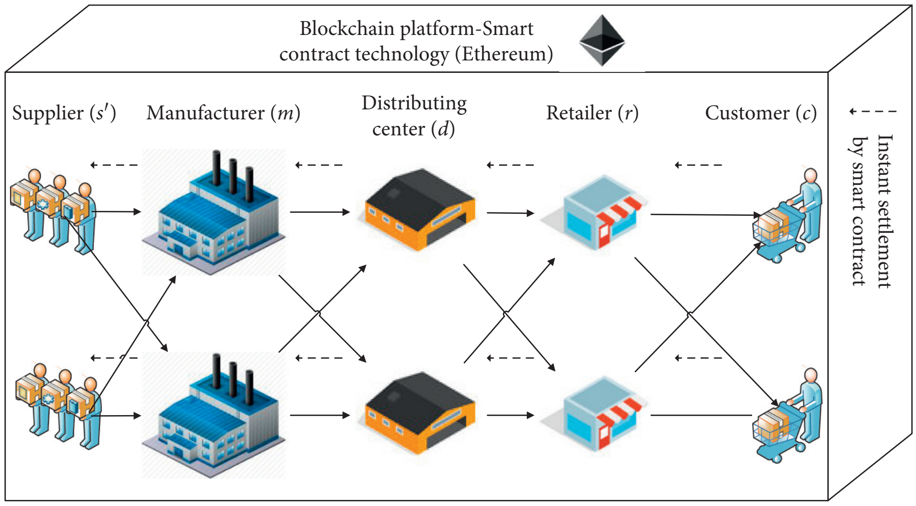

Figure 2: VSCND with considering BCT.

(iv) Sustainability constraints include emission and energy consumption are defined (sustainability)

(v) Flexible scenario-based capacity for the facility is as resilience strategy (resiliency)

(vi) Using robust stochastic programming to cope with fluctuation of demand (resiliency) [2, 21]

(vii) Variable cost after activating BCT is less than that without BCT

3.1. Model 1: VSCNDBCT

$$\min Z = (1-\lambda)\left(\sum_s p_s\Gamma_s + z_\alpha \sum p_s\left|\Gamma_s - \sum_s p_s\Gamma_s\right|\right) + \lambda \max(\Gamma_s), \tag{1}$$

$$\Gamma_s = \mathrm{FC} + \mathrm{VC}_s, \tag{2}$$

$$\mathrm{FC} = \mathrm{FCF} + \mathrm{FCBT}, \tag{3}$$

$$\mathrm{FCF} = \sum_{s'} fs_{s'}xs_{s'} + \sum_m fm_m xm_m + \sum_d fc_d xd_d + \sum_r fr_r xr_r, \tag{4}$$

$$\mathrm{FCBT} = fbt \cdot xbt + \sum_t \sum_s mbt_{ts} xbt, \tag{5}$$

$$\mathrm{VC}_s = \mathrm{VC1}_s(1-xbt) + \mathrm{VC2}_s xbt = \mathrm{VC1}_s - (\mathrm{VC1}_s - \mathrm{VC2}_s)xbt, \quad \forall s, \tag{6}$$

$$\mathrm{VC1}_s = \sum_p \sum_t \left(\sum_{s'} \sum_m vsm_{s'mpts}qsm_{s'mpts} + \sum_m \sum_d vmc_{mdpts}qmd_{mdpts} + \sum_d \sum_r vdr_{drpts}qdr_{drpts} + \sum_r \sum_c vrc_{rcpts}qrc_{rcpts}\right), \quad \forall s, \tag{7}$$

$$\mathrm{VC2}_s = \sum_p \sum_t \left(\sum_{s'} \sum_m vsm'_{s'mpts}qsm_{s'mpts} + \sum_m \sum_d vmc'_{mdpts}qmd_{mdpts} + \sum_d \sum_r vdr'_{drpts}qdr_{drpts} + \sum_r \sum_c vrc'_{rcpts}qrc_{rcpts}\right), \quad \forall s, \tag{8}$$

subject to the following.

Flow quantity constraints:

$$\sum_{r} qrc_{rcpts} \geq d_{cpts}, \quad \forall c, p, t, s, \tag{9}$$

$$\sum_{d} qdr_{drpts} = \sum_{c} qrc_{rcpts}, \quad \forall r, p, t, s, \tag{10}$$

$$\sum_{m} qmd_{mdpts} = \sum_{r} qdr_{drpts}, \quad \forall d, p, t, s, \tag{11}$$

$$\sum_{s'} qsm_{s'mpts} = \sum_{d} qmd_{mdpts}, \quad \forall m, p, t, s. \tag{12}$$

Resiliency strategy (flexible capacity based on scenarios):

$$\sum_{c} qrc_{rcpts} \leq \rho_r \text{Capr}_{rpts} xr_r, \quad \forall r, p, t, s, \tag{13}$$

$$\sum_{r} qdr_{drpts} \leq \rho_d \text{Capd}_{dpts} xd_d, \quad \forall d, p, t, s, \tag{14}$$

$$\sum_{d} qmd_{mdpts} \leq \rho_m \text{Capm}_{mpts} xm_m, \quad \forall m, p, t, s, \tag{15}$$

$$\sum_{m} qsm_{s'mpts} \leq \rho_{s'} \text{Caps}_{s'pts} xs_{s'}, \quad \forall s', p, t, s. \tag{16}$$

Sustainability strategy (allowed emission and energy consumption):

$$\sum_{p} \left(\sum_{s'} \sum_{m} emsm_{s'mpts} qsm_{s'mpts} + \sum_{m} \sum_{d} emmc_{mdpts} qmd_{mdpts} + \sum_{d} \sum_{r} emdr_{drpts} qdr_{drpts} + \sum_{r} \sum_{c} emrc_{rcpts} qrc_{rcpts} \right) \leq \text{EM}_{ts}, \quad \forall t, s, \tag{17}$$

$$\sum_{p} \left(\sum_{s'} \sum_{m} ensm_{s'mpts} qsm_{s'mpts} + \sum_{m} \sum_{d} enmc_{mdpts} qmd_{mdpts} + \sum_{d} \sum_{r} endr_{drpts} qdr_{drpts} + \sum_{r} \sum_{c} enrc_{rcpts} qrc_{rcpts} \right) \leq \text{EN}_{ts}, \quad \forall t, s. \tag{18}$$

Decision variables:

$$\begin{aligned} & xs_{s'}, \\ & xm_m, \\ & xd_d, \\ & xr_r, \\ & xbt \in \{0, 1\}, \quad \forall s', m, d, r, \end{aligned} \tag{19}$$

$$\begin{aligned} & qsm_{s'mpts}, \\ & qmd_{mdpts}, \\ & qdr_{drpts}, \\ & qrc_{rcpts} \geq 0, \quad \forall s', m, d, r, p, t, s. \end{aligned} \tag{20}$$

The objective function (1) minimizes the weighted expected and maximum cost function in each scenario. We proposed this form to increase robustness against demand disruption and consider the worst case. Constraint (2) includes the summation of fix and variable costs. Constraints (3) to (5) include the fix cost of establishing facilities and BCT network in a central server and BCT maintenance. Constraints (6) to (8) indicate the variable cost after establishing facilities without running BCT and considering BCT. Constraints (9) show satisfaction of demand. Constraints (10) to (12) show flow quantity between facilities. Constraints (13) to (16) show resiliency strategy and facility and capacity constraints dependent of scenario. Constraints (17) and (18) show sustainability strategy and total emissions and energy are less than maximum emission and energy. Constraints (19) and (20) are decision variables, and constraints (19) are locations and binary variables and activating BCT. Constraints (20) are positive flow variables.

3.2. Linearization of Max and Absolute Function. We need to change objective function (1) and equation (6) from Mix Integer Nonlinear Programming (MINLP (to Mixed Integer Programming (MIP))) by operational research method. This process decreases the time solution [22, 23].

Linearization of max function and absolute function is as follows.

If $k = \max(\Omega_s)$, then we can replace these constraints with the model $k \geq \Omega_s, \forall s$.

If $k = |\Omega_s|$, then we can replace these constraints with the model $k = \alpha_s + \beta_s, \Omega_s = \alpha_s - \beta_s, \alpha_s, \beta_s \geq 0, \forall s$.

We can change and linearize a binary and a nonnegative variable that is produced.

Suppose $z = Ax$, if A is a nonnegative and positive variable and x is a binary variable. Therefore, we can replace these constraints with the model [24]

$$z \geq 0, \tag{21}$$

$$z \leq Mx, \tag{22}$$

$$z \leq A, \tag{23}$$

$$z \geq A - (1 - x)M. \tag{24}$$

It means that if $x$is zero, z is zero based on equations (21) and (22). If x is 1, then z is A based on equations (23) and (24).

3.3. Linearization of VSCNDBCT. We can write linearization of VSCNDBCT as follows.

Linearization of VSCNDBCT:

$$\min Z = (1-\lambda)\left(\sum_s p_s \Gamma_s + z_\alpha \sum p_s (va_s + vb_s)\right) + \lambda\delta, \tag{25}$$

subject to

$$\delta \geq \Gamma_s, \quad \forall s, \tag{26}$$

$$\Gamma_s - \sum_s p_s \Gamma_s = va_s - vb_s, \quad \forall s, \tag{27}$$

$$va_s, vb_s \geq 0, \quad \forall s, \tag{28}$$

$$\mathrm{VC}_s = \mathrm{VC1}_s - \eta_s, \quad \forall s, \tag{29}$$

$$\eta_s \leq (\mathrm{VC1}_s - \mathrm{VC2}_s), \quad \forall s, \tag{30}$$

$$\eta_s \geq (\mathrm{VC1}_s - \mathrm{VC2}_s) - M(1 - xbt), \quad \forall s, \tag{31}$$

$$\eta_s \geq 0, \quad \forall s, \tag{32}$$

$$\eta_s \leq M(xbt), \quad \forall s, \tag{33}$$

constraints (2)–(5) and (7)–(20).

We linearize model (1) by changing MINLP to MIP. When we linearize it, speed solving and the complexity of the model are more straightforward than MINLP in all solvers. We show the complexity of VSCND; the numbers of binary, free, and nonnegative variables and constraints are calculated as follows:

$$\text{binary variables} = |s'| + |m| + |d| + |r| + 1, \tag{34}$$

$$\text{positive variables} = |p| \cdot |t| \cdot |s|\left(|s'| \cdot |m| + |m| \cdot |d| + |d| \cdot |r| + |r| \cdot |c|\right) + 3|s|, \tag{35}$$

$$\text{free variables} = 11 + 2|s|, \tag{36}$$

$$\text{constraints} = 10 + 10|s| + |p| \cdot |t| \cdot |s|\left(|c| + 2|r| + 2|d| + 2|m| + |s'|\right). \tag{37}$$

It can be seen that scenario sets positively affect the number of constraints and positive and free variables and make the model scale grow. Therefore, applying methods that reduce scenarios such as Lagrangian relaxation (LR) and fix-and-optimize helps solve fast in minimum time.

3.4. Lagrangian Relaxation (Lower Bound for Large Scale). Lagrangian relaxation (LR) is an exact method that relaxes complex constraints in a difficult problem, and because of removing constraints, solution time decreases. This method removes complex constraints and adds a penalty to the objective with the Lagrange multiplier. In practice, this relaxed problem can give us a lower bound for minimization and can often be solved more quickly than the main problem [25–27].

Formulation of a MIP and changing to LR form are as follows:

$$Z_{IP} \coloneqq \min c^T x, \tag{38}$$

subject to

$$Ax \geq b, \tag{39}$$

$$Dx \geq d, \tag{40}$$

$$x \text{ integer}. \tag{41}$$

In this step, we remove constraint (39) and add it to objective function (38) with the form of penalty cost and used the Lagrange coefficient for this situation:

$$Z(\lambda) \coloneqq \min c^T x + \lambda(b - Ax), \tag{42}$$

subject to constraints (40) and (41).

We need to find the maximum of λ that minimizes $Z(\lambda)$:

$$Z_D := \max_{\lambda \geq 0} Z(\lambda),$$
$$Z(\lambda) := \min_{i=1,\ldots,m} \left\{ c^T x^i + \lambda^T \left(b - Ax^i \right) \right\}, \tag{43}$$

subject to constraints (40) and (41).

In each iteration, we update λ based on these methods:

$$\lambda^{t+1} = \lambda^t + \gamma^t \nabla Z\left(\lambda^t\right),$$
$$\lambda^0 = 0,$$
$$t = 0,$$
$$\lambda^{t+1} = \lambda^t + \gamma^t \left(b - Ax^i \right),$$
$$\lambda^{t+1} = \max\left\{ 0, \lambda^t + \gamma^t \left(b - Ax^i \right) \right\},$$
$$\sum_{t=0}^{\infty} \gamma^t = \infty, \tag{44}$$
$$\lim_{t \longrightarrow \infty} \gamma^t = 0,$$
$$\gamma^t = \mu^t \frac{z* - z\left(\lambda^t\right)}{\sum_{i=1}^{m} \left(b_i - \sum_{j=1}^{n} a_{ij} x^t \right)^2},$$
$$\gamma^{t+1} = \alpha \gamma^t, \quad 0 \leq \alpha \leq 1, T > 1.$$

Therefore, based on these steps, the objective function (45) is LR of cost based on objective (25) that relax constraint (9). Figure 3 shows the steps of the LR algorithm that we applied to this research:

$$\min \text{LR obj} = Z + \sum_c \sum_p \sum_t \sum_s ud_{cpts} \left(\sum_r qrc_{rcpts} - d_{cpts} \right). \tag{45}$$

Subject to constraints (1)–(8), (10)–(20) and (26)–(33).

As can be seen, the complexity of the LR algorithm is as follows: binary, positive, and free variables are the same as equations (34)–(36). But constraints change into equation (46). This subject decreases the time solution:

$$\text{constraints} = 11 + 10|s| + |p| \cdot |t| \cdot |s| \left(2|r| + 2|d| + 2|m| + |s'| \right). \tag{46}$$

3.5. Fix-and-Optimize (Upper Bound for Large Scale). Because this problem is Np-hard, we need an algorithm to decrease the scale of this problem, produce an appropriate upper bound, and solve the model in minimum time. We suggest a new fix-and-optimize algorithm that creates an upper bound based on Figure 4. Relaxation of each constraint makes the upper bound for the objective function and equal to or greater than the amount of the primary objective function [21]. Fixing the binary variables by this method produce an appropriate upper bound. Finally, the objective function of the proposed method is always equal to or bigger than the main model.

This technique produces a close upper bound for the primary model explained in Helber and Sahling [28].

These steps of the new fix-and-optimize are as follows:

(1) Relax binary variables by changing them between zero and one and solve the model (relax constraint (19)).

(2) After solving step 1, we receive a lower bound, and our model is LP form.

(3) Loop:

   (a) Summarize binary variables for each set and round them up
   (b) Solve the model with a new fix binary variable
   (c) If the model obtains optimum value, it is an upper bound, and we save it in a list
   (d) Loop until the difference between two steps is less than 0.001

(4) Sort ascending objective function and report less upper bound objective function.

The complexity of the fix-and-optimize algorithm is as follows: binary variables are removed, and free, nonnegative variables and constraints are the same as equations (35)–(37). This subject decreases the time solution.

4. Results and Discussion

This section had a case study and estimated parameters defined in the notation list by the manager's information from the computer supply chain. We tried to show the performance of the proposed model. The number of sets is presented in Table 2, and amount of parameters are assigned in Table 3. The probability of occurrence is the same, and optimistic, pessimistic, and possible scenarios happen.

We applied a computer with this configuration: CPU 3.2 GHz, Processor Core i3-3210, 6.00 GB RAM, 64-bit operating system. Finally, we solve the mathematical models by GAMS-CPLEX solver.

We drew the potential location for assigning components of VSCND in Iran (c.f. Table 4 and Figure 5). After solving the model, it suggests that we activate BCT and determine the location and flow of SC components. The objective function is 2839008.413, shown in Table 2, and the final location-allocation is drawn in Figure 6. Eventually, we compare the model with BCT and without BCT in Table 5. We can see that without BCT, costs are almost 0.99% greater than with BCT.

4.1. Variation on the Scale of the Main Model. We determine several large-scale problems in Table 6. When the scale of problems increases, the time and cost increase as shown in Figures 7 and 8. As shown in Figure 8, the time solution is exponential and NP-hard on a large scale. Therefore, we need to solve the model by heuristic, metaheuristic [29], and new exact solution in minimum time on a large scale.

4.2. Variation on the Conservative Coefficient. The conservative coefficient (λ) is the number of conservative decision-makers. We change it by varying between 0 and 1 that the conservation of decision-maker has been changed. If the conservative coefficient increases to 1, the cost function

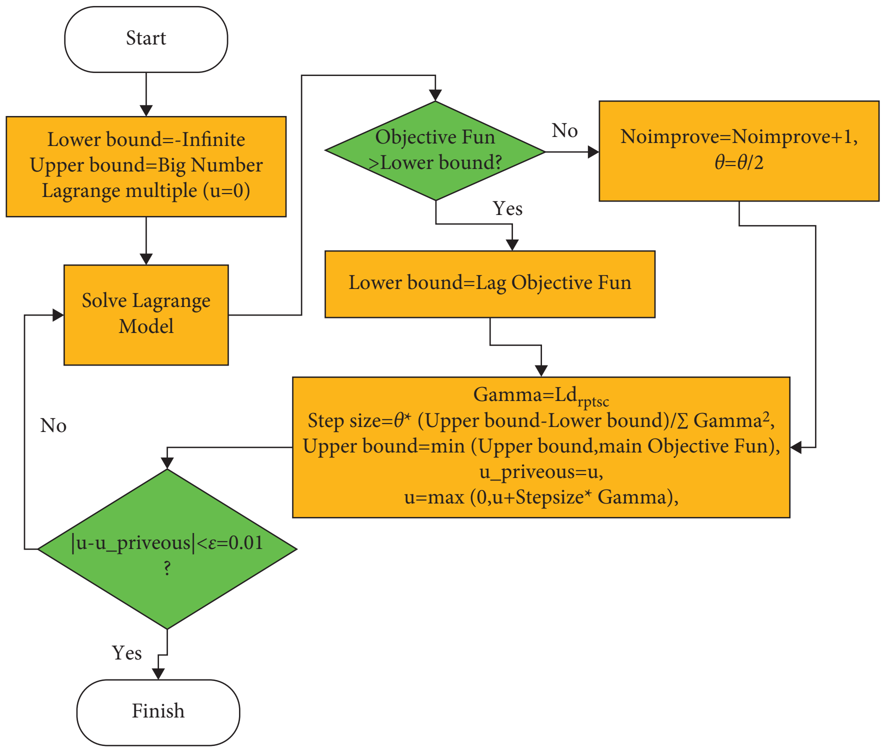

FIGURE 3: Solution approach for lower bound LR algorithm.

grows in Table 7 and Figures 9 and 10. If λ increases by 25%, the cost will increase by 0.3%, but the time solution does not change significantly.

4.3. Variation on Demand. As shown in Table 8, the application of BCT decreases and is not economical when decreasing demand happens definitely. When demand changes and increases, the cost will grow, and establishing BCT is required to decrease cost (c.f. Figure 11). By reducing 40% for demand, the cost function decreases by 22%, and BCT is not applicable.

4.4. Producing Bounds for the Main Model. We generate lower and upper bounds and compare the main model with the LR algorithm and a new fix-and-optimize strategy (c.f. Table 9). In addition, by relaxing constraint (19) that is LP form, we generate a lower bound for validating the LR algorithm. The comparison of the three methods is determined in Figures 12 and 13. We see that the fix-and-optimize strategy produces a suitable solution with a gap minimum of 10% and the LR algorithm produces a lower bound with a gap of less than 32% for the main model. Also, it can be seen that the cost function of P5 shows a difference between methods for three methods (c.f. Figure 14). We suggest using both approaches, but the fix-and-optimize strategy is better than the LR algorithm for large-scale problems.

5. Managerial Insights and Practical Implications

As managers of the SC, we should move forward to using novel technology in SC to decrease cost and increase resiliency and agility. BCT and cryptocurrency, renewable energy, and Internet of Things are new technologies that all of us need to use to improve the performance of SC. BCT and cryptocurrency are some of the best technologies that can facilitate financial transactions between customers and suppliers. As a result, operational and extra costs have been removed and make SC lean and agile. This research designed a SCND by considering and establishing BCT and cryptocurrency. We apply SC run traditional or consider BCT. Therefore, using BCT enables reducing variable costs. We draw a model that can select BCT with higher variable costs or select BCT with lower variable costs, fix cost, and maintenance costs for establishing BCT. We found that applying cryptocurrency can help SC to attain sustainability by decreasing cost and being agile. When demand is high, using BCT and cryptocurrency is an economic justification. Finally, we design a model for all risk-neutral decision-makers until

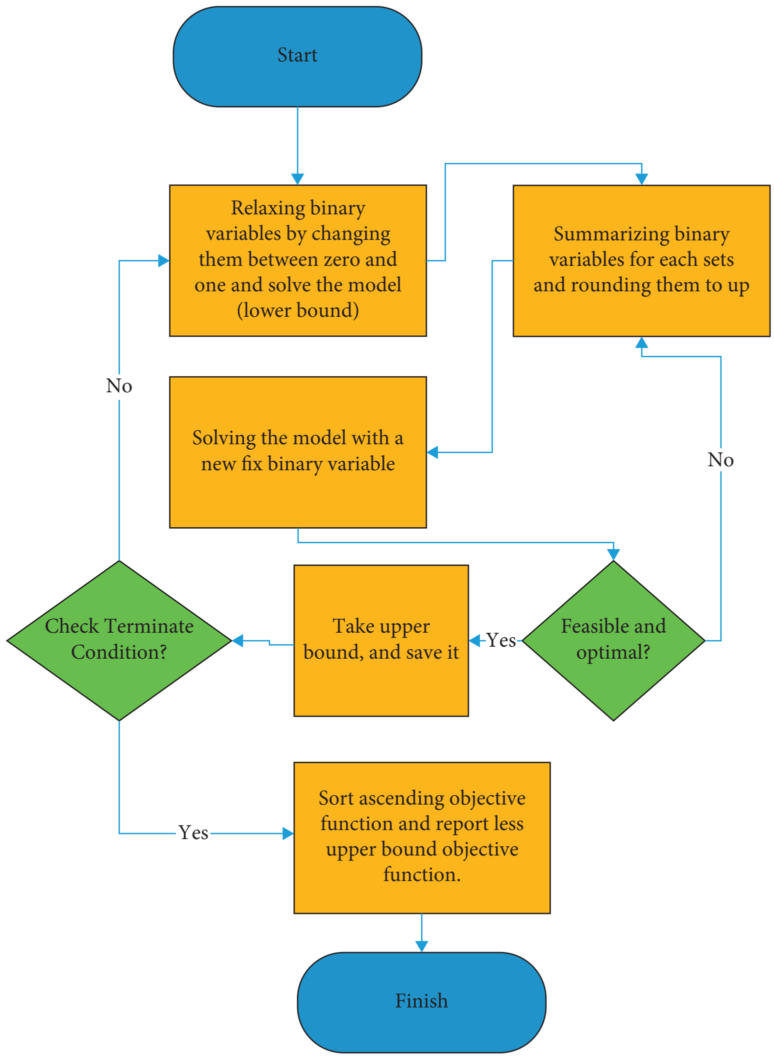

Figure 4: Fix-and-optimize solution approach (upper bound).

Table 2: The number of sets, variables, and constraints.

Problem	$\lvert s'\rvert \cdot \lvert m\rvert \cdot \lvert d\rvert \cdot \lvert r\rvert \cdot \lvert c\rvert \cdot \lvert p\rvert \cdot \lvert t\rvert \cdot \lvert s\rvert$	Binary variable	Positive variable	Free variable	Constraint	Cost function	Time (seconds)
P1-main	3.3.3.3.3.3.3.3	13	981	17	688	2839008.413	1.012

Table 3: Parameters of case study.

Parameters	Value	Unit	Parameters	Value	Unit
dd_{cpts}	[U (2000, 2100)].1000. (s-1)/(|s| − 1-).0.2 + 0.9)	Num.	fd_d	[U (80,85)].1000	$
$vsm_{s'mpts}$	U (0.002,0.003)	$/Num.	fr_d	[U(200,210)].1500	$
vmd_{mdpts}	U (0.004,0.005)	$/Num.	fr_r	[U(200,210)].200;	$
vdr_{drpts}	U (0.002,0.003)	$/Num.	fbt	[U(200,210)].200	$
vrc_{rcpts}	U (0.001,0.002)	$/Num.	pp_s	1/|s|	%
$vsm'_{s'mpts}$	0.9.U (0.002,0.003)	$	λ	50	%
vmd'_{mdpts}	0.9.U (0.004,0.005)	$	M	10^{500}	-
vdr'_{drpts}	0.9.U (0.002,0.003)	$	$emsm_{s'mpts}$	U $(4,5).10^{-4}$	Ton/Num.
vrc'_{rcpts}	0.9.U (0.001,0.002)	$	$emmd_{mdpts}$	U $(4,5).10^{-4}$	Ton/Num.
mbt_{ts}	[U(3,4)].100	$	$emdr_{drpts}$	U $(4,5).10^{-4}$	Ton/Num.
$esm_{s'mpts}$	U $(4,5).10^{-3}$	$/Num.	$emrc_{rcpts}$	U $(4,5).10^{-4}$	Ton/Num.

Table 3: Continued.

Parameters	Value	Unit	Parameters	Value	Unit
emd_{mdpts}	U (4,5).10^{-3}	\$/Num.	$ensm_{s'mpts}$	U (1,2).10^{-4}	MJ/Num.
edr_{drpts}	U (4,5).10^{-3}	\$/Num.	$enmd_{mdpts}$	U (1,2).10^{-4}	MJ/Num.
erc_{rcpts}	U (4,5).10^{-3}	\$/Num.	$endr_{drpts}$	U (1,2).10^{-4}	MJ/Num.
$\mathrm{Caps}_{s'pts}$	[U (5500,6600)].1000	Num.	$enrc_{rcpts}$	U (1,2).10^{-4}	MJ/Num.
Capm_{mpts}	[U (55000,66000)].1000	Num.	EM_{ts}	$50000 \cdot \lvert s'\rvert \cdot \lvert m\rvert \cdot \lvert d\rvert \cdot \lvert r\rvert \cdot \lvert s\rvert$	Ton
Capd_{dpts}	[U (3300,4400)].1000	Num.	EN_{ts}	$70000 \cdot \lvert s'\rvert \cdot \lvert m\rvert \cdot \lvert d\rvert \cdot \lvert r\rvert \cdot \lvert s\rvert$	MJ
Capr_{rpts}	[U (3300,4400)].1000	Num.	$\rho_{s'} = \rho_m = \rho_d = \rho_r = 90$	%	
$fs_{s'}$	[U(200,210)].1000	\$	z_α	0.5	-
fm_m	[U(200,210)].4000	\$		[]: sign	

Table 4: Assigning location for the facility of SC and BCT.

Problem: P1	Variables	City		
Supplier	$xs_{s'}$	Yazd 0	Chabahar 1	Behbahan 1
Manufacturer	xm_m	Khorramdareh 0	Zahedan 0	Kashan 1
DC	xd_d	Kashan 1	Kashmar 1	Sanandaj 1
Retailer	xr_r	Tehran 1	Borojerd 1	Khoy 1

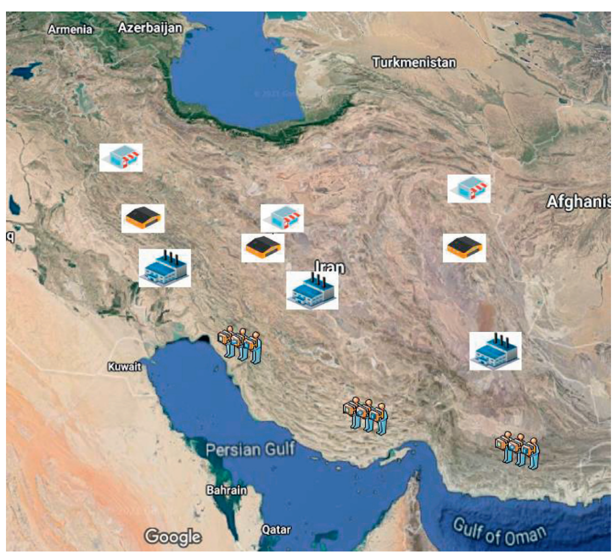

Figure 5: Potential location for the facilities.

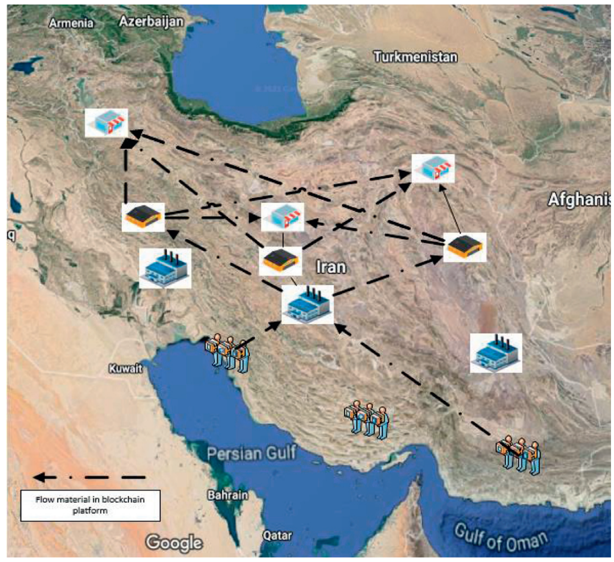

FIGURE 6: Final location of the SC facility with BCT platform.

TABLE 5: Compare P1 with BCT and without BCT.

Model	P1-with BCT	P1-without BCT	Gap (%)
Profit	2839008.413	2867283.546	0.99

TABLE 6: Cost and time solution for different problems.

Prob.	$\lvert s'\rvert \cdot \lvert m\rvert \cdot \lvert d\rvert \cdot \lvert r\rvert \cdot \lvert c\rvert \cdot \lvert p\rvert \cdot \lvert t\rvert \cdot \lvert s\rvert$	Binary var.	Positive var.	Free var.	Constraint	Cost function	Time (seconds)
P1	3.3.3.3.3.3.3.3	13	981	17	688	2839008.413	1.012
P2	3.3.3.3.3.3.3.5	13	1635	21	1140	2868628.538	2.857
P3	4.4.4.4.4.4.4.3	17	3081	17	1576	3931302.815	15.437
P4	4.4.4.6.4.4.4.4	19	5132	19	2354	3813256.048	26.237
P5	5.5.5.6.5.5.5.5	22	13765	21	5310	5525665.563	538.483
P6	8.8.8.6.8.8.8.5	31	71695	21	19260	—	—
P7	12.12.12.12.12.12.8.5	49	276495	21	46140	—	—
P8	20.8.8.12.15.15.20.7	49	1050021	25	191180	—	—
P9	30.8.8.12.20.20.30.10	59	3840030	31	636110	—	—
P10	40.8.8.12.30.35.40.15	69	17640045	41	2646160	—	—

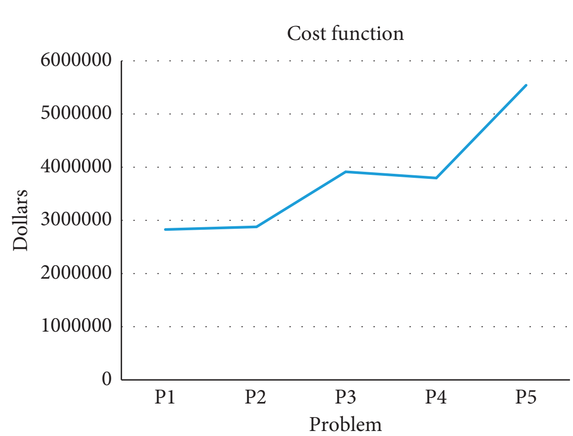

FIGURE 7: Cost function for problems.

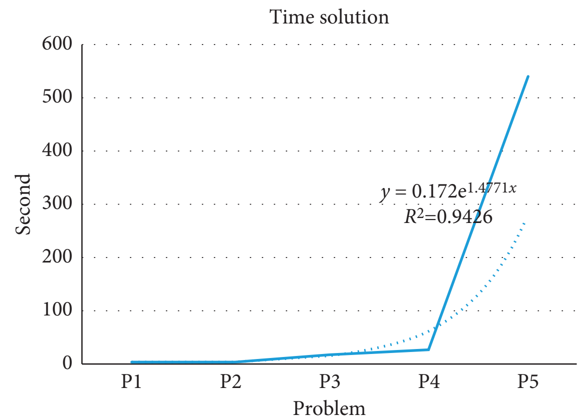

Figure 8: Time solution for problems.

Table 7: Variation on conservative coefficient.

Problem	Conservative coefficient (λ)	Cost function	Time (seconds)	Cost variation (%)
P1	0.00	2822175.206	0.911	−0.59
P1	0.25	3031098.187	1.373	6.77
P1-main model	0.5	2839008.413	1.012	0.00
P1	0.75	2847425.016	1.267	0.30
P1	1.00	2855003.861	0.896	0.56

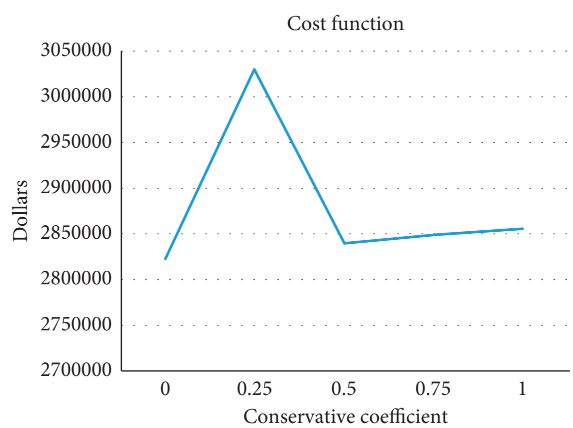

Figure 9: The cost function for variation on conservative coefficient.

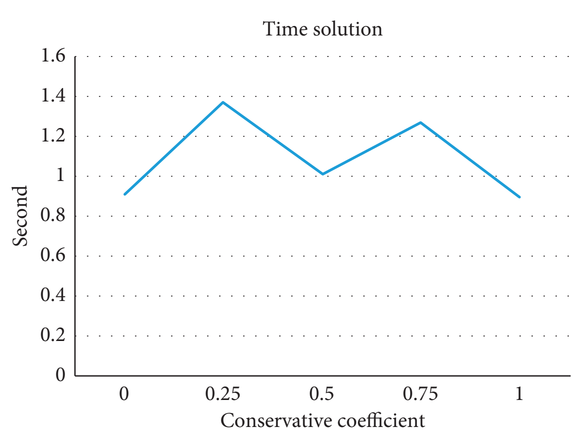

Figure 10: Time solution for variation on conservative coefficient.

Table 8: Variation of demand.

Problem	Variation of demand (%)	Cost function	Time (seconds)	BCT	Cost variation (%)
P1	−50	2208505.182	1.230	No need	−22.21
P1	−40	2065840.501	1.009	No need	−22.21
P1	−20	2381482.610	1.678	Needed	−27.23
P1-main model	0	2839008.413	1.012	Needed	0.00
P1	+20	2954586.691	1.119	Needed	4.07
P1	+40	3072017.106	0.763	Needed	8.21

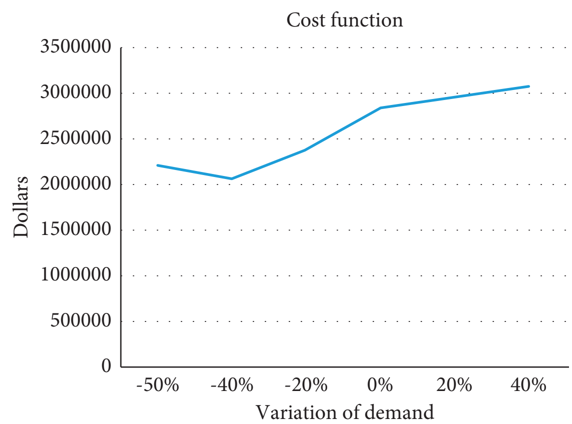

Figure 11: Effects of variation on demand.

Table 9: Comparing three algorithms with the main model.

Problem	LP model lower bound (A)		LR model lower bound (B)		Main model (B)		Fix-and-opt. upper bound (C)		GAP_1(%)	GAP_2(%)
	Cost	Time (seconds)	Cost	Time (seconds)	Cost	Time (seconds)	Cost	Time (seconds)		
P1	1603085.131	0.256	1917317.456	1.544	2839008.413	1.012	2841080.44	0.832	−32.47	0.07
P2	1621637.956	0.342	1938656.333	3.332	2868628.538	2.857	2869908.32	1.108	−30.17	0.04
P3	2696941.848	1.220	2794259.9	22.468	3931302.815	15.437	3941819.72	2.501	−28.92	0.27
P4	2726058.808	0.674	2748952.713	49.748	3813256.048	26.237	3826966.74	30.755	−27.91	0.36
P5	4186057.711	14.921	4479146.692	534.824	5525665.563	538.483	6119280.37	16.347	−18.94	10.74
P6	1.259045 E + 7	456.623	—	—	—	—	1.250087 E + 7	978.651	—	—
P7	2.5671 E + 7	2464.913	—	—	—	—	2.376011 E + 7	40152.25	—	—

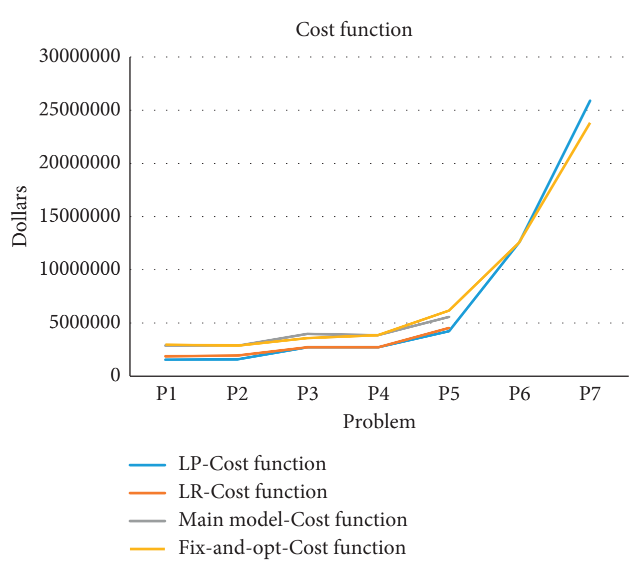

Figure 12: The cost function for models.

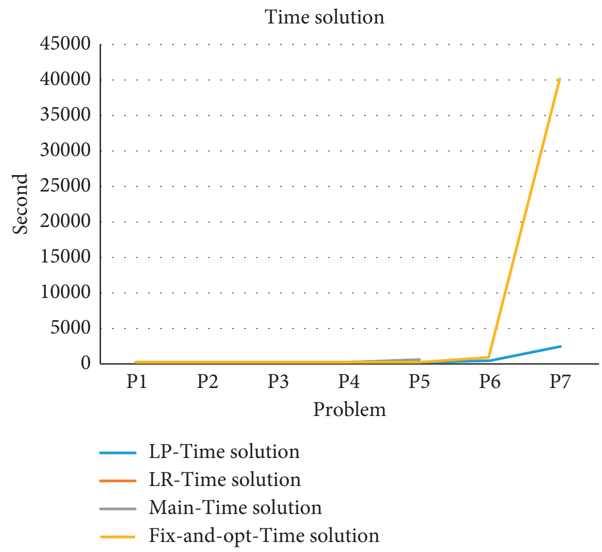

Figure 13: Time solution for models.

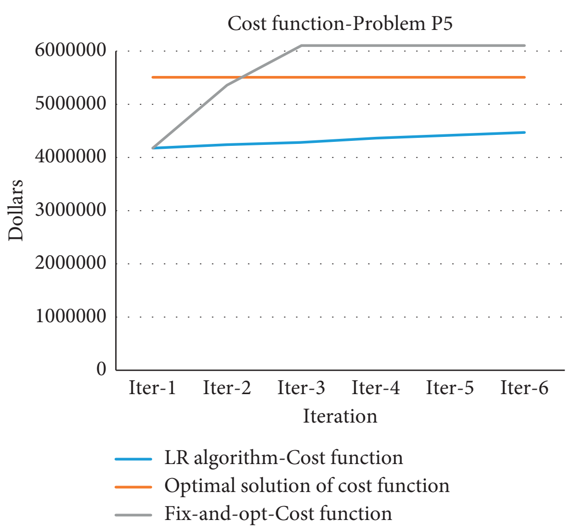

Figure 14: Attaining bounds for problem P5.

risk-averse and cover all spectrum types. We surveyed this model on a large scale and contributed fix-and-optimize and Lagrange relaxation to generate upper and lower bound when the solver cannot solve in logical time.

6. Conclusions and Outlook

Using a novel technology by SC is grown every day. Technologies, such as cryptocurrency and blockchain, make SC agile and lean and decrease operational costs. VSCND applied resiliency, sustainability, and agility by embedding cryptocurrency and BCT. We used a new robust two-stage stochastic MIP for modeling this problem. We utilized GAMS-CPLEX to solve the problem. We found that establishing BCT and cryptocurrency for transaction reduce costs for SC with high demand.

The findings are as follows:

(1) The cost and time increase when the scale of problems increases in Figures 7 and 8.

(2) If the conservative coefficient increases to 1, the cost function grows in Table 7 and Figures 9 and 10. When the conservative coefficient increases by 25%, the cost increases by 0.3%, but the time solution does not change significantly.

(3) The application of BCT decreases and is not economical when decreasing demand happens. When demand increases, it increases the cost function, and establishing BCT is needed for reducing cost (c.f. Figure 11). By reducing 40% of demand, the cost function decreases by 22%, and BCT is not applicable.

(4) We utilize fix-and-optimize and LR to generate lower and upper bound to estimate large scale in minimum time. The results show that the gap between the main model and fix-and-optimize is better than the LR algorithm.

One of the important research limitations is solving the large-scale main model. We propose applying exact algorithms such as benders decomposition, branch and price, branch-and-cut, and metaheuristic algorithms [30, 31]. We can add other resilience, sustainable strategy, and multiobjectives [18, 19] to the model and increase resiliency and sustainability such as backup suppliers and improve node complexity.

Further, we suggest considering robust risk criteria such as Robust Conditional and Entropic Value at Risk (RCVaR and EVaR) [32, 33]. Researchers intend to investigate uncertainty methods such as robust convex and stochastic programming to close to the real world [34]. Using fuzzy and novel robust optimization as a data-driven approach is advantageous for a risk-averse decision-maker in the recent decade. Eventually, we suggest equipping all SC with novel technology such as Internet of Things (IoT) and RFID [35] to increase SC's viability.

Abbreviations

Notation list

Indices

s': Set of suppliers $s' \in \{1, 2, \ldots, S'\}$
m: Set of manufacturers
d: Set of distributing centers (DC) $d \in \{1, 2, \ldots, D\}$
r: Set of retailers $r \in \{1, 2, \ldots, R\}$
c: Set of customers $c \in \{1, 2, \ldots, C\}$
p: Set of products (commodities) $p \in \{1, 2, \ldots, P\}$
t: Set of time periods $t \in \{1, 2, \ldots, T\}$
s: Set of scenarios $s \in \{1, 2, \ldots, S\}$

Parameters

dd_{cpts}: Demand of customer c for commodity p in period $t$on scenario s
$vsm_{s'mpts}$: Variable cost from supplier s' to manufacture m for commodity p in period t on scenario s
vmd_{mdpts}: Variable cost from manufacture m to DC d for commodity p in period t on scenario s
vdr_{drpts}: Variable cost from DC d to retailer r for commodity p in period t on scenario s
vrc_{rcpts}: Variable cost from retailer r to customer c for commodity p in period t on scenario s
$vsm_{s'mpts}'$: Variable cost from supplier s' to manufacture m for commodity p in period t on scenario s with considering BCT ($vsm_{s'mpts} \geq vsm_{s'mpts}'$),
vmd_{mdpts}': Variable cost from manufacture m to DC d for commodity p in period $t$on scenario s with considering BCT ($vmd_{mdpts} \geq vmd_{mdpts}'$),
vdr_{drpts}': Variable cost from DC d to retailer r for commodity p in period t on scenario s with considering BCT ($vdr_{drpts} \geq vdr_{drpts}'$),
vrc_{rcpts}': Variable cost from retailer r to customer c for commodity p in period t on scenario s with considering BCT ($vrc_{rcpts} \geq vrc_{rcpts}'$),
$fs_{s'}$: Activation cost for supplier s'
fm_m: Activation cost for manufacture m
fd_d: Activation cost for DC d
fr_r: Activation cost for retailer r
fbt: Activation cost for running BCT,
mbt_{ts}: Cost of maintenance for BCT in period t on scenario s
$emsm_{s'mpts}$: CO_2 produced for movement from supplier s' to manufacture m for commodity p in period t on scenario s
$emmd_{mdpts}$: CO_2 produced for movement from manufacture m to DC d for commodity p in period t on scenario s
$emdr_{drpts}$: CO2 produced for movement from DC d to retailer r for commodity p in period t on scenario s
$emrc_{rcpts}$: CO2 produced for movement from retailer r to customer c for commodity p in period t on scenario s
$ensm_{s'mpts}$: Energy utilization for movement from supplier s' to manufacture m for commodity p in period t on scenario s
$enmd_{mdpts}$: Energy utilization for movement from manufacture m to DC d for commodity p in period t on scenario s
$endr_{drpts}$: Energy utilization for movement from DC d to retailer r for commodity p in period t on scenario s
$enrc_{rcpts}$: Energy utilization for movement from retailer $r$to customer c for commodity p in period $t$on scenario s
$\mathrm{Caps}_{s'pts}$: Capacity of supplier s' for commodity p in period t on scenario s
Capm_{mpts}: Capacity of manufacture m for commodity p in period t on scenario s
Capd_{dpts}: Capacity of DC d for commodity p in period t on scenario s
Capr_{rpts}: Capacity of retailer r for commodity p in period t on scenario s
p_s: Probably of scenario s
λ: Coefficient of conservative,
M: Very large number,
EM_{ts}: Maximum emission is allowed in period t on scenario s
EN_{ts}: Maximum energy is allowed in period t on scenario s
z_α: Confidence in α level,
$\rho_{s'}$: Availability coefficient of supplier s'
ρ_m: Availability coefficient of manufacture m
ρ_d: Availability coefficient of DC d
ρ_r: Availability coefficient of retailer r

Decision variables

Binary variables

$xs_{s'}$: Equal 1, if supplier s' is established; else 0
xm_m: Equal 1, if manufacture m is established; else 0
xd_d: Equal 1, if DC d is established; else 0
xr_r: Equal 1, if retailer r is established; else 0
xbt: Equal 1, if BCT network is established and activated for SC in the central sever; else 0

Continues variables

$qsm_{s'mpts}$: Flow between supplier s' and manufacture m for commodity p in period t on scenario s
qmd_{mdpts}: Flow between manufacture m and DC d for commodity p in period t on scenario s
qdr_{drpts}: Flow between DC d and retailer r for commodity p in period t on scenario s
qrc_{rcpts}: Flow between retailer r and customer c for commodity p in period t on scenario s

Auxiliary variables

FC: Fixed cost include FC1, FC2, FC3
VC_s: Variable cost includes $\mathrm{VC1}_s$ related to SCND without BCT and $\mathrm{VC2}_s$ related to VSCNDBCT for scenario s
Γ_s: Fixed and variable cost under scenario s
δ: Auxiliary variable for linearizing max function
η_s: Auxiliary variable for linearizing CVaR
va_s, vb_s: Auxiliary variable for linearizing absolute function.

Data Availability

The authors confirm that the data supporting the findings of this study are available within the article.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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Research Article

Designing an Agile Closed-Loop Supply Chain with Environmental Aspects Using a Novel Multiobjective Metaheuristic Algorithm

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Success in supply chain implementation depends on the way of dealing with market changes and customer needs. Agility is a concept that has been introduced in recent years to improve the supply chain. On the other hand, paying attention to environmental problems is another issue, and chains are trying to increase their popularity by focusing on this issue. Considering the importance of this issue, designing a multiobjective closed-loop supply chain network has been discussed in this research. The main contribution of this research is the integration of green and agility concepts in supply chain design. In this regard, a mathematical model is presented with economic, environmental, and agility objectives. First, the mathematical model is solved using the Epsilon constraint method, and then, the multiobjective weed algorithm is proposed to solve the model. The results of comparisons between the two methods show that the multiobjective weed algorithm has performed well in terms of various metrics of NPS, SNS, and Max Spread. In terms of the solving time, the average solving time of this algorithm was about 0.1% of the solving time of the Epsilon constraint method. Moreover, all cases show the superiority of the multiobjective weed algorithm over the Epsilon constraint method in solving the proposed mathematical model.

1. Introduction

The inability to deal with challenges can lead to falling and loss in competition among supply chains. This may seem concerning to some people, but it more or less emphasizes the need to develop new ways of thinking, finding solutions, and new criteria to maintain its potential ability in solving changing and unpredictable market challenges. Many analyses have proposed different solutions to deal with these unstable changes more successfully: networking, reengineering, modular organizations, virtual cooperation, high-efficient organizations, staff development, and flexible and just-in-time manufacturing systems [1]. Among them, the concepts of the agile institution and lean manufacturing system are more influential.

An agile supply chain means adaptability and flexibility and plans the chain in such a way that it uses a new way to deliver services and goods to respond to customer needs and reduce premium costs quickly. The customer who uses the goods or service at least wants to use innovative technologies and products which are different from previous products and services [2]. An agile chain changes its work environment using information technology so that in addition to responding to changes in customer needs, it can reduce prices effectively, forecast these changes to some extent, and deal with them with appropriate decisions. The organization's human resources and innovational capabilities are two essential and constituent factors in creating an agile company [3]. An agile supply chain emphasizes the flexibility and improvement of the quality of manufacturing and responds quickly to market changes and customer needs. Each supply chain, which is considered an agile supply chain, makes its own operational changes. In the changes section, new ideas and solutions resulting from innovation in the organization are provided by the human resources. This creativity in human resources and innovation cause improvement in the technology of products and services that can compete in a competitive market. In this regard, the use of agility criteria by a supply chain not only maintains it but also distinguishes it from other supply chains. Due to constant changes in the market, an agile organization must also constantly change over time in order to adapt to market changes [4].

Paying attention to the environmental problems of supply chains is one of the important concerns of communities. Pollution caused by manufacturing and transportation causes the most damage to the environment. Therefore, in addition to trying to achieve more profits and more agility to deal with market changes, supply chains must consider minimizing their environmental pollution [5]. Accordingly, this study deals with the integration of agile and green supply chains. In the second section, the newest relevant studies will be presented. In the third section, mathematical models and, in the fourth section, optimization methods will be introduced. The fifth section will present the numerical results of model optimization, and the research will be summarized in the seventh section.

The trend toward a green and agile supply chain creates a vital opportunity to simultaneously address issues of sustainability and business and environmental performance. The chain has led companies to redesign their products to fit the environment, in addition to the obvious costs, minimizing intangible costs that are not included in the cost of the product and can have a negative impact on the environment. Reviewing the studies conducted in the field of supply chain network design, it can be seen that despite the importance of both agile and green aspects, these two aspects have not been considered together and only separate studies have been done in this regard. Therefore, in order to cover the research gap, this study will design a green and agile closed-loop supply chain network for the first time. Also, the metaheuristic multiobjective invasive weed algorithm will be used to optimize this problem, which is one of the newest multiobjective solution methods.

2. Literature Review

The green supply chain has received much attention in recent years. Liang and Questa [6] designed the green supply chain for fuel transportation. They introduced energy optimization and emissions reduction as the most important objectives of this chain. This study that was conducted in Japan offers a solution that balances energy costs and environmental pollution. Yadav et al. [7] designed a two-objective optimization supply chain network with a sustainability approach. In the mathematical model, the reduction of pollutants is considered along with the reduction of costs. GAMS software has been used to solve this mathematical model. Hasani et al. [8] presented a multiobjective optimization approach for green and resilient supply chain network design. In the proposed model of this research, cost reduction along with environmental goals are included as objective functions in the mathematical model, and a robust multiobjective optimization model is designed. Strength Pareto Evolutionary Algorithm 2 (SPEA2) has been used to solve the proposed model. The results indicate that the designed supply chain network will be able to meet the needs of customers in an agile and green form.

Recycling is an industrial process in which disposable products are recycled with the aim of reusing and returning products to the consumption cycle. Paying attention to this concept along with the green supply chain will strengthen the supply chain as much as possible. Prakash et al. [9] designed a closed-loop supply chain using an integrated robust optimization approach. The proposed model is considered based on risk and demand uncertainty. Mixed-integer programming has been used in the design of this network. The goods are distributed directly from the factory to the customer through distribution channels. In addition, supply risk and transportation risk are included in the model, along with uncertain customer demand. The proposed model is implemented in an Indian e-commerce company. Boronoos et al. [10] designed a multiobjective closed-loop green supply chain network. Reducing environmental pollutants along and reducing costs are considered objective functions in the mathematical model. Flexibility and uncertainty are included as innovations in the mathematical model. In order to show the efficiency of the proposed mathematical model, it has been implemented in the printing industry, the results of which show the efficiency of this model.

Yavari and Geraeli [11] used a metaheuristic method to robust optimize the green closed-loop supply chain network using an innovative method. The intended product is perishable products. The proposed model was multiperiod and included four echelons: suppliers, manufacturers, warehouses, retailers, and product collection centers. Paksoy et al. [12], in their proposed model, considered a green closed-loop supply chain along with the lean concept. This model simultaneously minimizes transportation costs, purchase, and operating costs and also minimizes fixed facility costs, environmental costs, shipping costs, and late delivery. The fuzzy analytic hierarchy process method is used to solve a numerical example to confirm the validity of the proposed model. Gholizadeh and Fazlollahtabar [13] investigated the robust optimization of a green closed-loop supply chain scheme and solved it using a genetically modified algorithm. The proposed model is investigated under an uncertain environment. The intended objective is to reduce costs and environmental pollutants. A case study was conducted in the ironworks industry to bring the problem closer to the real world. The results of the implementation of the model with a genetic algorithm indicated the effectiveness and application of the proposed model. Ghahremani-Nahr et al. [14] designed a green closed-loop supply chain network considering the discount. The proposed model is presented in terms of uncertainty.

Nowadays, many organizations and companies face a lot of competition and an uncertain environment that has intensified due to technological innovations and changing customer needs [4]. As mentioned, one of the ways to deal with such challenges is agility. Moradi et al. [1] introduced a multiobjective model for agile supply chain design. In this mathematical model, the pricing of products was carried out in uncertain conditions. The objectives of this mathematical model were to reduce total costs and total delivery time. A fuzzy programming approach was used to solve this mathematical model. Numerical examples are used to show the validity of the proposed model. Mahmoodi [15] designed a multiobjective lean supply chain network with transportation constraints. In this mathematical model, supply chain agility and manufacturing and distribution risks were considered. The objectives of this mathematical model included minimizing total costs, minimizing total supply chain risk, and maximizing supply chain flexibility. Using the NSGA-II algorithm, the proposed model is solved. The results showed the effect of agility on supply chain design and better market policies. Pahlevan et al. [16] proposed a mathematical model to design the closed-loop supply chain of the aluminum industry. They used Red Deer Algorithm (RDA) to optimize this model. Du et al. [17] presented a systematic literature review on supply chain agility. In this study, the evolution of the concept of the agile supply chain has been investigated, and a systematic literature review approach has been used to understand the research gap. The results show that, in the current competitive environment, supply chain agility increases customer satisfaction and thus profit. On the other hand, achieving the concept of agility in the organization requires continuous planning, so the allocation of resources to improve aspects of agility is one of the requirements of organizations in global markets. Therefore, in this research, methods to achieve supply chain agility are mentioned.

Table 1 provides a summary of studies in this field.

As can be seen in Table 1, this research gap includes the integration of green supply chain and agile supply chain. None of the reviewed studies have investigated the simultaneous optimization of agility and environmental pollution. Also, the metaheuristic multiobjective invasive weed algorithm will be used to optimize this problem, which is one of the newest multiobjective solving methods.

3. Mathematical Model of the Research

This study examines the supply chain of dairy products. In this supply chain, milk and other raw materials are received from various suppliers. Excess demand is also supplied by the milk collection station, which is an intermediary. After the products were produced, they will be sent to the distribution centers, and they maintain these products after inspecting them and distribute them among the customers at the proper time. Distributors have the ability to deliver stored products in the future. These conditions cause the corruption of some of the products in the warehouse, which need to be returned to the factory. The manufacturing factory processes a percentage of the returned products and takes them back to the distribution and sales cycle. The rest of these products, which were returned, are disposed of as waste.

Other assumptions of the mathematical model are as follows:

(i) The supply chain proposed in this research consists of echelons. These four echelons are supplier, manufacturer, distributor, and customers

(ii) In order to supply the excess required milk, in addition to the suppliers, a milk collection station has been considered

(iii) There are different transportation systems among the chain members; each has the fixed costs and variable costs

(iv) Only access to one transportation system between each supplier and distributor as well as the between each distributor and customer is allowed

(v) The chain must meet the total forecasted demand of customers

(vi) There are a number of potential centers for distribution centers and several potential centers for factories, in which the network is required to establish one or more

(vii) The number of centers required for the establishment is not known, but the mathematical model must choose the one that is the best possible, according to the demand of the network and the costs of establishment and transportation

(viii) The objectives of the proposed mathematical model of this research are reducing total costs and reducing greenhouse gases and optimizing supply chain flexibility

3.1. Indices

S: index of fixed location of suppliers ($s = 1, 2, \ldots, S$)

i: index of fixed location of factories ($i = 1, 2, \ldots, I$)

j: index of potential locations for distribution centers ($j = 1, 2, \ldots, J$)

c: index of fixed locations of customers ($c = 1, 2, \ldots, C$)

p: index of products ($p = 1, 2, \ldots, P$)

r: index of raw materials ($r = 1, 2, \ldots, R$)

l: index of product transportation systems ($l = 1, 2, \ldots, L$)

t: index of time periods ($t = 1, 2, \ldots, T$)

3.2. Parameters

D_{cp}^{t}: demand of customer c for product p during period t

SC_{sr}^{t}: the purchasing cost of one unit of raw material r from supplier s during period t

$\dot{M}C_{ip}^{t}$: the manufacturing cost of each unit of product p in factory i during period t

IC_{jp}^{t}: the inspection and recycling cost of each unit of product p in distribution center j during period t

HC_{jp}^{t}: maintaining the cost of each unit of product p in distribution center j during period t

Table 1: Summary of the works related to the topic.

Researcher	Year	Location	Allocation	Distribution	Multiproduct	Multiperiod	Environmental pollution	Agility
Liang and Quesada	2019	✓	✓				✓	
Moradi et al.	2019			✓	✓	✓		✓
Mahmoodi	2019		✓		✓	✓		✓
Paksoy et al.	2019			✓		✓	✓	
Yadav et al.	2019	✓	✓	✓			✓	
Yavari, and Geraeli	2019			✓		✓	✓	
Ghahremani-Nahr et al.	2020			✓	✓	✓	✓	
Gholizadeh and Fazlollahtaba	2020				✓		✓	
Hasani et al.	2021	✓		✓	✓	✓	✓	
Boronoos et al.	2021			✓	✓		✓	
Pahlevan et al.	2021	✓		✓	✓		✓	
Current research	2021	✓	✓	✓	✓	✓	✓	✓

FX_i^t: the fixed cost of setting up the factory i during period t

FY_j^t: the fixed cost of setting up the distribution center j during period t

CS_{sr}^t: the capacity of supplier s for supplier r during period t

CX_i^t: the manufacturing capacity in factory i during period t

CY_j^t: the capacity of the distribution center j during period t

CSI_{sir}^t: the transportation cost of each unit of raw material r from supplier s to factory i during period t

CIJ_{ijpl}^t: the transportation cost of each unit of product p from factory i to distribution center j during period t with transportation system l

CJC_{jcpl}^t: the transportation cost of each unit of product p from distribution center j to customer c with transportation system l during period t

CJI_{jipl}^t: the transportation cost of each unit of product p from distribution center j to factory i during period t with transportation system l

CTR_l^t: the fixed cost of using transportation system l during period t

ESI_{sir}^t: the unit of CO_2 pollution resulting from the transportation of raw material r from supplier s to factory i during period t

EIJ_{ijpl}^t: the unit of CO_2 pollution resulting from the transportation of product p from factory i to distribution center j during period t with transportation system l

EJI_{jipl}^t: the unit of CO_2 pollution resulting from the transportation of product p from distribution center j to factory i during period t with transportation system l

EJC_{jcpl}^t: the unit of CO_2 pollution resulting from the transportation of product p from distribution center j to customer c with transportation system l during period t

$\dot{EC}_{ip}^t$: the unit of CO_2 pollution resulting from the manufacture of product p in factory i during period t

n_{rp}: the consumption coefficient of raw material r in product p

m_p: the rate of capacity utilization in manufacture of product p

R_p: the percentage of return of product p to the factory

Rp_p: the percentage of processing product p from the returned products to the factory

BM: a very large number

$W1$: the impact (weight) of agility of factories on the agility of the whole supply chain

$W2$: the impact (weight) of agility of distribution centers on the agility of the whole supply chain

$W3$: the impact (weight) of agility of suppliers on the agility of the whole supply chain

3.3. Decision Variables

QSI_{sir}^t: the amount of raw material r sent from supplier s to factory i during period t

$QS0_{ir}^t$: the amount of raw material r sent from the raw material supply station to factory i during period t

QI_{ip}^t: the amount of product p manufactured in factory i during period t

QIJ_{ijpl}^t: the amount of product p sent from factory i to distribution center j with transportation system l during period t

INV_{jp}^t: the inventory of product p in distribution center j at the end of period t

QJC_{jcpl}^t: the amount of product p transported from the distribution center j to the customer c with the transport system l during period t

QJI_{jipl}^t: the amount of product p sent from the distribution center j to factory i with the transportation system l during period t

W_s^t: a binary variable equal to 1 if it is selected from the supplier s during period t

X_i^t: a binary variable equal to 1 if a factory is established at point i during period t

Y^t_J: a binary variable equal to 1 if the distribution center is set up at point j during period t

A^t_{ijl}: a binary variable equal to 1 if the transportation system l connects factory i and distribution center j during period t

B^t_{jcl}: a binary variable equal to 1 if the transportation system l connects the distribution center j to the customer c during period t

3.4. Mathematical Model Relations

$$\begin{aligned} Min\, Z1 = {} & \sum_t \sum_j FY^t_j \left(Y^t_j\right) + \sum_t \sum_i FX^t_i \left(X^t_i\right) \\ & + \sum_t \sum_s \sum_i \sum_r \left(QSI^t_{sir} + QS0^t_{ir}\right) SC^t_{sr} + \sum_i \sum_p \sum_t QI^t_{ip} MC^t_{ip} \\ & + \sum_t \sum_c \sum_j \sum_p \sum_l QJC^t_{jcpl} IC^t_{Jp} + \sum_t \sum_j \sum_p INV^t_{jp} HC^t_p \\ & + \sum_t \sum_s \sum_i \sum_r QSI^t_{sir} CSI^t_{sir} + \sum_t \sum_i \sum_j \sum_p \sum_l QIJ^t_{ijpl} CIJ^t_{ijpl} \\ & + \sum_t \sum_j \sum_c \sum_p \sum_l QJC^t_{jcpl} CJC^t_{jcpl} + \sum_t \sum_i \sum_j \sum_p \sum_l QJI^t_{jipl} CJI^t_{jipl} \\ & + \sum_t \sum_j \sum_i \sum_l A^t_{ijl} CTR^t_l + \sum_t \sum_j \sum_c \sum_l B^t_{jcl} CTR^t_l, \end{aligned} \tag{1}$$

$$\begin{aligned} Min\, Z2 = {} & \sum_i \sum_p \sum_t QI^t_{ip} EC^t_{ip} \\ & + \sum_t \sum_s \sum_i \sum_r QSI^t_{sir} ESI^t_{sir} + \sum_t \sum_i \sum_j \sum_p \sum_l QIJ^t_{ijpl} EIJ^t_{ijpl} \\ & + \sum_t \sum_j \sum_c \sum_p \sum_l QJC^t_{jcpl} EJC^t_{jcpl} + \sum_t \sum_i \sum_j \sum_p \sum_l QJI^t_{jipl} EJI^t_{jipl}, \end{aligned} \tag{2}$$

$$Min\, Z3 = \sum_t w1\, AI_t + \sum_t w2\, AJ_t + \sum_t w3\, AS_t, \tag{3}$$

$$AI_t = \sum_i CX^t_i X^t_i - \sum_c \sum_p D^t_{cp}, \tag{4}$$

$$AS_t = \sum_s \sum_r CS^t_{sr} W^t_s - \sum_c \sum_p D^t_{cp}, \tag{5}$$

$$AJ_t = \sum_j CY^t_j Y^t_j - \sum_c \sum_p D^t_{cp}, \tag{6}$$

$$\sum_j \sum_P \sum_l n_{rp} QIJ^t_{ijpl} = \sum_s QSI^t_{sir}, \quad \forall i, r, t, \tag{7}$$

$$INV^{t-1}_{jp} + \sum_i \sum_l QIJ^t_{ijpl} = INV^t_{jp} + \sum_c \sum_l QJC^t_{jcpl} + \sum_i \sum_l QJI^t_{jipl}, \quad \forall j, p, t, \tag{8}$$

$$\sum_j \sum_l QJC^t_{jcpl} = D^t_{cp}, \quad \forall c, p, t, \tag{9}$$

$$\sum_i QSI^t_{sir} \le CS^t_{sr} W^t_s, \quad \forall s, r, t, \tag{10}$$

$$\sum_j \sum_p \sum_l m_p QIJ^t_{ijpl} \le CX^t_i X^t_i, \quad \forall i, t, \tag{11}$$

$$\sum_{p} INV^{t}_{jp} + \sum_{c}\sum_{p}\sum_{l} QJC^{t}_{jcpl} \leq CY^{t}_{j}Y^{t}_{j}, \quad \forall j, t, \tag{12}$$

$$\sum_{l} A^{t}_{ijl} \leq 1, \quad \forall i, j, t, \tag{13}$$

$$\sum_{l} B^{t}_{jcl} \leq 1, \quad \forall j, c, t, \tag{14}$$

$$A^{t}_{ijl} \leq \sum_{p} QIJ^{t}_{ijpl}, \quad \forall i, j, l, t, \tag{15}$$

$$B^{t}_{jcl} \leq \sum_{p} QJC^{t}_{jcpl}, \quad \forall j, c, l, t, \tag{16}$$

$$\sum_{p} QIJ^{t}_{ijpl} + QJI^{t}_{jipl} \leq BM * A^{t}_{ijl}, \quad \forall i, j, l, t, \tag{17}$$

$$\sum_{p} QJC^{t}_{jcp} \leq BM * B^{t}_{jcl}, \quad \forall j, c, l, t, \tag{18}$$

$$\sum_{i} QJI^{t}_{jipl} = R_{p} * INV^{t}_{jp}, \quad \forall j, p, l, t, \tag{19}$$

$$\sum_{j} QIJ^{t}_{ijpl} = QI^{t}_{ip} + Rp_{p} * \sum_{j} QJI^{t}_{jipl}, \quad \forall i, p, l, t. \tag{20}$$

Equation (1) shows the total costs in each period of the chain. These costs are fixed costs related to the establishment of distribution centers and purchases from suppliers, manufacturing costs, operating costs formed in distribution centers, inventory costs in distribution centers, and transmission costs for different transport systems in the chain. Equation (2) also minimizes the total amount of CO_2 emitted from the manufacture of products, transportation from supplier to the factory, transportation from factory to distribution centers, and transportation from distribution centers to customers. Equation (3) determines the total amount of supply chain agility. Therefore, because the agility of supply, manufacture, and distribution may not be equally significant, the weighted sum of agility of supply, manufacture, and distribution is introduced as the agility of the whole supply chain. Equation (4) shows the agility of factories or the level of manufacture. Equation (5) shows the agility of suppliers or the level of supply. Equation (6) shows the agility of the distributors or the level of distribution. Equation (7) shows that, in each period, the amount of raw material entering each factory is equal to the amount of output from that factory in the same period. Equation (8) guarantees that, in each period and for each product, the amount of input to each of the distribution centers and the remaining inventory from the previous period is equal to the amount sent to customers and the rest of the inventory at the end of the period. This equation is known as the inventory balance equation. Equation (9) states that, in each period and for each product, the inventory available in each of the distribution centers must be able to meet the demand for the product in question. Equation (10) ensures that the amount of each of the raw materials sent from the suppliers does not exceed their capacity. Equation (11) expresses the capacity of materials in factories similar to suppliers. Equation (12) states that inventory in each distribution center should not exceed the capacity of the center. Equations (13) and (14) state that only one transportation system can be used in each member of the chain. Equations (15) and (16) express that members of the chain who work together are allowed to use the transportation system. Equations (17) and (18) express that unrelated members of the chain do not send any products. Equation (19) determines the amount of returned products. This amount is determined as a percentage of the distributor's inventory. Equation (20) indicates that the amount of products sent from the factory to the distribution centers is equal to the amount manufactured in the factory, which is a percentage of returned products that is reprocessed.

4. Solution Methods

The proposed mathematical model in this research is multiobjective. Therefore multiobjective optimization methods are needed to solve it. Therefore, the Epsilon constraint method and multiobjective invasive weed metaheuristic algorithm have been used, which are described in the following.

4.1. Epsilon Constraint Method. The Epsilon constraint method is an exact solution method for solving mathematical models with multiobjective functions. This method leads to the optimization of multiobjective mathematical models by maintaining only one objective function and transferring other objective functions to constraints. This general model is as follows.

$$\begin{aligned} &\text{Minimize} f_\mu(x) \\ &\text{subject to} \quad f_m(m) \le \varepsilon_m, m = 1, 2, \ldots, M \text{ and } m \ne \mu \\ &\qquad g_j(x) \ge 0, \quad j = 1, 2, \ldots, J. \end{aligned} \tag{21}$$

In the above model, the parameter ε_m indicates the upper limit of the value f_m. To show how this method works, consider the problem with the two objectives f_1 and f_2. Also, suppose that $f_2$remains in the objective function and f_1 is added to the set of constraints $(f_1(x) \le \varepsilon_1)$.

Assume that initially $\varepsilon_1 = \varepsilon_1^c$. The problem resulting from considering this constraint divides the main feasible objective space into two parts of $f_1(x) \le \varepsilon_1^c$ and $f_1(x) > \varepsilon_1^c$. The left part of the feasible space obtains the feasible solution to the problem. Now, the mission of the resulting problem is to find a solution that is the minimum value of this feasible space. It is obvious from the figure that c is the minimum solution. According to this figure, intermediate solutions can be obtained in problems with nonconvex objective space using the ε-constraint method.

4.2. Multiobjective Invasive Weed Optimization Algorithm. The invasive weed optimization algorithm (IWO) is a nature-inspired metaheuristic algorithm that is inspired by weed behavior and its growth. They grow widely and strikingly so that they cannot be removed and controlled by humans. One claim about weeds is that weeds always win. In general, the reasons for this claim can be stated as follows:

(i) Existence of weeds after thousands of years of agriculture
(ii) Existence of weeds even after using various pesticides
(iii) The emergence of new species of weeds widely on the ground
(iv) Adapting to the environment

The above characteristics show that weeds are vigorous and interfere with agriculture. On the other hand, weeds adapt themselves to the environment and change their behavior to grow. The success of weeds depends on their ecology and biology. In the following, optimization based on invasive weed behavior is investigated. The stages of the invasive weed optimization algorithm are as follows:

(i) First stage: spreading the seeds in the desired area
(ii) Second stage: seed growth according to utility (sprouting) and spatial dispersal
(iii) Third stage: survival of weeds with more utility (competitive elimination)
(iv) Fourth stage: continuing the process until reaching the plants with the most utility

Details of the steps of the invasive weeds optimization algorithm are as follows:

First step: generating the random initial population and evaluating their objective function

According to this stage, a certain number of seeds are produced from each plant. The seeds produced depend on their fitness level as well as the maximum and minimum fitness of the colony of the weeds, and this number will increase linearly with increasing the amount of fitness. On the other hand, the number of seeds produced by each plant depends on the proportion of the plant to its environment; this relationship is linear, which means that the best solution from the current population gives the highest new solution and the worst solution leads to the generation of the lowest new solution. The number of solutions varies linearly between these two limits.

Second stage: reproduction based on fitness and updating of standard deviation

Invasive weeds may reproduce with or without using sex cells, depending on the type of the plant. In the method of sexual reproduction, seeds or spores are used. In this case, the plant is born and begins its life by being fertilized. Then, the seeds are dispersed by various factors such as wind, water, and animals, until the seed has a chance to grow. If the conditions are good, the seeds will start to germinate and grow. The process of growth will continue with other neighbor plants until they become mature plants. In the last stage of the life cycle, they become flowering plants and cause seed production.

Third stage: competitive exclusion

If a plant does not reproduce, it will die. Therefore, competition between plants is needed to limit the maximum number of plants in a colony. After producing seeds around each weed, we can only transfer the predetermined maximum number of plants (*Pmax*) of the total weeds and seeds to the next generation. Plants that have a chance of surviving reproduce and repeat the above stages so that the solutions obtained in each of the iterations would be fitter. This mechanism gives plants with low proportions a chance to reproduce, and if the seeds produced by them have a good proportion in the colony, then they can survive. This algorithm stops when the number of iterations reaches the maximum number allowed. The maximum number of preset plants can be equal to the number of the initial population, in which case one of the parameters of the algorithm is removed.

Fourth stage: checking the termination conditions

Types of termination conditions in metaheuristic methods are as follows:

(i) Obtaining an acceptable minimum of solutions

In this case, which is one of the termination conditions, assume that the total cost of a company is

1000 monetary units and the manager of the company tends to reduce this cost to 800 units, which is a desirable amount from the manager's point of view. It is noteworthy that the value of 800 is not the optimal point, and the value of the objective function may become less than 800 units. For example, in Figure 1, point A shows the desired point from the manager's point of view, which is one of the termination conditions.

(ii) The passage of time or determined iteration

In this case, a determined iteration is introduced for the algorithm to end the algorithm. For example, in iteration 100, the algorithm ends, and there would be no need for iterations after 100, although the value of the objective function may improve after the determined iteration.

(iii) The passage of time or determined iteration without observing much improvement in the result

If, after implementing the algorithm in successive iterations, the value of the objective function does not improve or improves insignificantly, the algorithm will stop. For example, if it does not improve from point *a* to *b* with *n* iterations or improves insignificantly, the algorithm will stop. In Figure 2, the value of the objective function is constant in iteration a to iteration *b* that causes the algorithm to stop.

The general structure of MOIWO and IWO is similar. The only difference between them is that, in each iteration, the nondominated solutions are separated. This method is presented in Section 4.2.1. The pseudocode of the MOIWO algorithm is shown in Figure 3.

4.2.1. Nondominated Sorting. First, two parameters n_p and S_p must be calculated; n_p is actually the number of solutions that have dominated the solution *p*, and S_p is the set of solutions that have been dominated by the solution *p*. Then, a set of solutions can be ranked, and they can be placed on different fronts in terms of nondomination degrees. All solutions with $n_p = 0$ take the first rank and are placed in the first front. Then, for each solution *p* with the first rank, each member (*q*) from the set of S_p is met, and its n_q is reduced to one unit. Thus, if $n_q = 0$, then the solution *q* takes the second rank and is placed in the second front. In the same way, the next fronts are formed. In the following, the fast nondominated sorting is presented in the form of pseudocode and figure. Figure 1 shows the nondominated sorting of a population of solutions in the MOIWO metaheuristic algorithm.

5. Numerical Results

5.1. Performance Metrics for Comparison of Metaheuristic Algorithms. In this section, quantitative and qualitative metrics are introduced. The main application of these metrics is to compare the performance of metaheuristic algorithms.

5.1.1. SNS. This metric, also called the spread metric, is used to calculate the degree of variation of Pareto solutions. The priority of the algorithm depends on the value of this metric. Using the following equation, the value of this metric can be calculated.

$$\mathrm{SNS} = \sqrt{\frac{\sum_{i=1}^{n} (\mathrm{MID} - C_i)^2}{n-1}}. \quad (22)$$

In this equation, n represents the number of nondominated solutions. Using the following equation, C_i can be calculated.

$$C_i = \sqrt{f_1^2 + f_2^2 + f_3^2}. \quad (23)$$

In the above equation, f_{1i} and f_{2i} are, respectively, the values of the first and second objective functions for the nondominated solution of *i*.

5.1.2. Max Spread Metric. It is necessary to calculate the optimal Pareto front solutions obtained by the algorithm in terms of scope. The Max Spread metric is used for this. The larger the value of this metric is, the higher the priority of the algorithm will be. The value of this metric is calculated using the following equation:

$$\mathrm{DM} = \sqrt{\sum_{i=1}^{I} (\mathrm{Min}\, f_i - \mathrm{Max}\, f_i)^2}. \quad (24)$$

In the above equation, Min f_i represents the minimum value of the objective function among all nondominated solutions obtained from the algorithm, and Max f_i represents the maximum value of the objective function among all nondominated solutions obtained from the algorithm.

5.1.3. MID (Mean Ideal Distance). Using this metric, the proximity among the obtained nondominated solutions and the ideal point is measured. The priority of the algorithm is inversely related to the value of this metric. The following equation is used to calculate this metric.

$$\mathrm{MID} = \frac{\sum_{i=1}^{n} \sqrt{\left((f1_i - f1_{\mathrm{best}})/\left(f1_{\mathrm{total}}^{\max} - f1_{\mathrm{total}}^{\min}\right)\right)^2 + \left((f2_i - f2_{\mathrm{best}})/\left(f2_{\mathrm{total}}^{\max} - f2_{\mathrm{total}}^{\min}\right)\right)^2}}{n}. \quad (25)$$

```
Fast Non-dominated sorting (P)
for each p ∈ P
    S_p = 0
    n_p = 0
    for each q ∈ P
        if (p < q) then                    if p dominates q
            S_p = S_p U {q}                Add q to the set of solutions dominated by p
        else if (q < p) then
                n_p = n_p + 1              Increment the domination counter od p
    if n_p = 0 then                        p belongs to the first front
        r_p = 1                            rank of solutions in the first fron
        F_1 = F_1 U {p}
i = 1                                      initialize the front counter
while F_i ≠ Ø
        Q = Ø                              Used to store the members of the next front
        for each p ∈ F_i
            for each q ∈ S_p
                n_q = n_q −1
                if n_q = 0 then            q belongs to the next front
                    r_q = i + 1
                    Q = Q U {q}
        i = i + 1
```

Figure 1: Pseudocode of the fast nondominated sorting procedure.

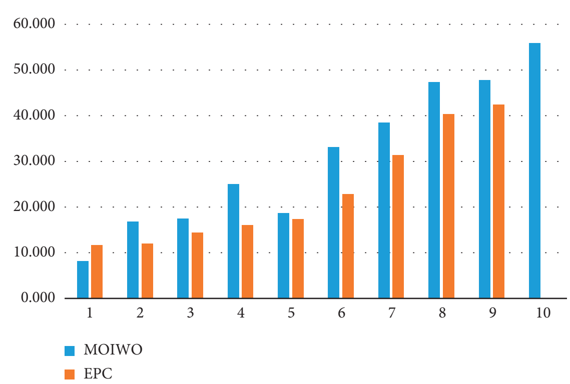

Figure 2: Comparison of solving methods based on Max Spread metric.

```
1. Initial solutions (W)
2. While iteration<=MaxIt
a. Calculate the fitness value for each solution in W;
b. Compute maximum and minimum fitness in the colony;
c. for each solution w ∈ W
    i. Compute the number of seeds of w, corresponding to its fitness;
    ii. Randomly distribute the generated seeds over the search space with normal
    distribution around the parent plant (w);
    iii. Add generated seeds to the solution set, W;
d. if (|W| = N) > Pmax
    i. Sort the population W in descending order of their fitness;
    ii. Truncate population of weeds with smaller fitness until N = Pmax;
3. Next iter;
```

Figure 3: Pseudocode of MOIW algorithm.

In the above equation, $f1_{\text{total}}^{\max}$ is the largest value between nondominated solutions. Also, $f2_{\text{total}}^{\min}$ is considered as the smallest value between the nondominated solutions obtained by the algorithm.

5.1.4. RAS (The Rate of Achievement to Objectives Simultaneously). This metric seeks a balance in achieving each of the objectives and its value is calculated using the following equation:

$$\text{RAS} = \frac{\sum_{i=1}^{n}\left[\left|\left(f_{1i}(x) - f_{1i}^{\text{best}}(x)\right)/f_{1i}^{\text{best}}(x)\right| + \left|\left(f_{2i}(x) - f_{2i}^{\text{best}}(x)\right)/f_{2i}^{\text{best}}(x)\right|\right]}{n}. \tag{26}$$

The value of this metric is inversely related to the priority of the algorithm.

5.1.5. Spacing. By using this metric, the uniformity of the distribution of nondominated solutions is obtained according to the following equation. The value of this metric is inversely related to the priority of the algorithm.

$$\text{SM} = \frac{\sum_{i=1}^{n}\left|\overline{d} - d_i\right|}{(n-1)\,\overline{d}}. \tag{27}$$

In the above equation, n is the number of obtained nondominated solutions, d_i is the smallest Euclidean distance between the solution i and the solutions found in the set of obtained nondominated solutions, and $\overline{d}$ is the average of these distances.

5.1.6. NPS. This metric is used to calculate the number of nondominated solutions. The value of this metric is directly related to the priority of the algorithm.

It is worth noting that the introduced metrics are presented for a problem with three objective functions. In the case of increasing the number of objective functions, it is enough to include the values of the objective functions in the formula and generalize the desired formula. It should be considered that Max Spread, NPS, Spacing, SNS, RAS, and MID metrics have been used in this study to compare the efficiency of solving methods.

5.2. Investigation of the Efficiency of the Proposed Solving Methods. To compare the considered methods based on the studied metrics, 10 examples in different scales have been produced. These examples have been randomly produced. The information of these examples is as shown in Table 2. It should be considered that the time limit of 3600 seconds is regarded for each solving method.

Then, the values of quality metrics of the problem solution are calculated for both solving methods and reported in Tables 3 and 4.

5.2.1. Investigation of Solving Methods Based on MID Metric. The average of this metric is 17.5 for the Epsilon constraint and 22.10 for the MOIWO algorithm. In Figure 4, the value of this metric is shown for each of the solved examples by two algorithms.

According to the results, it is concluded that the value of MOIWO was higher in all examples because using EPC, the best values are obtained. Therefore, the short distance between the metaheuristic method and these values shows the quality of this method.

5.2.2. Investigation of Solving Methods Based on Max Spread Metric. The average of this metric is 23.15 for the Epsilon constraint and 31.87 for the MOIWO algorithm. Figure 2 shows the value of this metric for each of the examples solved by the two solving methods.

According to Figure 5, the EPC method provided a better value than MOIWO only in the first example. In other examples, the MOIWO method provided a better value. That shows the efficiency of this method to find the solutions.

5.2.3. Investigation of the Solving Methods Based on SNS Metric. The average of this metric is 22.65 for the Epsilon constraint and 31.40 for the MOIWO algorithm. Figure 6 shows the value of this metric for each of the examples solved by the two solving methods.

Regarding the SNS metric, same as the Max Spread metric, the ability of the MOIWO algorithm to find optimal solutions is obvious. Following the increase in the number of problems, the superiority of the MOIWO method in terms of the SNS metric becomes more evident.

5.2.4. Investigation of the Solving Methods Based on NPS Metric. The average of this metric is 13.55 for the Epsilon constraint and 30.60 for the MOIWO algorithm. Figure 6 shows the value of this metric for each of the examples solved by the two solving methods.

The NPS metric is a metric that shows the priority of the MOIWO method compared to ECP. Due to the constraints which are added to the problem, the ability of the EPC method to find different solutions reduces. MOIWO algorithm can find more optimal solutions, which is the reason that this algorithm performs better in terms of this metric.

5.2.5. Investigation of the Solving Methods Based on RAS Metric. The average of this metric is 1.47 for the Epsilon constraint and 2.24 for the MOIWO algorithm. Figure 7 shows the value of this metric for each of the solved examples by the two solving methods.

As can be seen, the MOIWO algorithm provides higher values compared to the EPC. This small difference in many

Table 2: Information of numerical problems.

Example number	Number of suppliers	Number of factories	Number of distribution centers	Number of products	Number of raw materials	Number of transportation systems	Number of time periods
1	5	2	4	1	1	1	7
2	7	3	6	3	2	1	7
3	9	4	8	5	3	1	9
4	11	5	10	7	4	2	9
5	13	6	12	9	5	2	12
6	15	7	14	11	6	2	12
7	17	8	16	13	7	3	15
8	19	9	18	15	8	3	15
9	21	10	20	17	9	3	20
10	23	12	22	19	10	4	20

Table 3: Epsilon constraint output for solved examples.

Example number	MID	Max_Spread	SM	NPS	RAS	Spacing	CPU time
1	12.522	11.641	7.994	7	0.318	7.884	6.243
2	13.347	12.001	9.927	10	0.391	9.779	13.923
3	16.219	14.434	9.719	11	0.638	12.031	80.205
4	16.318	16.057	15.639	11	0.682	17.772	425.727
5	18.037	17.34	20.293	13	0.897	21.792	994.581
6	17.844	22.863	22.848	15	1.528	23.336	1272.391
7	20.006	31.395	30.102	17	2.064	33.215	2464.165
8	20.405	40.311	34.497	19	3.109	35.137	3600.299
9	21.629	42.374	52.884	19	3.616	49.15	3600.571
10	0	0	0	0	0	0	Not solved
Average	17.369	23.157	22.656	13.556	1.471	23.344	1384.234

Table 4: MOIWO output for solved examples.

Example number	MID	Max_Spread	SNS	NPS	RAS	Spacing	CPU time
1	18.863	8.128	10.083	7	0.446	7.038	13.628
2	21.198	16.778	12.985	19	0.554	9.126	13.067
3	14.086	17.496	13.515	17	0.767	17.506	31.58
4	20.849	24.965	24.499	22	0.786	16.45	57.938
5	25.844	18.693	26.859	20	1.224	24.946	74.544
6	19.884	33.126	24.651	37	1.577	30.373	96.803
7	20.778	38.493	30.473	40	2.529	46.129	129.095
8	27.458	47.356	49.158	49	4.223	43.533	134.002
9	25.433	47.813	60.994	47	3.865	53.544	159.827
10	26.681	55.862	60.842	48	6.493	64.762	171.294
Average	22.107	30.871	31.4059	30.6	2.247	31.341	88.17783

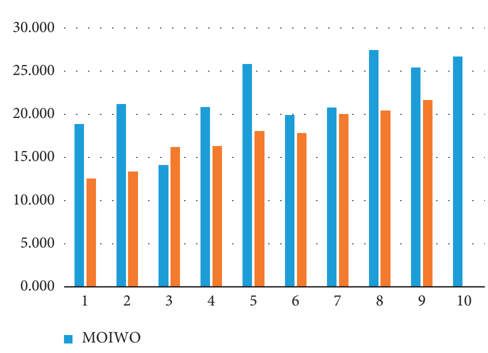

Figure 4: Comparison of solving methods based on MID metric.

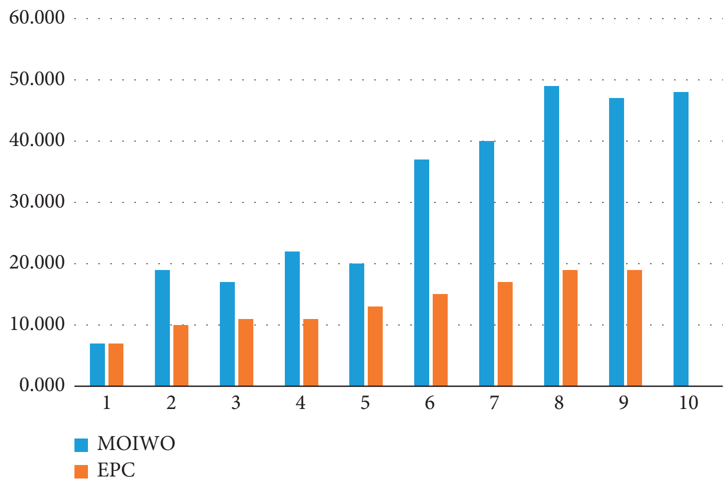

Figure 5: Comparison of solving methods based on NPS metric.

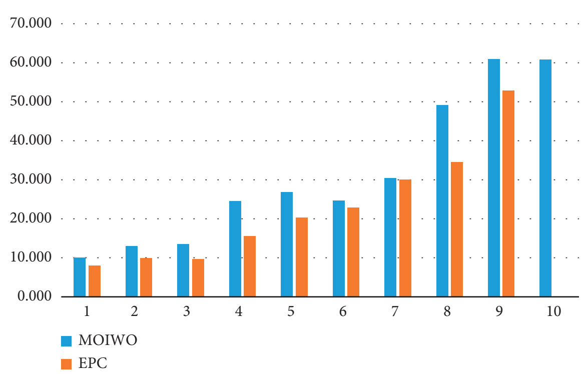

Figure 6: Comparison of solving methods based on SNS metric.

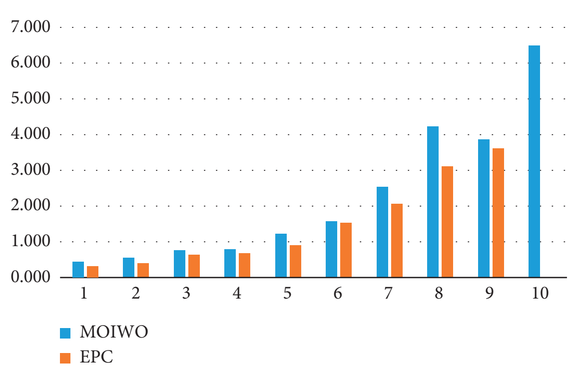

Figure 7: Comparison of solving methods based on RAS metric.

examples between the MOIWO algorithm and the EPC method, which is on average about 0.6, indicates the ability of the MOIWO algorithm.

5.2.6. Investigation of the Solving Methods Based on the Spacing Metric. The average of this metric is 23.34 for the Epsilon constraint and 32.34 for the MOIWO algorithm. Figure 8 shows the value of this metric for each of the solved examples by the two algorithms.

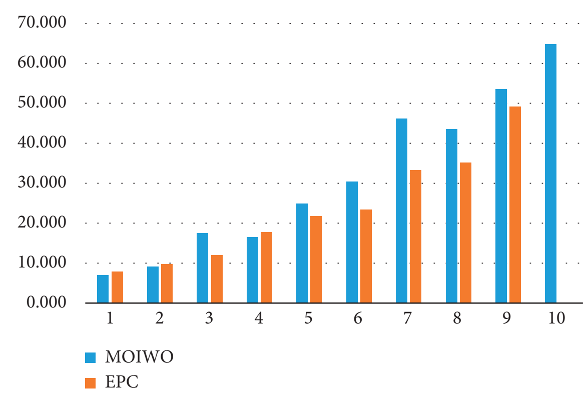

Figure 8: Comparison of solving methods based on SNS metric.

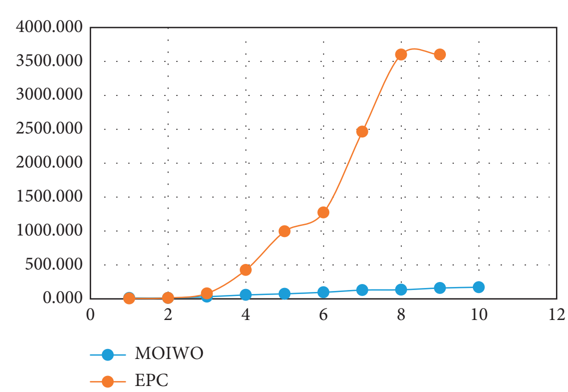

Figure 9: Comparison of the solving time of the two methods.

The analysis of this metric is the same as the RAS metric. The solution obtained from the EPC method has lower values, and the MOIWO algorithm provides an SNS value close to this method. The above results show the fact that this algorithm has been able to achieve the near-ideal solution.

5.2.7. Investigation of the Solving Methods Based on Solving Time. Epsilon constraint has an average solving time of 1384.23 seconds. However, this metric is 88.17 for MOIWO.

A comparison of the solving times of the two methods is shown in Figure 9.

The solving time of the EPC method has an ascending solution time to solve with a very steep slope. This method solved problems 7 and 8 with the maximum possible time and also could not solve problem 10. On the other hand, the solving time of the MOIWO algorithm has increased with a very low slope.

As a result, it is determined that the MOIWO algorithm can provide the outputs very close to the optimal solution in much less time than EPC and even perform better than EPC in some metrics. This issue well demonstrates the ability of the MOIWO algorithm to solve the problem.

6. Conclusion

In this study, a multiobjective mathematical model with a green and agile approach was presented. The integration of agility and environmental concepts in supply chain design is an important innovation of research. The use of a new multiobjective metaheuristic algorithm called MOIWO is the next innovation of this research. The results showed that economic, environmental, and agility objectives in the supply chain are in conflict with each other, and their independent optimization is not efficient enough to be used in the supply chain. Also, the MOIWO algorithm has performed well compared with the Epsilon constraint method. This algorithm has been better than the Epsilon constraint method in terms of NPS, SNS, and Max Spread metrics. In terms of the solving time, the average solving time of this algorithm was about 0.1% of the solving time of the Epsilon constraint method. Therefore, the efficiency of this multiobjective algorithm has been confirmed by various metrics, and this algorithm can be introduced as an appropriate tool for solving supply chain design problems. To develop this research and for future studies, it is suggested that uncertainty be considered in the model parameters such as customer demand, manufacturing, and distribution costs in the mathematical model. This uncertainty can be implemented with approaches such as possibilistic programming or robust optimization and the results can be examined. It is also recommended to use another metaheuristic algorithm and compare them with each other. To demonstrate the performance of the proposed mathematical model, it is suggested that the model be implemented in the real world and the results are reported.

Data Availability

No data are available for sharing.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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Research Article

Application of an Intelligent Hybrid Metaheuristic Algorithm for Multiobjective Redundancy Allocation Problem with Sustainable Maintenance

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The present study aimed to optimize the redundancy allocation problem based on sustainable maintenance. For this purpose, the goal is to design a complex system based on redundancy allocation by considering the weight and reliability criteria of the system and the maintenance and repair costs through the sustainability approach. In this regard, a mathematical model has been developed. This model minimizes system reliability and system weight simultaneously. There are also budget constraints on repair costs, environmental costs, purchase of spare parts, and energy risk costs. In order to optimize this model, a hybrid algorithm based on Whale Optimization Algorithm (WOA), Genetic Algorithm (GA), and Simulated Annealing (SA) is proposed. Accordingly, 81 test problems are provided and optimized by the proposed algorithm. The obtained numerical results indicate that, with increasing failure time of each component, the system's reliability increases and the weight of the whole system increases. Moreover, changing the Weibull distribution parameters directly affects the total amount of system reliability, but does not have a definite and accurate effect on the total weight of the system. Moreover, increasing the budget for maintenance leads to finding solutions with more reliability and less weight.

1. Introduction

The redundancy allocation problem (RAP) is an essential issue in optimizing the reliability of complex high-tech, high-component systems that require a high level of reliability. Classic reliability models usually consider both healthy and faulty conditions for each of the operating components of the system. However, in recent years, in the field of reliability research, several models have been proposed considering performance measurements for each component. Accordingly, each component with different probabilities has different performance rates. In general, redundancy allocation involves adding surplus components to the system under conditions that, while increasing its reliability, optimize the designed system configuration. Since adding more components will increase the cost, volume, and weight of the system, the interaction between these factors is presented in the form of a multiobjective problem.

Sustainable maintenance in RAP was first introduced by [1]. In their paper, first, the initial system was designed; then, using the obtained information, the aspects of production program and maintenance costs and sustainability performance were evaluated. As a result, based on sustainable maintenance, the reliability of each component and the whole system are improved. The economic aspect of sustainability and customer satisfaction increase; environmental pollutions and maintenance costs were reduced by providing a reliability-based program. Adding this style of maintenance can address the challenges of maintaining reliability in redundancy allocation.

This research develops the study of [1–3]. As a novel contribution in the field of RAP, this study deals with the multiobjective optimization of redundancy allocation under maintenance with a sustainability approach. For this purpose, the system under study, in addition to complying with weight and configuration constraints, must clearly respect the views of customers' satisfaction.

As a novel contribution, it is assumed that customers have a utility function that is inversely related to the continuous failures that occur in the system. Also, the maintenance process should not lead to damage to the environment. To consider the economic perspective, the costs of designing and maintaining the system must be controlled. There are three main aspects of the proposed optimization model. (1) Minimize system design based on its weight; (2) maximize customer satisfaction based on system reliability; (3) control the pollutions, maintenance, and operational costs. Since the optimization of the problem is a challenging issue, the hybrid multiobjective solution method based on a whale optimization algorithm, genetic algorithms, and simulated annealing is used.

The main question of this research is how to present and apply a new metaheuristic algorithm to solve the redundancy allocating problem that has the best possible solution and the shortest solution time.

In the rest of the article and in Section 2, the most critical research items in this field are presented. In Section 3, the mathematical model of this research is presented, and in Section 4, the proposed metaheuristic algorithm to solve this model is presented. In Section 5, numerical results are presented, and finally, in Section 6, conclusions are presented.

2. Literature Review

Lins and Droguett [4] used a multiobjective genetic algorithm and its combination with discrete simulation to solve the redundancy allocation problem. Liang and Lo [5] developed a variable neighborhood search (VNS) algorithm to solve multiobjective redundancy allocation problems. The efficiency of this algorithm was tested on three sets of problems with 5, 14, and 24 subsystems, respectively. Uysal [6] modeled four different types of multiobjective reliability optimization problems using distance values. To solve these models, an advanced genetic algorithm and the concept of the Pareto solution set have been used. Sadjadi and Soltani [7] presented a bee optimization algorithm to solve reliability optimization problems. Chambari et al. [8] developed a two-objective model of redundancy allocation. They presented the two-objective reliability in a series-parallel system with a certain level of component redundancy strategy. To solve this model, they used two NSGA-II algorithms and a multiobjective particle swarm optimization algorithm. Ghorabaee et al. [9] presented a new and efficient approach to modeling the objective function of their redundancy allocation problem. Their proposed approach is based on simulation and optimization methods through response level simulation using Enterprise Dynamic (ED) simulation software. Next, the relationship between decision and response variables has been obtained using experimental design. Ardakan and Hamadani [10] studied two-objective RAP based on maximizing the total reliability and minimizing the total volume of the system. They then used two statistical methods and comparative decision-making based on the quality of the solutions obtained and also the processing time, and finally ranked among the existing solution methods. Zhang and Chen [11] presented a mathematical model to maximizes the average operating time of the system. They used two metaheuristic algorithms and particle swarm optimization to solve their proposed redundancy allocation problem.

Salmasnia et al. [12] modeled a series-parallel redundancy allocation problem in which system reliability is maximized, and the total cost is minimized. Teimoori et al. [13] developed an electromagnetic mechanism metaheuristic algorithm to solve a redundancy allocation problem. Long et al. [14] introduced a redundancy allocation problem with multiple strategy choices in which the concepts of active redundancy and standby redundancy were considered simultaneously. They used particle swarm motion optimization to optimize their problem. Karevan and Vasili [1] presented a two-objective model for the redundancy allocation problem. In this model, reliability, as well as various maintenance and environmental costs, are optimized. Budget constraints are also included in the allocation of redundancy. Ouyang et al. [3] proposed a reliability-RAP problem with considering standby components and cold strategy. Moreover, they applied an improved version of the particle swarm optimization algorithm with a flexible design. Zaretalab et al. [15] considered a multistate component in RAP. In this research, the reliability of the supplier is investigated. In order to find the optimal solution, they proposed a mathematical model with the objective to maximize the total reliability and used a Memetic algorithm to solve it. Reference [16] proposed a multiobjective mathematical model for a multitype system. In this model, the optimal redundancy strategy is obtained by using the NSGA-II algorithm.

Table 1 reviews the most important articles in the field of RAP.

After reviewing various research on redundancy RAP optimization, it is clear that the most important research gap in this area is the optimization of redundancy allocation under preventive maintenance with a sustainability approach. Therefore, as a novel contribution, the present study optimizes the redundancy allocation problem based on sustainable maintenance. For this purpose, the goal is to design a complex system under conditions that, in addition to considering the weight and reliability criteria of the system, the maintenance and repair costs of the system are controlled through the sustainability approach. Moreover, a novel metaheuristic approach based on WOA, GA, and SA is proposed which is a specific contribution in the field of RAP optimization.

3. Research Mathematical Model

In this research, a series of parallel series elements that contain k components are considered in a way that can be used for each component of a number of spare parts as parallel. For this purpose, it is assumed that for the first part n_1 spare part, for the second part n_2 spare part up to k_m part, n_k spare parts can be used. Figure 1 shows such a structure.

Accordingly, there is a specific operational budget because each of the spare parts has different prices. Also, the weight of the system should not be increased from a certain limit.

It is assumed that the probabilistic function for each component in the series-parallel structure follows the Weibull distribution. According to equation (1), the reliability of the part i ($i \in \{1, 2, \ldots, k\}$) in time t is calculated as follows:

$$R_i = e^{(t/\theta_i)\beta_i}, \quad i \in \{1, 2, \ldots, k\}, \tag{1}$$

where the parameters β_i and θ_i are the shape and scale parameters of the i_m component, respectively. Next, according to equation (2), the reliability of a set of components of type i_m when n_i spare items are added is calculated as follows:

$$R_i^T = 1 - (1 - R_i)^{n_i+1}, \quad i \in \{1, 2, \ldots, k\}. \tag{2}$$

Next, based on equation (3), the total reliability of the series-parallel system can be calculated:

$$R_i^T = \prod_{i=1}^{k}\left(1 - (1 - R_i)^{n_i+1}\right), \quad i \in \{1, 2, \ldots, k\}. \tag{3}$$

In equations (2) and (3), it was assumed that spare parts would be applied to all components. To solve this challenge, suppose the integer variable x_i represents the number of spare parts that can be used for component i_m. In this case, equations (4) and (5) are rewritten as follows. In this case, equations (4) and (5) are rewritten as follows:

$$R_i^T = 1 - (1 - R_i)^{x_i+1}, \quad i \in \{1, 2, \ldots, k\}, \tag{4}$$

$$R_i^T = \prod_{i=1}^{k}\left(1 - (1 - R_i)^{x_i+1}\right), \quad i \in \{1, 2, \ldots, k\}. \tag{5}$$

After stating the structure of the reliability calculation, the mathematical model of the redundancy allocation problem without considering permanent maintenance will be as follows:

$$\max R_i^T = \prod_{i=1}^{k}\left(1 - (1 - R_i)^{x_i+1}\right). \tag{6}$$

Subject to

$$R_i = e^{-\left(t^{\beta_i}/\theta_i\right)}, \quad i \in \{1, 2, \ldots, k\}, \tag{7}$$

$$\sum_{i=1}^{k} c_i x_i \le \beta^c, \tag{8}$$

$$\sum_{i=1}^{k} w_i (x_i + 1) \le \beta^w, \quad x_i \in \{0, 1, \ldots, n_i\}. \tag{9}$$

In the presented basic mathematical model, the values of c_i and w_i are the purchase cost and the weight, respectively, except for type i. The values β^c and β^w also show the budgets associated with the maximum justified cost for the system and the maximum acceptable weight for the whole system. Equation (6) is the model's objective, which aims to maximize the reliability of the whole system. Equation (7) calculates the reliability of each component. Equation (8) is required to consider the weight of the original components in the calculation of the overall weight of the system. But this is not needed to limit the budget deficit in equation (9) since the budget is considered only for the purchase of spare parts and should not be considered the existence of the original components. In order to develop the presented mathematical model and reflect preventive maintenance, it is assumed that α_i percentage of components type i may need to be replaced. Accordingly, the fixed cost of reinstallation is calculated based on the following:

$$RA_{ECO1(t)} = \frac{\sum_{i=1}^{k} C_i (1 - R_i)^{y_i}}{(1 + r_m)^t}, \tag{10}$$

where $y_i = \alpha_i n_i$ and r_m is the discount rate. C_i is the fixed cost of supplying a spare part for the Type i part. Equation (11) represents the second economic aspect. This equation identifies the variable costs of supply spare parts:

$$RA_{ECO2(t)} = \frac{\sum_{i=1}^{k} (1 - R_i)^{y_i} * [(n_i * \text{Cust}_i)]}{(1 + r_m)^t}, \tag{11}$$

Table 1: The summary of the reviewed literature.

Research	Budget constraint	Weight constraint	Single objective	Multiobjective	Corrective maintenance	Preventive maintenance	Sustainability	Solution method
Sahoo et al. [17]		√		√				Improved genetic algorithm
Sadjadi and Soltani [7]	√	√		√	√			Bee colony optimization
Abouei Ardakan et al. [10]	√		√				√	Differential evolution
Zhang and Chen [11]		√	√				√	Particle swarm optimization
Chambari et al. [8]		√		√	√			NSGA-II
Lins and Droguett [4]	√			√		√		Genetic algorithm
Liang and Lo [5]	√			√				Variable neighborhood search
Long et al. [14]				√	√			Particle swarm optimization
Karevan and Vasili [1]	√			√		√	√	Multiobjective particle swarm optimization
Ouyang et al. [3]			√		√			Particle swarm optimization
Zaretalab et al. [15]		√	√			√		Memetic algorithm
Wang et al. [16]	√	√		√				NSGA-II
Present research	√	√		√		√	√	Hybrid whale-genetic simulated annealing

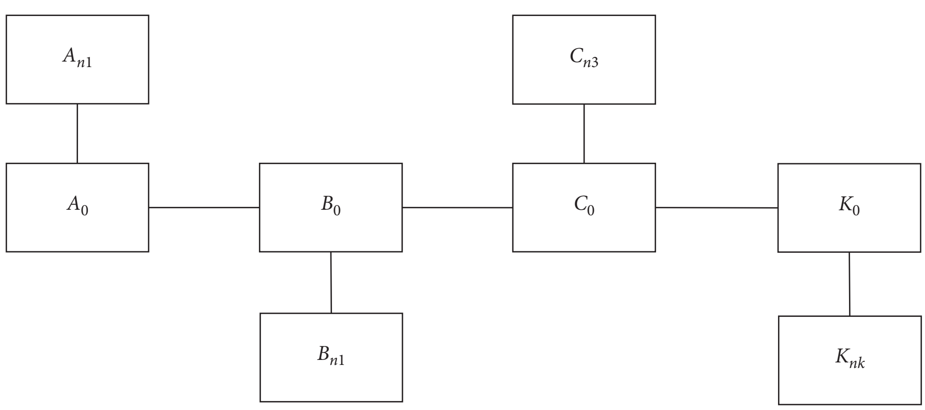

Figure 1: The proposed RAP series-parallel system structure.

where Cust_i is related to the variable cost of each component of type i. In equation (12), mean downtime (MDT) is used and indicates the time to find fault and fix it. As a result, equation (12) shows the total lost amount of time:

$$RA_{SOC1(t)} = \sum_{i=1}^{k} (1 - R_i)^{y_i} * MDT \ * y_i. \tag{12}$$

Equation (13) shows the sum of the total cost of the customer dissatisfaction resulting from the suspension of the system. In this equation, ch_i is the cost of customer dissatisfaction is due to each hour of system downtime:

$$RA_{SOC2(t)} = ch * RA_{SOC1(t)} = \sum_{i=1}^{k} (1 - R_i)^{y_i} * ch * MDT \ * y_i. \tag{13}$$

Equations (14) and (15) represent carbon emission cost and the amount of energy cost, respectively. In these equations, CD is the carbon emission cost for each repair activity and EC represents the cost of consumed energy for each repair activity.

$$RA_{ENV1(t)} = \sum_{i=1}^{k} (1 - R_i)^{y_i} * CD, \tag{14}$$

$$RA_{ENV2(t)} = \sum_{i=1}^{k} (1 - R_i)^{y_i} * EC. \tag{15}$$

Based on the above equations, the developed multi-objective mathematical model of redundancy allocation with respect to preventive maintenance can be presented as follows:

$$\max f_1 = \prod_{i=1}^{k} \left(1 - (1 - R_i)^{x_i+1}\right), \tag{16}$$

$$\min f_2 = \sum_{i=1}^{k} w_i (x_i + 1). \tag{17}$$

Subject to

$$\begin{aligned}
R_i &= e^{-\left(t^{\beta_i}/\theta_i\right)}, \quad i \in \{1, 2, \ldots, k\},\\
&\sum_{i=1}^{k} c_i x_i + RA_{ECO1(t)} + RA_{ECO2(t)} + RA_{SOC2(t)}\\
&+ RA_{ENV1(t)} + RA_{ENV2(t)} \leq \beta^c,\\
RA_{ECO1(t)} &= \frac{\sum_{i=1}^{k} C_i (1 - R_i)^{y_i}}{(1 + r_m)^t},\\
RA_{ECO2(t)} &= \frac{\sum_{i=1}^{k} (1 - R_i)^{y_i} * [(n_i * \text{Cust}_i)]}{(1 + r_m)^t},\\
RA_{SOC2(t)} &= \frac{\sum_{i=1}^{k} (1 - R_i)^{y_i} * ch * MDT * y_i}{(1 + r_m)^t},\\
RA_{ENV1(t)} &= \frac{\sum_{i=1}^{k} (1 - R_i)^{y_i} * CD}{(1 + r_m)^t},\\
RA_{ENV2(t)} &= \sum_{i=1}^{k} (1 - R_i)^{y_i} * EC, \quad x_i \in \{0, 1, \ldots, n_i\}.
\end{aligned} \tag{18}$$

4. Hybrid Whale-Genetic-Simulated Annealing Algorithm

In order to present the proposed hybrid algorithm, first, the whale optimization algorithm (WOA) is described, which is one of the newest presented metaheuristic algorithms. The WOA algorithm is one of the nature-inspired and population-based optimization algorithms that can be used in various fields [18]. The details of this metaheuristic algorithm are explained as follows.

The whales can identify the location of the chase and surround them. In WOA, each solution is interpreted as a whale with a specific position. Since the optimal design space is not known in the search space, the algorithm assumes that the best candidate solution for the present is the target hunt or is close to the desired state. After the best search factor is identified, other search factors try to update their location relative to the best search factor. This behavior is expressed through the following equations:

$$\overrightarrow{D} = \left|C \cdot X^* (t) - X (t)\right|, \tag{19}$$

$$X (t + 1) = X^* (t) - \overrightarrow{A} \cdot \overrightarrow{D}, \tag{20}$$

where t denotes the current iteration, A and C are the coefficient vectors, X^* the location vector is the best solution obtained now, and X the location vector of the current solution. It should be noted that if there is a better solution, X^* should be updated in each iteration. Vectors A and C are calculated as follows:

$$\overrightarrow{A} = 2\overrightarrow{a} \cdot \overrightarrow{r} - \overrightarrow{a}, \tag{21}$$

$$\overrightarrow{C} = 2 \cdot \overrightarrow{r}, \tag{22}$$

where a is a controllable parameter that linearly decreases from 2 to 0 and r is a random vector at a distance of 0 to 1.

In this research, a solution method based on whale optimization, genetics, and simulated annealing algorithms is developed and called HWGSA to extract the non-dominated solutions of the proposed mathematical model. In this hybrid algorithm, siege hunting is used in the WOA algorithm to generate neighbor solutions. Moreover, the crossover operator in the GA algorithm is used to converge the solutions (exploration). Finally, to create variation in the solutions, the neighborhood creation operator is used in the SA algorithm (exploitation).

4.1. The HWGSA Steps

Step 1 (solution structure): in the HWGSA algorithm, the number of spare parts with K different component is displayed in the form of a vector as shown in Figure 2. In this vector, each cell demonstrates the number of allocation redundant component to the system.

According to Figure 2, n_1 is the number of redundant spare parts allocated to the first item of the system. Other cells can be defined in the same way. By using this solution representation, it can be a guarantee that all decision variables and the model constraints can be handled in the proposed algorithm.

Step 2: randomly generate POP initial solutions and calculate the values of the objective functions (f_1, f_2) for each member of the population based on equations (16) and (17).

Step 3: generate a set of new solutions based on equations (19)–(22) in the WOA algorithm and set them into P set.

n_1	n_2	...	n_k

Figure 2: Solution representation.

Step 4: repeat steps 5 to 19 for $IT_{\max}$ times

Step 5: for each solution (S) in the POP, set $k \longleftarrow 0$ and $y \longleftarrow 0$ and go to step 6.

Step 6: compare S with each solution (j) in Pset.

Step 6.1: if $f_1(S) \geq f_1^{Pset}(j)$ and $f_2(S) \leq f_2^{Pset}(j)$,

$$P\text{set} \longleftarrow \frac{P\text{set}}{j}. \tag{23}$$

Step 6.2: else, if $f_1(S) > f_1^{Pset}(j)$ or $f_2(S) < f_2^{Pset}(j)$,

$$k \longleftarrow k+1. \tag{24}$$

Step 6.3: else, if $f_1(S) \leq f_1^{Pset}(j)$ or $f_2(S) \geq f_2^{Pset}(j)$,

$$y \longleftarrow y+1. \tag{25}$$

Step 6.4: if $k > 0$ and $y == 0$,

$$P\text{set} \longleftarrow P\text{set} \cup S. \tag{26}$$

Step 7: for each solution: $S_i = \{n_{1i}, n_{2i}, \ldots, n_{ki}\}$ and $S_j = \{n_{1j}, n_{2j}, \ldots, n_{kj}\}$ from Pset, repeat step 8.

Step 8: calculate the new S^{new} solution using the crossover operator in the GA algorithm:

$$S^{\text{new}} \longleftarrow \left\{ <\left(n_{1i} * n_{1j}\right)^{0.5>} \cup <\left(n_{2i} * n_{2j}\right)^{0.5>} \cup, \ldots, \cup <\left(n_{ki} * n_{kj}\right)^{0.5>} \right\}. \tag{27}$$

Step 9: $T \longleftarrow T^{\max}$.

Step 10: repeat steps 11–16 while $T > T^{\min}$ (based on SA algorithm).

Step 11: generate a random number in the range $\{1, 2, \ldots, 2K\}$.

Step 12: if $a == 2 * i \in \{1, 2, \ldots, 2K\}$.

Generate a random b number b in the range $b \in [1, n_i^{\max}]$.

Step 12.1: if $n_i + b \leq n_i^{\max}$, then

$$S^{\text{new}}\{n_i\} \longleftarrow S^{\text{new}}\{n_i\} + b. \tag{28}$$

Step 13: if $a == 2 * i - 1$, thengenerate a random b number b in the range $b \in [1, n_i^{\max}]$.

Step: 13.1: if $S^{\text{new}}\{n_i\} - b \geq 0$,

$$S^{\text{new}}\{n_i\} \longleftarrow S^{\text{new}}\{n_i\} - b. \tag{29}$$

Step 14: for S^{new}, calculate the values of the objective functions f_1, f_2 based on equations (16) and (17).

Step 15: if $f_1(S^{\text{new}}) \geq f_1(S)$ and $f_2(S^{\text{new}}) \leq f_2(S)$,

$$S \longleftarrow S^{\text{new}}. \tag{30}$$

Step 15.1: if $f_1(S^{\text{new}}) > f_1(S)$ or $f_2(S^{\text{new}}) < f_2(S)$,

$$\begin{aligned}
&\Delta e_1 \longleftarrow f_1(S) - f_1(S^{\text{new}}),\\
&\Delta E \longleftarrow f_2(S^{\text{new}}) - f_2(S),\\
&\Delta E \longleftarrow \lambda_1 \Delta e_1 + \lambda_2 \Delta e_2,\\
&\lambda_1 = 1 \text{ whether } (\Delta e_1 > 0) \text{ or } 0\ (\Delta e_1 \leq 0),\\
&\lambda_2 = 1 \text{ whether } (\Delta e_2 > 0) \text{ or } 0\ (\Delta e_2 \leq 0),\\
&A \longleftarrow e^{-(\Delta E/KT)}.
\end{aligned} \tag{31}$$

Step 15.2: if random $< A$,

$$S \longleftarrow S^{\text{new}}. \tag{32}$$

Step 16: $T \longleftarrow T * \delta$ and return to step 10.

Step 17: NewPOP $\longrightarrow$ NewPOP $\cup S^{\text{new}}$

Step 18: insert POP $\longrightarrow$ NewPOP and go to step 4.

Step 19: display the P_{set} set.

In order to adjust the parameters of the algorithm, several problems have been randomly generated and optimized. Then, with the trial and error approach, the best values for the algorithm parameters are selected. $IT_{\max} = 100$, $A = 0.3$, and $T^{\min} = 1$ are set accordingly.

5. Numerical Results

First, it is necessary to examine the results of the algorithm by solving an important case study in Iran. In this case study, a system with 5 components is available. The reliability of each component in this system is measured based on the Weibull distribution with the beta and theta parameters, which have values of 2 and 10, respectively. According to the previous data, up to 30% of the parts are damaged in each component. The average failure time is estimated at 2 days. The cost of providing each spare part is 5 currency units and the repair fee is equal to 3.5 currency units. The cost of customer dissatisfaction with each day of part failure is equivalent to 1 currency. The interest rate is 10% and the maximum maintenance budget is 200 currency units. Regarding environmental pollution, the amount of CO_2 produced per day of system activity is equal to 1.7 units and the amount of energy consumed per day is equal to 1.5 units.

With this information and the design of the HWGSA algorithm in the MATLAB R2016, the redundancy allocation problem is optimized. After executing the HWGSA algorithm, a set of Pareto solutions is obtained, which is shown in Figure 3.

As shown in Figure 3, the value of the first objective function varies between 0.05 and 0.45. The value of the second objective function fluctuates between 120 and 320. Since the first objective function is of the maximization type, the ideal value for it is 0.45. Also, since the second objective function is of the minimization type, the ideal value for it is 120. When the first objective function moves from 0.05 to its ideal value, the second objective function moves away from its ideal value. In other words, in the set of Pareto solutions obtained, it is never possible to approach both goals at the

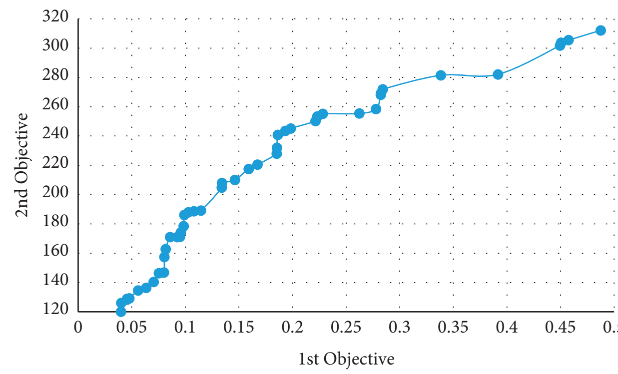

Figure 3: The obtained Pareto solutions from the proposed hybrid algorithm.

Table 2: The information of the generated test problems.

Test problem	MDT	θ_i	β_i	β^c
$p1$	2	3	2	150
$p2$	4	3	2	150
$p3$	6	3	2	150
$p4$	2	7	2	150
$p5$	4	7	2	150
$p6$	6	7	2	150
$p7$	2	12	2	150
$p8$	4	12	2	150
$p9$	6	12	2	150
$p10$	2	3	3	150
$p11$	4	3	3	150
$p12$	6	3	3	150
$p13$	2	7	3	150
$p14$	4	7	3	150
$p15$	6	7	3	150
$p16$	2	12	3	150
$p17$	4	12	3	150
$p18$	6	12	3	150
$p19$	2	3	4	150
$p20$	4	3	4	150
$p21$	6	3	4	150
$p22$	2	7	4	150
$p23$	4	7	4	150
$p24$	6	7	4	150
$p25$	2	12	4	150
$p26$	4	12	4	150
$p27$	6	12	4	150
$p28$	2	3	2	200
$p29$	4	3	2	200
$p30$	6	3	2	200
$p31$	2	7	2	200
$p32$	4	7	2	200
$p33$	6	7	2	200
$p34$	2	12	2	200
$p35$	4	12	2	200
$p36$	6	12	2	200
$p37$	2	3	3	200
$p38$	4	3	3	200
$p39$	6	3	3	200
$p40$	2	7	3	200
$p41$	4	7	3	200

Table 2: Continued.

Test problem	MDT	θ_i	β_i	β^c
$p42$	6	7	3	200
$p43$	2	12	3	200
$p44$	4	12	3	200
$p45$	6	12	3	200
$p46$	2	3	4	200
$p47$	4	3	4	200
$p48$	6	3	4	200
$p49$	2	7	4	200
$p50$	4	7	4	200
$p51$	6	7	4	200
$p52$	2	12	4	200
$p53$	4	12	4	200
$p54$	6	12	4	200
$p55$	2	3	2	350
$p56$	4	3	2	350
$p57$	6	3	2	350
$p58$	2	7	2	350
$p59$	4	7	2	350
$p60$	6	7	2	350
$p61$	2	12	2	350
$p62$	4	12	2	350
$p63$	6	12	2	350
$p64$	2	3	3	350
$p65$	4	3	3	350
$p66$	6	3	3	350
$p67$	2	7	3	350
$p68$	4	7	3	350
$p69$	6	7	3	350
$p70$	2	12	3	350
$p71$	4	12	3	350
$p72$	6	12	3	350
$p73$	2	3	4	350
$p74$	4	3	4	350
$p75$	6	3	4	350
$p76$	2	7	4	350
$p77$	4	7	4	350
$p78$	6	7	4	350
$p79$	2	12	4	350
$p80$	4	12	4	350
$p81$	6	12	4	350

same time to their ideal values. This indicates that the goals used are in conflict with each other. Proof of such a conflict confirms that the multiobjective consideration of the mathematical model is quite correct and logical and that the use of the HWGSA algorithm can well find Pareto's set of solutions to this problem.

5.1. Results of Implementation. In this part of the research, various test problems of the proposed mathematical model are optimized in order to determine the effect of different parameters of the problem on the optimal solutions of the model. In this regard, the information provided in Section 5 is used. Also, for four important parameters of the mathematical model, namely β_c, β_i, θ_i, and MDT, 3 values each are proposed. Therefore, a total of 81 test problems have been designed. Details of each of these issues are provided in Table 2.

After designing 81 different numerical examples, each of them was optimized in Matlab software using the HWGSA algorithm. After execution, a set of Pareto solutions to each test problem was obtained. Then, the mean values of the first and second objective functions of the Pareto solutions and also the number of Pareto solutions were reported. This report is in accordance with Table 3.

5.2. Numerical Analysis. The first parameter studied is the average failure time for which the values of 2, 4, and 6 days were considered. Figures 4 and 5 show the effect of the value of this parameter on the mean of the first objective function and the second objective function.

As shown in Figure 4, the longer the failure time, the higher the average system reliability. The reason for this is that the longer the failure time, the more parts are allocated to each component. Accordingly, to the system reliability

Table 3: The results of implementing test problems.

Test problem	Number of Pareto solutions	Average of the first objective	Average of the second objective
$p1$	47	$4.63E-08$	7778
$p2$	50	$1.90E-07$	10418
$p3$	43	$4.44E-07$	11685
$p4$	47	$4.00E-08$	7806
$p5$	50	$1.53E-07$	10012
$p6$	50	$4.35E-07$	11987
$p7$	50	$3.68E-08$	7400
$p8$	50	$1.17E-07$	9065
$p9$	47	$3.98E-07$	11974
$p10$	49	0.01662008	8835
$p11$	48	0.03045951	9929
$p12$	49	0.072815946	13343
$p13$	49	0.013728675	8404
$p14$	48	0.037327078	11058
$p15$	48	0.063445359	12667
$p16$	48	0.010736866	7748
$p17$	47	0.026810576	9781
$p18$	50	0.053703995	12076
$p19$	50	0.226867023	8415
$p20$	50	0.355636589	10608
$p21$	48	0.476344384	13027
$p22$	49	0.199889028	7810
$p23$	49	0.323638156	9890
$p24$	49	0.449719356	12334
$p25$	50	0.212840018	8075
$p26$	50	0.315307874	9771
$p27$	45	0.42569378	11862
$p28$	45	$4.10E-13$	7575
$p29$	47	$1.71E-12$	10087
$p30$	50	$4.54E-12$	12018
$p31$	50	$3.73E-13$	7751
$p32$	48	$1.35E-12$	9494
$p33$	45	$4.38E-12$	12209
$p34$	49	$3.63E-13$	7710
$p35$	45	$1.20E-12$	9478
$p36$	49	$3.00E-12$	10554
$p37$	50	0.00017731	8309
$p38$	47	0.000592272	10591
$p39$	50	0.001369745	12721
$p40$	50	0.000179898	8621
$p41$	46	0.000445769	9745
$p42$	46	0.001063624	11771
$p43$	46	0.000103981	7192
$p44$	50	0.000419827	9963
$p45$	49	0.001049651	11854
$p46$	48	0.03452181	8191
$p47$	47	0.081674209	10598
$p48$	47	0.152745337	13447
$p49$	47	0.031635127	7964
$p50$	50	0.060361023	9335
$p51$	50	0.133430003	12419
$p52$	47	0.031239782	7892
$p53$	47	0.065909873	9920
$p54$	45	0.130330611	12522
$p55$	50	$3.64E-18$	7555
$p56$	49	$1.37E-17$	9683
$p57$	46	$4.26E-17$	12421
$p58$	49	$3.18E-18$	7753
$p59$	48	$1.18E-17$	9760
$p60$	46	$3.71E-17$	12045

Table 3: Continued.

Test problem	Number of Pareto solutions	Average of the first objective	Average of the second objective
$p61$	47	$3.12E-18$	7544
$p62$	50	$8.92E-18$	9106
$p63$	47	$2.76E-17$	11049
$p64$	47	$1.13E-06$	7768
$p65$	50	$3.99E-06$	9129
$p66$	50	$1.37E-05$	12406
$p67$	50	$1.32E-06$	8025
$p68$	45	$3.78E-06$	9788
$p69$	50	$1.11E-05$	12303
$p70$	49	$9.25E-07$	7256
$p71$	47	$3.75E-06$	9945
$p72$	46	$9.68E-06$	11952
$p73$	50	0.002756355	7505
$p74$	47	0.009871848	10485
$p75$	49	0.021730016	13178
$p76$	50	0.002644596	7776
$p77$	48	0.007916174	9692
$p78$	47	0.01986529	12681
$p79$	50	0.002472504	7409
$p80$	50	0.00670114	9371
$p81$	50	0.017636415	12516

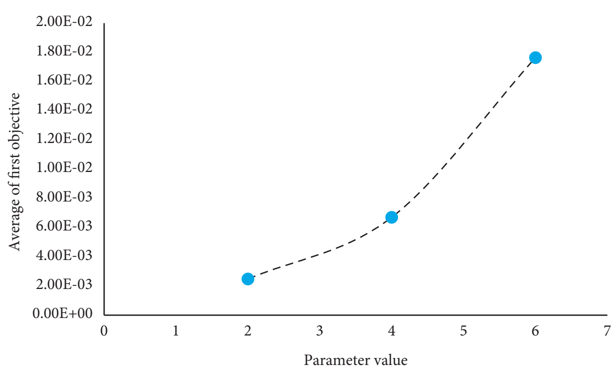

Figure 4: Impact of failure time parameter on the first objective function.

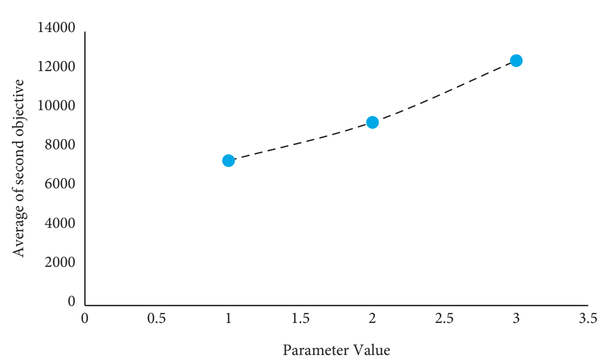

Figure 5: Impact of failure time on the second objective function.

relationship, the more allocated parts, the amount of reliability also increases. The same is true of the second objective function. As the failure time increases, the number of allocated parts increases, and therefore the total weight of the system increases. Therefore, according to Figure 5, the trend of the second objective function is ascending.

In Figures 6 and 7, the effect of the theta parameter or the Weibull distribution scale parameter on the first and second objective functions is investigated.

As shown in Figure 6, the larger the scale parameter, the lower the reliability of the entire system. The reason for this is that as the scale parameter increases, the reliability of each component decreases, and therefore the total reliability of the system decreases. But the effect of this parameter on the total weight of the system does not follow a specific trend. In Figure 7, by increasing the scale parameter, first, the total weight of the system increases and then decreases. In other words, the second objective function is not directly affected by changes in this parameter.

In Figures 8 and 9, the effect of another parameter of the Weibull distribution, namely the beta or shape parameter, is investigated.

According to Figure 8, the higher the value of the figure parameter, the higher the reliability of the whole system. The reason for this is that as the shape parameter increases, the reliability of each component increases, and as a result, the reliability of the whole system increases. But this parameter does not have a significant effect on the heading function. This is also well seen in Figure 9. In general, it is concluded that Weibull distribution behavior does not have a direct effect on the relationship of the second objective function.

Finally, the effect of the maximum available budget parameter on the objective functions is investigated.

Figures 10 and 11 show that the higher the maximum budget, the more reliability moves towards greater values, and the maximum weight moves towards lower values. In other words, by increasing this parameter, both targets move towards better values. The reason for this is that with the increase in the maximum budget, the solution space of the

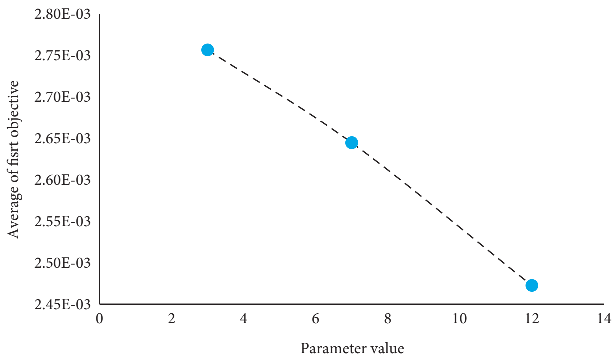

Figure 6: The effect of the scale parameter of the Weibull function on the first objective.

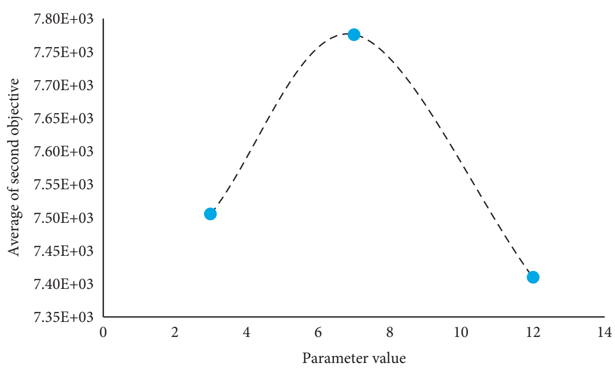

Figure 7: The effect of the scale parameter of the Weibull function on the second objective.

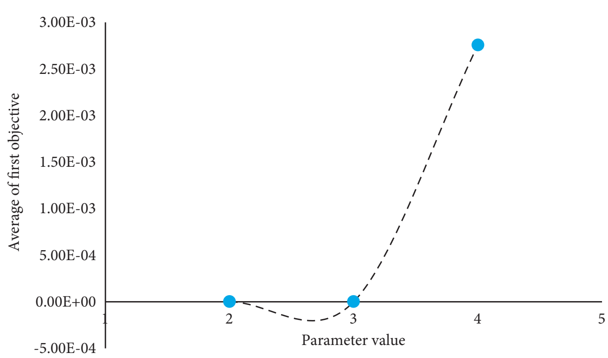

Figure 8: The effect of the shape parameter of the weibull function on the first objective.

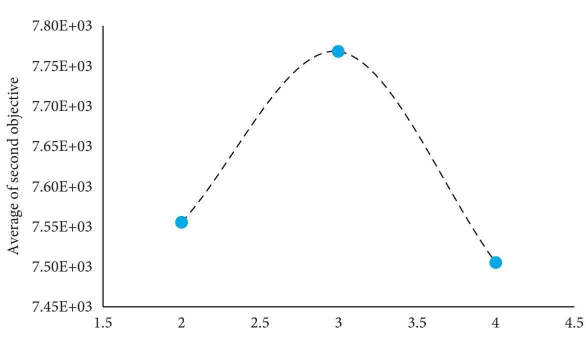

Figure 9: The effect of the shape parameter of the Weibull function on the second objective.

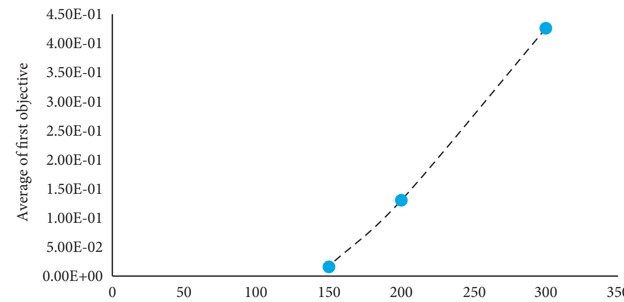

Figure 10: The effect of the maximum budget parameter on the first objective.

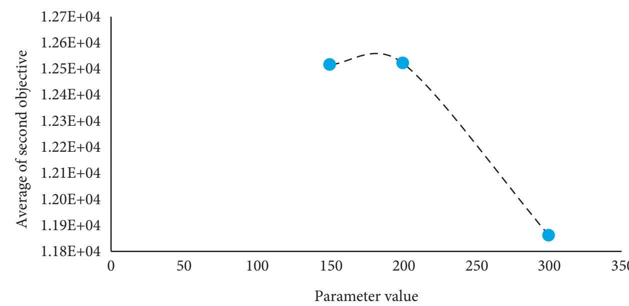

Figure 11: Impact of the maximum budget parameter on the second objective.

problem increases, and as a result, the objective functions can find better values for themselves.

6. Conclusion

In this research, first, the most critical research items in the field of redundancy allocation were reviewed. Next, it became clear that the issue of environmental pollution and sustainable maintenance repairs are two new and up-to-date topics for research in this field. Therefore, in this study, as a key innovation, we sought to provide a model that allocates redundancy in a complex system so that it covers environmental pollution and sustainable maintenance repairs well. In this regard, after a deep understanding of the basic articles, a developed model was designed for this purpose. Due to the high complexity of the model and its nonlinearity, designing a suitable and up-to-date approximate solution method for it was necessary. Therefore, the whale optimization, genetic and simulated annealing in a multiobjective mode was combined as a novel solution method.

In the numerical results, first, it was cleared that the objectives used in this research, i.e., maximizing the reliability of the system and reducing the weight of the whole system, are two completely conflicting ones. That is, increasing reliability leads to an increase in the weight of the entire system and vice versa. Therefore, optimizing these two objectives simultaneously leads to finding a set of optimal solutions, which we call the Pareto set of solutions. Next, 81 sample problems were designed and optimized by the proposed algorithm. The results of this section show that with increasing the failure time of each component, the reliability of the system increases, and also the weight of the whole system increases. Also, changing the Weibull distribution parameters has a direct effect on the total amount of system reliability but does not have a definite and accurate effect on the total weight of the system. Also, increasing the budget at hand for maintenance leads to finding solutions with more reliability and less weight.

The most important advantage of the proposed mathematical model of research is that it has been able to show the aspects of sustainability in the redundancy allocation problem and also has formulated repairs and maintenance of complex systems in a simple way. The designed metaheuristic algorithm also has the advantage of optimizing mathematical models with multiple objectives and variables in a short time. This issue can be considered as the most important managerial insight of this research. Another managerial insight of this research is that it is possible to manage the repair and maintenance planning of complex systems in such a way that in addition to reducing system costs, the productivity of manpower specialized in repair maintenance is increased.

In order to develop this research, the authors suggest considering uncertainty in the important parameters in the mathematical model and also using another novel metaheuristic algorithm such as the gray wolf optimizer and runner-root algorithm.

Data Availability

The input data for analysis of the mathematical method and metaheuristic algorithms which are used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that there are no conflicts of interest regarding the publication of this paper.

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Research Article

Development of a Method to Measure the Quality of Working Life Using the Improved Metaheuristic Grasshopper Optimization Algorithm

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This paper provides a method to numerically measure the quality of working life based on the reduction of human resource risks. It is conducted through the improved metaheuristic grasshopper optimization algorithm in two phases. First, a go-to study is carried out to identify the relationship between quality of working life and human resource risks in the capital market and to obtain the factors from quality of working life which reduce the risks. Then, a method is presented for the numerical measurement of these factors using a fuzzy inference system based on an adaptive neural network and a new hybrid method called the improved grasshopper optimization algorithm. This algorithm consists of the grasshopper optimization algorithm and the bees algorithm. It is found that the newly proposed method performs better and provides more accurate results than the conventional one.

1. Introduction

Working life keeps changing like any other environmental condition of human life in today's world. To ensure survival in this turbulent environment, organizations and employees have no chance but to adapt to the working environment changes, which will not happen unless the quality of working life (QWL) is improved. Focusing on the improvement of the working-life quality leads to increased employee vitality and satisfaction and, in turn, the success of employees, organizations, and stakeholders [1]. Since the satisfaction of employees affects their physical conditions and mental health, organizations need to keep their employees satisfied in terms of both the work environment and the work itself, thus accomplishing the intended goals [2]. Previous studies have shown that employees with good mental health are more committed and efficient than those in low spirits [3]. Therefore, the quality of working life reflects organizational or management culture, based on which employees can experience being self-directed, responsible, and self-esteemed. In this regard, an organization's effectiveness and efficiency can be enhanced if it provides opportunities for the employees to progress [4].

Furthermore, human resources are increasingly viewed as capital [5]. Accordingly, the viability and profitability of organizations in today's turbulent situation largely depend on their ability to cope with the rapid changes in the environment and utilize the created opportunities [6]. This is possible only by the use of enterprise risk management techniques, such as holistic threats and opportunities management. To increase the value for stakeholders in the short or long term, the organization provides funds and supervises its risks by managing the market value, controlling and utilizing any possible source [7]. From an organizational perspective, the accepted definitions of risk often refer to adverse outcomes caused by an unpredictable event in the business environment [8]. There are other opinions such that risk has variable consequences, i.e., sometimes positive and sometimes negative [9]. In a general definition, human resource risks refer to the set of risks associated with the programs and processes in the human resource of an organization [10]. Ernest & Young Institute considers the risks in employee-related plans and processes as the risks in human resources that, if properly managed, will make the organization one of the market leaders [11].

2. Literature Review

Previous studies on the quality of working life mainly measured QWL based on the level of need satisfaction [12]. For example, investigations were conducted on the relationship between QWL and job satisfaction [13] and the relationship between QWL and the organizational commitment among the lecturers in a Malaysian public research university [14]. One can also refer to the reports on QWL in child protection in two work environments [15], QWL amongst the workers of state-owned commercial banks in a Bangladesh northern region [16], QWL and the mental health of primary care physicians [17], QWL with an emphasis on human resource interventions in health units [18], QWL and the related factors for migrating workers in Guangdong Province, China [19], the effect of income and the relationship between leadership style and QWL [20] as well as QWL and burnout among nurses in critical care sections [21], quality of work life and contribution to productivity: assessing the moderator effects of burnout syndrome [22], quality of work life among young medical doctors [23], the effect of quality of work life (QWL) on job satisfaction and organization citizenship behavior [24], and determinants of quality of work life among nurses working [25].

There are also numerous studies on human resource risks such as investigations on substitution plans in New York State [10], risk perspective in human resources management [9], human resource risk management using the normal accident theory [26], and the impact of perceived human resource risk factors on financial problems [27]. According to the literature, the studies ever conducted in the field are either on quality of working life or on human resource risks. There is little research to examine these two issues together and their mutual effects. Accordingly, the present research seeks to propose a method of evaluating quality of working life on the basis of human resource risk reduction so as to enhance the quality of working life. It is to be noted that this type of study has never been carried out in the capital market. Therefore, in this study, a hybrid system is modelled to measure and improve working life quality based on the reduction of human resource risks.

3. Methodology

3.1. Framework. Using the tenets of previous studies, primary conceptual model has been made.

As shown in Figure 1, this model presents the various indicators widely reported, as in [28–31], for human resource risks. There are 11 categories of indicators identified to cover almost all human resource risks. Also to evaluate the quality of working life, Walton model [32] serves as a tool.

First of all, the conceptual model of the research (Figure 1) served as a basis to identify and investigate the factors that affect working life quality and human resource risks. Then, the effect of that quality on those risks was evaluated and the factors which could reduce the risks were identified. Finally, a method was proposed to numerically measure these factors.

The data used in this study were divided into training and testing categories. For the training part, questionnaires were collected from the experts, and the data were checked by the specialists. The training phase began according to the scores given by the experts and specialists. To improve the QWL model and analyze it, the adaptive neurofuzzy inference system (ANFIS) method was used. The rules of a fuzzy inference system are based on the "if-then" set, which forms the core of the system. Once the rules are put into practice, the relationship between input and output variables can be identified. This system can be used as a forecasting model in conditions where the input or output data are highly uncertain. The basis of this approach is a set of fuzzy inference system (FIS) input and output [33].

The statistical population of this study comprised the employees of the financial institutes in the Iranian capital market. In this regard, references were made to investing companies, investment funds, investment consulting centers, and the share market for securities in Tehran. Some of the experts in these institutes were randomly selected to provide the required data.

The steps of this research, as shown in Figure 2, are as follows:

(i) Conduction of measurements and the achievement of more precise and reliable results using the improved grasshopper optimization algorithm

(ii) Evaluation of the results and the use of the grasshopper optimization algorithm combined with the bees algorithm

(iii) Introduction of a measurement system by means of the neurofuzzy inference system

(iv) Identification of the factors affecting working life quality and human resource risks through a questionnaire and confirmatory factor analysis

(v) Exploration of the relationship between working life quality and human resource risks through a questionnaire and the structural equation modelling technique

3.2. Adaptive Neurofuzzy Inference System. In this paper, the rules for training a triangular membership network are examined. The network has three membership functions, and there are two membership functions for each input. In order to model the neural-fuzzy system, the data were segmented. The segmentation was, indeed, done to train and validate the system. Eighty percent of the data was taken into account as the training data, while the remaining twenty percent was used for testing and validation. The program was then executed based on the code generated in the MATLAB software and through the method already mentioned.

As shown in Figure 3, since the factors in the chain continuity framework were composed of one main layer and

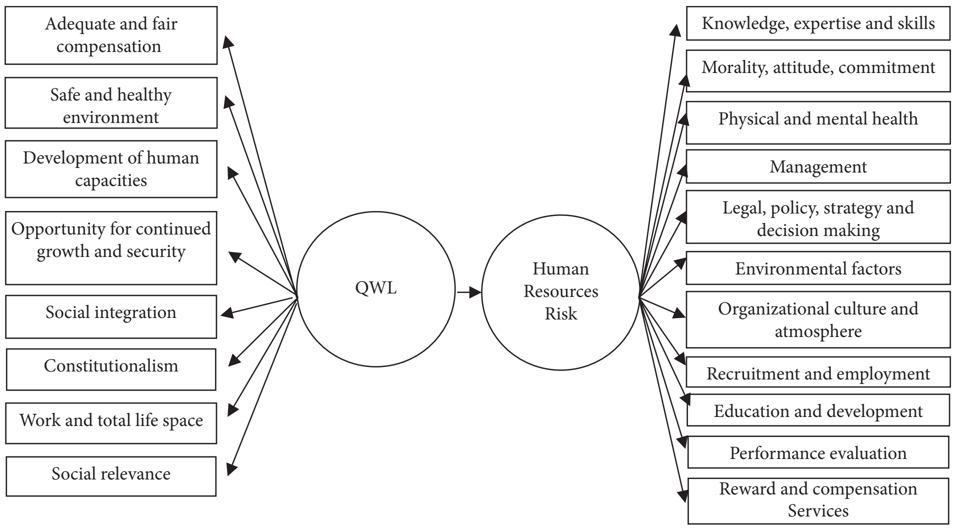


Figure 1: Conceptual research model.

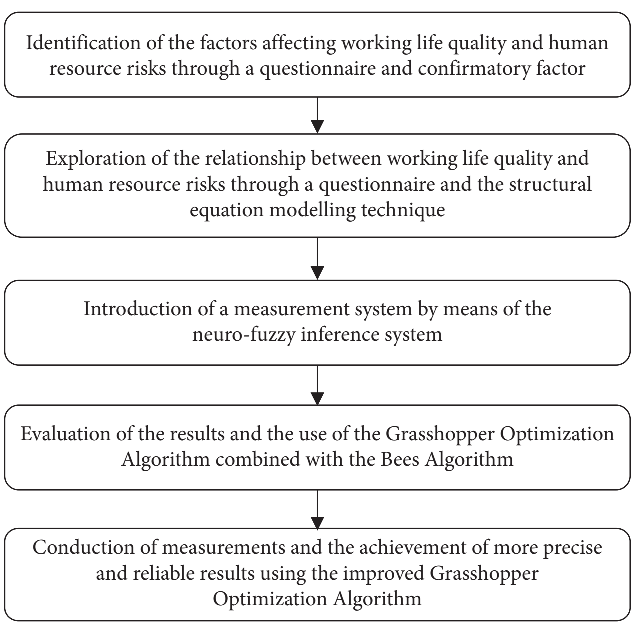


Figure 2: Flowchart of this research steps.

several sublayers, the neural-fuzzy inference system was modelled according to the number of the layers. At the end of the modelling phase, there were 8 neural-fuzzy systems.

3.3. Grasshopper Optimization Algorithm (GOA). Grasshopper optimization algorithm (GOA) is a metaheuristic algorithm inspired by nature. It mimics and simulates grasshoppers' behavior and their group movement toward food sources in nature. In order to solve an optimization problem, a GOA mathematical model is of benefit with its ability to mimic grasshoppers' behavior in nature [34]. Simulations have shown that, in comparison with the latest well-known algorithms, GOA can provide better results. Putting simulation results into practice has proven that

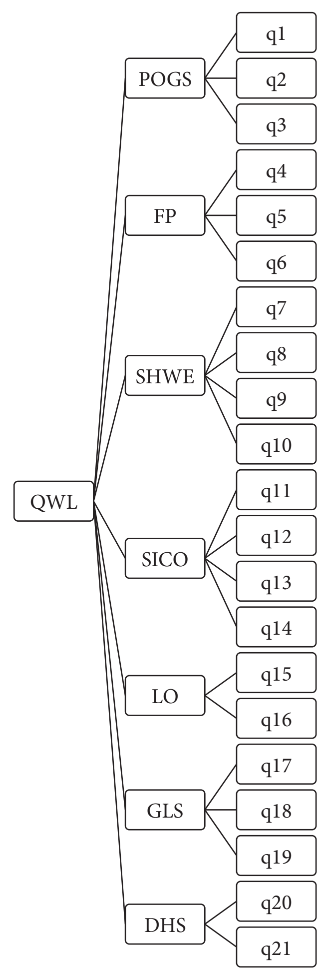


Figure 3: Structure of the layers in the adaptive neurofuzzy inference system.

GOA is capable of solving real problems with unknown space. The mathematical model used to simulate grasshoppers' behavior is as follows [35]:

$$X_i = S_i + G_i + A_i, \tag{1}$$

where X_i is the position of grasshopper number i, S_i is the social interaction, G_i is the gravitational force, and A_i is the wind flow rate.

To present a random behavior, the equation can be written as follows [36]:

$$X_i = r_1 S_i + r_2 G_i + r_3 A_i, \tag{2}$$

where r_1, r_2, r_3 are the random numbers in [0, 1].

In the above equation, d_{ij} is the distance between grasshoppers i and j, which can be calculated as $d_{ij} = |X_i - X_j|$. Moreover, S function, which stands for social interaction, can be obtained using the following equation:

$$S_i = \sum_{\substack{j=1 \\ j \neq i}}^{N} s\left(d_{ij}\right) \hat{d_{ij}}, \tag{3}$$

where G_i can also be calculated as $G_i = -g\hat{e}_g$, in which $e\wedge g$ is a unit vector that tends to the center of the earth.

Finally, A_i follows the equation below, where u is a fixed drift and $e\wedge w$ is a wind flow unit vector:

$$A_i = u\hat{e}_w. \tag{4}$$

In general, according to the equations presented, the mathematical model used to simulate the grasshoppers' behavior is as follows:

$$X_i = \sum_{\substack{j=1 \\ j \neq i}}^{N} s\left(\left|x_j - x_i\right|\right) \frac{x_j - x_i}{d_{ij}} - g\hat{e}_g + u\hat{e}_w. \tag{5}$$

In order to solve optimization problems, a modified version of this equation is presented as follows [37]:

$$X_i^d = c\left[\sum_{\substack{j=1 \\ j \neq i}}^{N} c\frac{ub_d - lb_d}{2} s\left(\left|x_j^d - x_i^d\right|\right) \frac{x_j - x_i}{d_{ij}}\right] + \hat{T}_d. \tag{6}$$

3.4. Bees Algorithm. In the bees algorithm, half of the bees' population is considered as workers and the other half as nonworkers. Since there is only one worker bee for each food source, the number of worker bees is equal to that of food sources around the hive. The working bees whose resources are provided by the supervising bees and the other worker bees transform into scout bees [38]. A supervisor bee selects a food source according to the probability value associated with that food source. The value is obtained from the following equation:

$$p_i = \frac{\text{fit}}{\sum_{n=1}^{\text{SN}} \text{fit}_n} \tag{7}$$

where p_i is the probability of selecting i bee, fit_i is the eligibility rate of i solution, and SN is the number of food sources.

In this algorithm, the worker bees share their information with the supervisor bees, and then the supervisor bees use this information to select a new food source around the previous one. To make this selection, the following equation is used [39]. In this equation, X_i is the answer to i optimization problem and v_i is the new answer around the answer x_i.

$$V_i = X_i + \phi_i\left(X_i - X_k\right), \quad K \in \{1.2 \ldots\ldots BN\} \& K \neq I. \tag{8}$$

3.5. Improved Grasshopper Optimization Algorithm (the Recommended Method in This Research). As shown in Figure 4, one of the disadvantages of using the grasshopper optimization algorithm is the convergence of grasshoppers in multiple repetitions [37].

In this study, the GOA and bees algorithm were combined to eliminate the weak point of GOA (i.e., grasshoppers' convergence in large numbers). The resulting algorithm was used as an improved grasshopper optimization algorithm. In other words, as GOA and bees algorithm were combined, a new grasshopper was added in each repetition, which prevented convergence. Ultimately, this new algorithm led to better, more accurate and more reliable results.

4. Results and Discussion

4.1. Phase I (Qualitative Phase): Descriptive Results. To check whether or not the distribution of the research variables was normal, the Kolmogorov-Smirnov test was used. As a statistical hypothesis, if the test significance level was greater than 0.05, the null hypothesis cannot be rejected. It was concluded that the distribution of the variables was not significantly different from a normal distribution. The test results are presented in Table 1.

In the next step, to identify the factors affecting the quality of working life and the human resource risks in the capital market, a confirmatory factor analysis model was employed. This model is made through a structural equation and the Smart-PLS software, which makes use of partial least squares. The data were collected through a questionnaire distributed among 38 capital market specialists selected from a statistical sample of 128 capital market employees. Considering the variables and the predicted relations, the data were fed into the Smart-PLS software for a hypothetical model. After the deletion of the unknown variables, the final model emerged as shown in Figure 5.

Figure 5 shows the final factors of QWL and human resource risks. The presented figures are the absolute values of the t scores above 1.96; those at the 95% confidence level were considered significant. To check the reliability of the model (i.e., the internal similarity between the observed variables), two indicators were used, a traditional indicator called Cronbach's alpha and a composite reliability

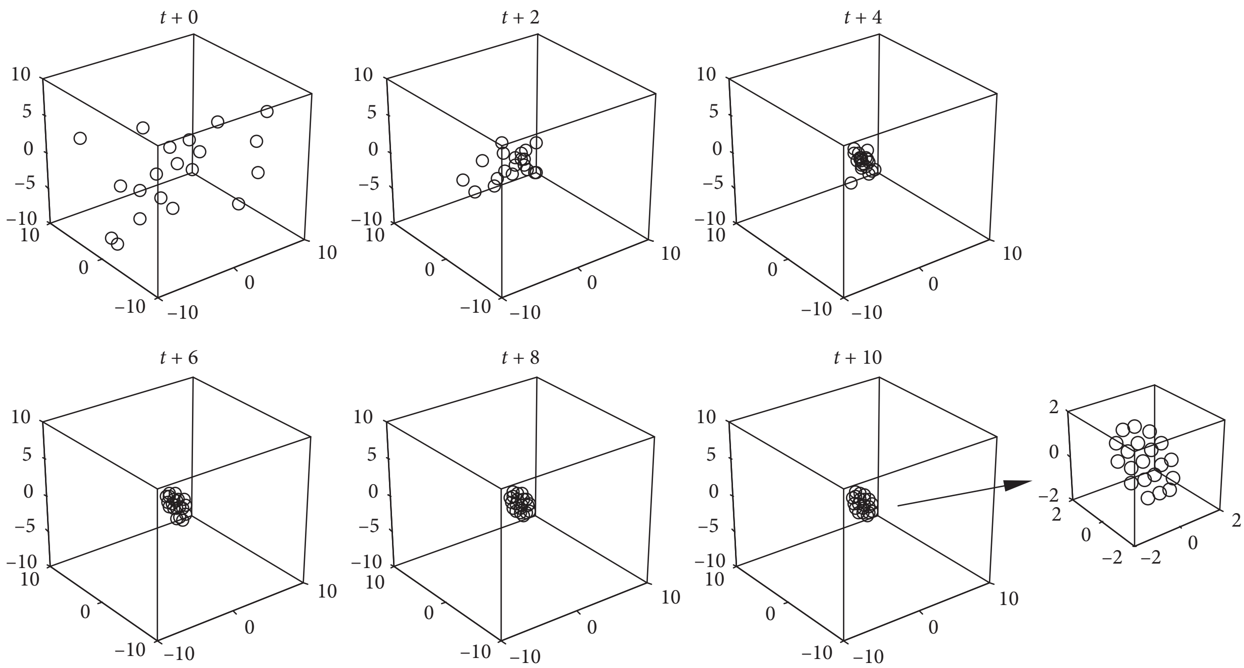


Figure 4: Convergence in the grasshopper optimization algorithm.

Table 1: Variable normality test results.

Kolmogorov–Smirnov test			
Quality of working life			
Variables	Z	Significance level	Test result
Adequate and fair compensation	1.280	0.075	Normal
Safe and healthy environment	1.355	0.051	Normal
Opportunity for continued growth and security	1.227	0.098	Normal
Constitutionalism	1.351	0.052	Normal
Work and total life space	0.978	0.294	Normal
Social integration	0.951	0.327	Normal
Development of human capacities	1.188	0.119	Normal
Social relevance	0.988	0.354	Normal
Human resource risks			
Knowledge, expertise, and skills	1.307	0.066	Normal
Morality, attitude, and commitment	1.346	0.054	Normal
Physical and mental health	1.107	0.173	Normal
Management	1.136	0.152	Normal
Legal affairs, policy, strategy, and decision making	1.512	0.061	Normal
Environmental	1.067	0.205	Normal
Organizational culture and atmosphere	1.125	0,159	Normal
Recruitment and employment	1.096	0.182	Normal
Education and development	0.759	0.613	Normal
Performance evaluation	0.656	0.782	Normal
Reward and compensation services	1.252	0.087	Normal

indicator. The acceptable criterion for the internal similarity of the indicators was 0.7, which was confirmed for both models. In order to check the validity, the AVE square root of each structure was compared with the correlation values between the structures. Since the coefficients of the correlation between each structure and the others were less than the AVE root square of that structure, the validity of both models was confirmed. The transverse load test and Fornell-Larcker test were also used to investigate the divergent validity; the output of the matrices proved the existence of divergent validity. To evaluate and prioritize the factors affecting human resource risks, it was necessary to identify them in the capital market. To this end, expert opinions were obtained by a two-section questionnaire. In the first section, the risks were scored, and the second was given to the pairwise comparisons of the RPN criteria. After the risk levels of the RPN factors were determined, the risk priority number (RPN) was used to determine the risk level of each

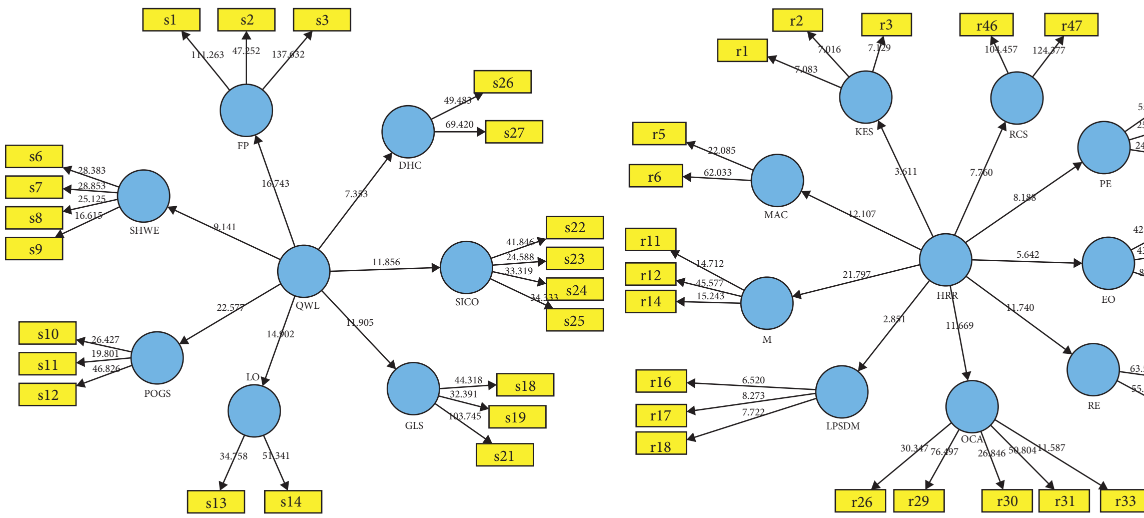


Figure 5: Final model of QWL and human resource risks management.

human resource risk. A RPN can be calculated using the following equation:

$$(\textbf{RPN} = \textbf{Severity} * \textbf{Occurance} * \textbf{De tection}). \quad (9)$$

As mentioned earlier, the failure modes and effects analysis (FMEA) method has several limitations for risk assessment. In this study, Fuzzy Analytical Hierarchy Process (FAHP) was implemented to address one of those limitations (considering the same importance for the RPN risk factors). To this end, in the second section of the questionnaire, the experts were asked to compare the matrices of the risk factor RPNs in a pairwise manner and state their preferences for the factors according to a fuzzy spectrum table. Then, in order to obtain the preferences of the decision-maker, a pairwise comparison of the matrices was conducted using fuzzy numbers (l. m. u). Thereafter, the obtained fuzzy values were diffused and normalized by the method of the center of gravity, and the risk factors were obtained for the RPNs.

According to Table 2, the risks of "conflict of interests in the organization, unethical behavior, and existence of lobbying culture in the organization" account for the highest RPNs, which means they are the most critical human resource risks in the capital market. On the other hand, the risks of "incompatibility of tasks with key skills and abilities of the organization's employees, failure to evaluate performance by specific criteria, and lack of proper feedback to employees" have the lowest RPNs, which means these risks are not of much importance for the capital market. To determine the RPNs of human resource risks in the capital market, the critical risks of this market need to be identified. To this end, the Pareto principle or 80–20 rule is used. The rule asserts that 80% of outcomes (or outputs) result from 20% of all the causes (or inputs) for any given event. In other words, 20% of human resource risks cause 80 problems. Therefore, it is not necessary to examine all the risks to reduce the adverse risks. According to the Pareto principle, human resource risks are as shown in Figure 6.

As Figure 6 suggests, the risks of *r*8 and those on its left are the ones that cause 80% of the problems. In other words, the risks that are considered critical in the Pareto principle include lack of cooperation and teamwork culture, lack of law enforcement oversight, incompatibility of training with human resources requirements, lack of up-to-date knowledge and skills in employees, wrong rules and policies, recruitment without rules or without considering the employees' qualifications, lack of human skills, poor leadership, lack of employee commitment and job abandonment, lack of managers' perceptual skills, lack of proper successor training process, low tendency to moral principles at work, lobbying culture in the organization, and unethical behavior and conflict of interests in the organization. In this study, since the Pareto principle is not proved yet, the specialists' opinions in the questionnaire were utilized to validate the results. To this end, in order to determine the risk priority number, the questionnaire also asked whether or not human resource risks were critical. In this case, the specialists' positive answers beyond the third quartile were considered as critical risks. These critical risks are shown in Table 3.

Therefore, through a correspondence made between the results obtained from the Pareto principle and those from the specialists, the commonality of the two sets of results was identified as the critical risks of human resources in the capital market. The risks are as follows:

(a) Unethical behavior (*R*1)

(b) Lack of managers' perceptual skills (*R*2)

(c) Poor leadership (*R*3)

(d) Wrong rules and policies (*R*4)

(e) Conflict of interests in the organization (*R*5)

(f) Recruitment without rules or without considering qualifications (*R*6)

After the identification of the factors affecting QWL and human resource risks, the QWL model was outlined for the

Table 2: Risk priority numbers (RPNs) of human resource risks.

Priority	RPN	Item
1	54.87	Conflict of interests in the organization
2	54.24	Unethical behavior
3	47.99	Lobbying culture in the organization
4	44.33	Low tendency for moral principles at work
5	37.90	Lack of proper successor training process
6	33.27	Lack of managers' perceptual skills
7	30.78	Lack of employee commitment and job abandonment
8	30.66	Poor leadership
9	29.22	Lack of human skills
10	29.19	Recruitment without rules
11	28.54	Wrong rules and policies
12	25.05	Lack of up-to-date knowledge and skills in employees
13	21.75	Incompatibility of training with human resources requirements
14	21.02	Lack of law enforcement oversight
15	20.82	Lack of cooperation and teamwork culture
16	19.96	Improper and inappropriate relationship between colleagues and managers
17	19.34	Lack of information management
18	15.03	Lack of trust in human resources units
19	14.29	Lack of proper procedures for identifying, developing, and retaining talented people
20	13.03	Noncompliance with routine laws
21	12.53	Lack of job description and appropriate structure
22	10.18	Inadequate payment scales compared to similar organizations
23	9.67	Employees' lack of knowledge and skill in the main activity fields of the organization
24	8.16	Incompatibility of tasks with the key skills and abilities of the employees
25	7.80	Failure to evaluate performance by specific criteria
26	6.91	Lack of proper feedback to employees

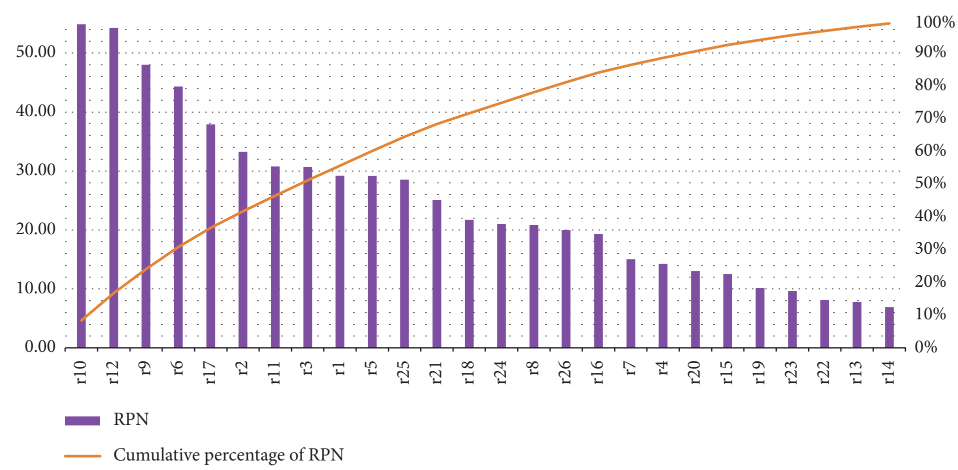


Figure 6: Pareto diagram of human resources risk priority number.

Table 3: Critical risks asked about in the questionnaire.

Item	% support	Critical
Lack of managers' perceptual skills	76	✓
Poor leadership	87	✓
Recruitment without rules or without considering qualifications	79	✓
Conflict of interests in the organization	82	✓
Unethical behavior	89	✓
Inadequate payment criteria compared to similar organizations	84	✓
Incompatibility of tasks with the key skills and abilities of the organization's employees	79	✓
Wrong rules and policies	87	✓

reduction of the critical risks in human resources. Once the normality, validity, and reliability of the model were confirmed, at first, the relationship of QWL with human resource risks was investigated, as shown in Figure 7.

After the general model was evaluated and fitted, the quality of working life as related to human resource risks was interpreted. Based on the results gained from the test of the model, it is concluded that the model has a perfect fit. The results of the structural equation modelling, i.e., the calculated characteristics of each model path including path coefficients and *t* values, were considered at a 5% error level, as presented in Table 4.

In the first step, to qualify the working life model on the basis of reducing the risk of human resources and investigate their relationships, a path model was implemented with the structural equation modelling technique and the Smart-PLS software. The software uses partial least squares (PLS) to provide structural equation models. This approach is less dependent on sample size than the covariance-based approach is; therefore, it can be used for small-size samples. On this basis, a hypothetical research model was introduced to the Smart-PLS software according to the predicted variables and relations. The examined model is displayed in Figure 8.

Figure 8 shows the calculated QWL model values based on reducing the risks of human resources significantly. The absolute values of the calculated quantities, if above 1.96, were considered significant at the confidence level of 95%. Based on the above integrated model, the second phase of the study could start. As it can be seen in the figure above, each factor of the quality of working life had at least one significant inverse relationship with one of the critical risk factors of human resources.

4.2. Phase II (Quantitative Phase). In this section, a method was presented to determine the quality of working life based on human resource risks. First, the experts scored the items based on an available scale. The items included providing opportunities for growth and continuous security, fair payment, safe and healthy work environment, integration and cohesion in the organization, legalism in the organization, general living space, and developing human capabilities. Then, they scored the quality of working life based on the scores given to those items. After the scoring, to perform the necessary fuzzy inference process, the questionnaire data were converted from qualitative to quantitative and entered into the system. Finally, the fuzzy values had to be converted to quantitative values and go into the defuzzification process. Individual symbols were also assigned to each item for convenience, which are shown in Table 5.

The Gaussian membership functions for the POGS item and the improved grasshopper optimization algorithm (for items 1, 2, and 3 from left to right) are as follows.

As shown in Figure 9, for each of the items, 13 figures were drawn in the same way as the above figure and according to the gradient descent and improved grasshopper algorithms. Figure 9 is just one example from those 13 figures. To create a managerial perspective and quickly evaluate the impacts of the items on the categories of the quality of working life model based on the reduction of human resource risks, the influence of each item is reported in comparison to its subitems; each item has two important subitems. POGS and FP, as two example items, are presented in Figure 10.

In the next step, an adaptive fuzzy neural inference system was used to implement a decision-making assistant system for institutions and organizations operating in the capital market. The aim was to measure the quality of working life, identify the best option to improve it, and quantify its effect. The inference engine of the adaptive neurofuzzy inference system was TSK level one, the default inference engine. The number of the rules in the adaptive neurofuzzy inference system was different for each item, which can be seen in Table 6.

In addition to the Gaussian membership function, the triangular membership function was also examined. Besides, an adaptive neurofuzzy inference system was performed based once on the gradient descent training algorithm (classic method) and once on the improved grasshopper optimization training algorithm. The results of these conductions were compared later. In order to evaluate the performance error of the employed methods, MAE, RMSE, and R^2 were used as three criteria. They are formulated as follows:

$$R^2 = \frac{\sum_{K=1}^{K} X_k Y_k}{\sqrt{\sum_{K=1}^{K} X_{k^2} \sum_{K=1}^{K} Y_{k^2}}},$$

$$\mathrm{RMSE} = \sqrt{\frac{1}{N}\sum_{t=T+1}^{T+N}\left(y_t^2 - y_t^{\wedge 2}\right)^2}, \tag{10}$$

$$\mathrm{MAE} = \frac{1}{N}\sum_{t=T+1}^{T+N}\left|y_t^2 - y_t^{\wedge 2}\right|.$$

In these three formulations, N represents the total number of the observations done in the predicted period, y_t and $y_t^{\wedge}$ denote the predicted value and the actual value at time t , respectively, and X_K, $Y_{K,}$ and K stand for the observational values, number of data, and estimated values, respectively.

As presented in Table 7, the adaptive neurofuzzy inference system was first implemented based on the Gaussian membership function and the gradient descent training algorithm with two and three membership functions. According to Table 8, the two criteria of MAE and RMSE from the adaptive neurofuzzy inference system with two membership functions at the values of 33.4 and 60.5, respectively, had much poorer performance than that with three membership functions and the values of 71.3 and 63.4. In addition, the $R2$ index of the adaptive neurofuzzy inference system with two membership functions and the value of 93.0 was smaller than that with three membership functions, which indicates the better performance of the adaptive neurofuzzy inference system with two membership functions. In general, it can be concluded that an adaptive neurofuzzy inference system with three membership

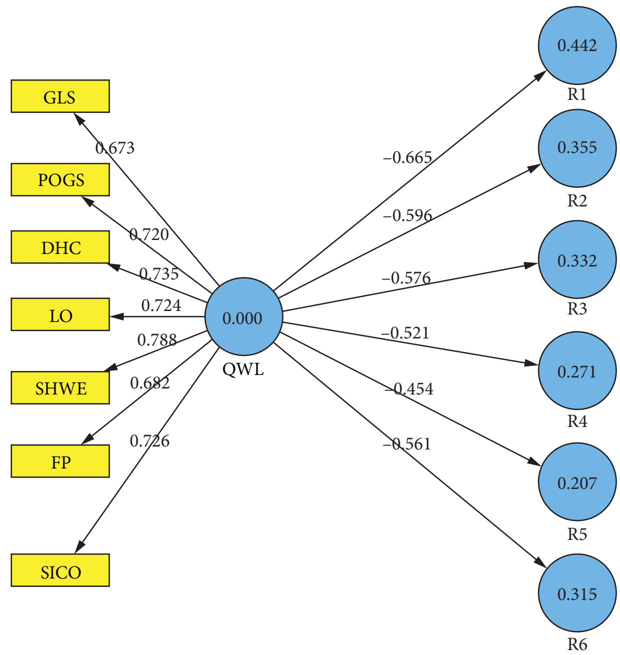


Figure 7: Relationship between QWL and human resource risks for the estimation of path coefficients.

Table 4: Results of the structural analysis of the model for the relationship between QWL and human resource risks.

Independent variable		Dependent variable	Path coefficient	Observed t	Critical t	Determination coefficient (R^2)	Test result
QWL	⟶	Risk 1	−0.665	9.221	1.96	0.442	Confirmed
QWL	⟶	Risk 2	−0.596	8.416	1.96	0.355	Confirmed
QWL	⟶	Risk 3	−0.576	8.562	1.96	0.332	Confirmed
QWL	⟶	Risk 4	−0.521	6.910	1.96	0.271	Confirmed
QWL	⟶	Risk 5	−0.454	6.156	1.96	0.207	Confirmed
QWL	⟶	Risk 6	−0.561	8.303	1.96	0.315	Confirmed

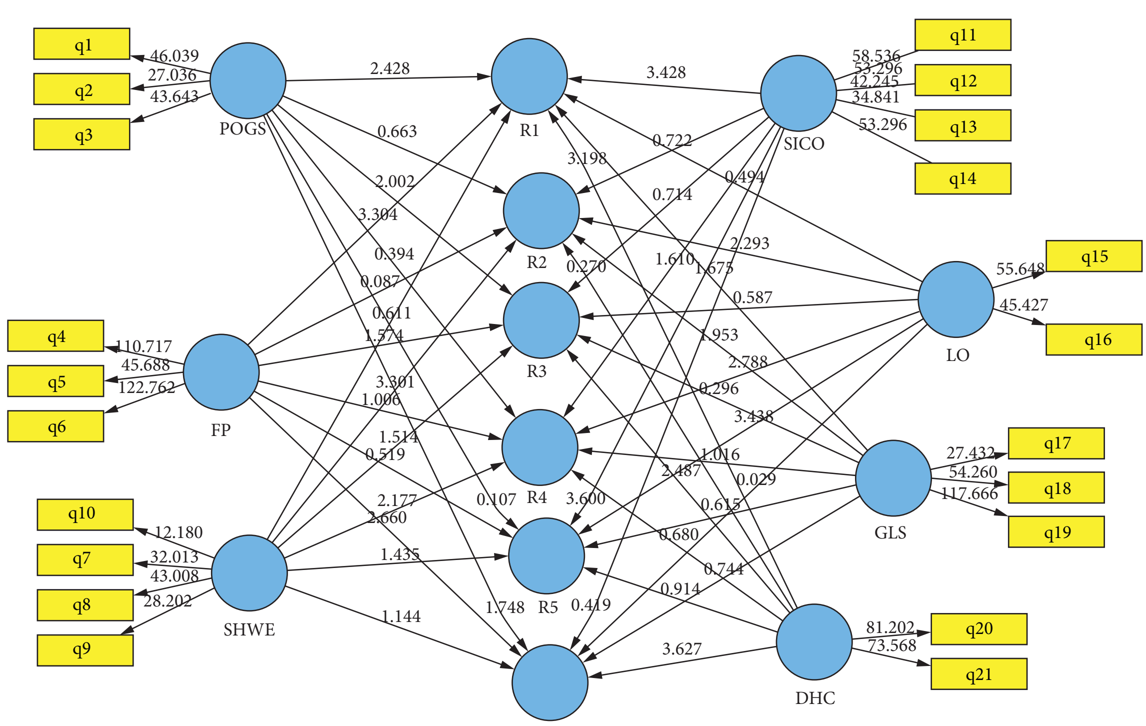


Figure 8: QWL path model based on the reduction of human resource risks.

Table 5: Symbols assigned to items.

Row	Item	Symbol
1	Opportunity for continued growth and security	POGS
2	Adequate and fair compensation	FP
3	Safe and healthy environment	SHWE
4	Social integration	SICO
5	Constitutionalism	LO
6	Work and total life space	GLS
7	Development of human capacities	DHC
8	Quality of working life	QWL

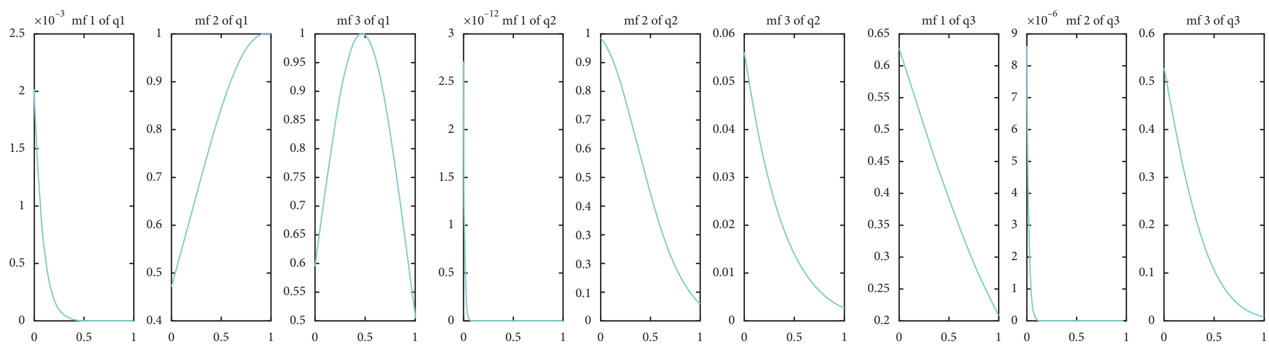
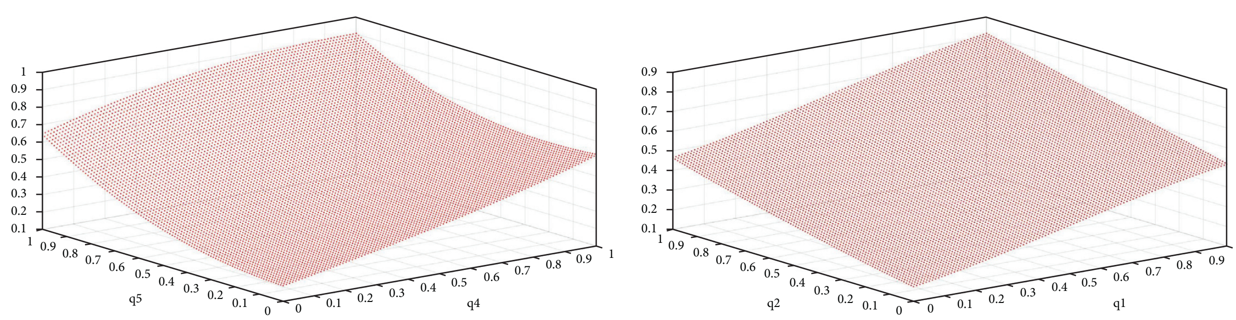


Figure 9: POGS membership functions with the gradient descent algorithm.



(a) (b)

Figure 10: Procedure for the change of (b) POGS and (a) FP items from two important subitems.

Table 6: Number of rules in the adaptive neurofuzzy inference system.

Row	Item	Number of rules for two membership functions	Number of rules for three membership functions
1	Opportunity for continued growth and security	8	27
2	Adequate and fair compensation	8	27
3	Safe and healthy environment	16	81
4	Social integration	16	81
5	Constitutionalism	4	9
6	Work and total life space	8	27
7	Development of human capacities	4	9
8	Quality of working life	128	2187
9	Total	**192**	2448

Table 7: ANFIS results based on the Gaussian membership function and the training gradient descent algorithm with two and three membership functions.

Row	Fuzzy system name	Training algorithm	Membership function type	MAE	RMSE	R^2	Mean MAE	Mean RMSE	Mean R^2
1	POGS	Gradient descent algorithm	Gaussian	3.8129* 2.6635**	4.5407* 3.3045**	0.9510* 0.9832**	4.33*	5.60*	0.93*
2	FP	Gradient descent algorithm	Gaussian	3.7419* 3.0903**	5.0911* 4.4631**	0.9462* 0.9440**			
3	SHWE	Gradient descent algorithm	Gaussian	4.3917* 4.6581**	6.1464* 5.6852**	0.8587* 0.9658**			
4	SICO	Gradient descent algorithm	Gaussian	4.3155* 3.0996**	6.1249* 3.6505**	0.8348* 0.9668**	3.71**	4.63**	0.97**
5	LO	Gradient descent algorithm	Gaussian	5.6783* 4.1208**	7.0991* 4.6918**	0.9365* 0.9815**			
6	GLS	Gradient descent algorithm	Gaussian	3.5099* 3.3579**	4.2705* 4.4981**	0.9871* 0.9750**			
7	DHC	Gradient descent algorithm	Gaussian	4.8871* 4.9693**	5.9606* 6.1204**	0.9729* 0.9649**			

*Data with two membership functions; **data with three membership functions.

Table 8: ANFIS results based on the Gaussian membership function and the improved GOA training algorithm with three membership functions.

Number of membership functions	Fuzzy system name	Training algorithm	MAE	RMSE	R^2	Mean MAE	Mean RMSE	Mean R^2
3	POGS	Improved GOA	2.5003* 29.1700**	3.3981* 38.5978**	0.9775* 0.0003**	3.64*	5.46*	0.92*
3	FP	Improved GOA	4.2157* 13.8877**	9.7254* 17.0780**	0.8272* 0.9493**			
3	SHWE	Improved GOA	2.3944* 49.8000**	4.4958* 50.8429**	0.9208* 0.0000**			
3	SICO	Improved GOA	5.4136* 38.1959**	6.5570* 40.1606**	0.8481* 0.3187**	25.29**	31.55**	0.32**
3	LO	Improved GOA	2.4389* 12.9235**	3.1366* 24.8688**	0.9846* 0.0046**			
3	GLS	Improved GOA	4.4709* 19.2800**	5.7869* 27.6839**	0.9756* 0.4655**			
3	DHC	Improved GOA	4.0547* 13.7609**	5.1343* 21.6240**	0.9346* 0.5081**			

*Gaussian membership function data; **triangular membership function data.

functions performs better than the one with two membership functions. Accordingly, instead of the conventional method (i.e., gradient descent method), the improved grasshopper optimization algorithm (which is a combination of GOA and bees algorithms) was put into practice. The results gained from this improved algorithm are presented in Table 8.

According to Tables 7 and 8, an ANFIS based on the Gaussian membership function and the improved grasshopper optimization training algorithm with three membership functions yields better results than those based on the Gaussian membership function and the gradient descent algorithm with three membership functions. It is to be noted that when the ANFIS was implemented through the improved grasshopper optimization training algorithm with a triangular membership function, as expected, it had a high error. Other membership functions, such as trapezoidal function, were abandoned due to nondifferentiability and lack of flexibility.

In general, according to the results of the second phase of the study, the use of the grasshopper optimization algorithm and its combination with the bees algorithm leads to more accurate results. Indeed, since grasshoppers' convergence in numerous repetitions is a disadvantage of using the GOA method, combining it with the bees algorithm provides more accurate and reliable results; it has been known that adding a new grasshopper at every repetition stage helps to avoid convergence.

5. Conclusion

Considering the gap in the literature on QWL and human resource risks and their evaluation, this study was conducted to devise a method for measuring QWL so as to reduce human resource risks in the capital market. The research was done in two phases. In the first phase, the factors affecting QWL and human resource risks as well as their mutual impacts were identified and studied. In the second phase, a method was provided to measure the characteristics obtained in the first phase. As the results of the first phase showed, all the identified QWL factors reduced at least one of the human resource risks. In this regard, the quality of working life was found to have the most significant impact on the reduction of the 'unethical behavior' as a risk. The unethical behavior of employees can indeed cause many problems. It can even push a business to failure. One way to cope with this problem is to pay special attention to the quality of working life and the reduction of risks in human resources. The best way to monitor a factor is to measure and display it numerically. This makes it possible to improve the plans for operation and the efficacy of the measures taken. The second phase of the study is dedicated to the method proposed for the measurement of the quality of working life in link with the risks involved in human resources. The measurements were made through the neurofuzzy inference system by means of the improved grasshopper optimization algorithm. This algorithm was a combination of the grasshopper optimization algorithm and the bees algorithm. In this respect, the results of the second phase of the research show that the proposed method to measure the quality of working life based on human resource risks is more accurate and reliable than the conventional method in the adaptive neural network (i.e., reduction gradient method). The proposed method serves to create a decision-assistant system for managers and business owners to measure the quality of working life, select the best option to improve it, and ultimately measure the feedbacks on its effectiveness numerically. Inspired by this method, capital market managers can obtain the QWL of their employees and take appropriate measures to improve it, which, in turn, leads to the reduction of risks in human resources and the growth of their business. According to the account provided in this research for the capital market, it is suggested that the issue is examined in other fields and occupations such as banking and insurance and that the results are compared with those of this research.

Data Availability

Some of the numerical data and software outputs data used to support the findings of this study are included within the article. Also this data in full are currently under embargo. But requests for data, after publication of this article, will be considered by the corresponding author.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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Review Article

Application of Machine Learning in Supply Chain Management: A Comprehensive Overview of the Main Areas

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In today's complex and ever-changing world, concerns about the lack of enough data have been replaced by concerns about too much data for supply chain management (SCM). The volume of data generated from all parts of the supply chain has changed the nature of SCM analysis. By increasing the volume of data, the efficiency and effectiveness of the traditional methods have decreased. Limitations of these methods in analyzing and interpreting a large amount of data have led scholars to generate some methods that have high capability to analyze and interpret big data. Therefore, the main purpose of this paper is to identify the applications of machine learning (ML) in SCM as one of the most well-known artificial intelligence (AI) techniques. By developing a conceptual framework, this paper identifies the contributions of ML techniques in selecting and segmenting suppliers, predicting supply chain risks, and estimating demand and sales, production, inventory management, transportation and distribution, sustainable development (SD), and circular economy (CE). Finally, the implications of the study on the main limitations and challenges are discussed, and then managerial insights and future research directions are given.

1. Introduction

In today's competitive environment, the advent of the information technology revolution, economic globalization, and high customer expectations has caused various changes in companies' supply chain management (SCM), highlighting the importance of competition among supply chains rather than companies [1–3]. SCM is the active integration of supply chain activities from original suppliers through end-users that provides services, products, and information that maximize customer value and achieve sustainable competitive advantage [4]. In the era of big data, a large amount of interactive data are routinely created, collected, and archived in different process industries, and these data are really an important asset in process operation, control, and design. Intelligent use of these data and the extraction of information and knowledge of them have a great potential to benefit. Explosive growth in the volume of data from various parts of SCM has forced companies to develop and implement new technologies which are able to rapidly and intelligently interpret a large amount of data [5, 6] as the traditional decision support system cannot face big data satisfactorily. Hence, in the big data era, supply chain professionals are seeking to handle big data to reach smart supply chains.

Artificial intelligence (AI) methods are the most appropriate methods to cope with this big data-related challenge. Machine learning (ML) techniques can be considered as the popular subdisciplines in AI which identify and extract automatically the patterns among variables using large datasets [7]. ML algorithms can detect unknown patterns among data, generate new insights, and direct researchers towards suitable destinations. ML techniques can be used in a different context, including manufacturing, operations, healthcare, and housing [8]. Moreover, ML is widely used in managing different areas and aspects of the supply chain. Recently, ML algorithms and their applications in managing the supply chain have gained interest among researchers. Weaknesses of traditional methods in analyzing big data have led scholars to utilize ML methods that have high capabilities to analyze and interpret large volumes of data. There are many reasons to replace traditional methods with ML techniques. First, traditional methods cannot handle nonlinear problems that are widespread in real-world supply chains. ML techniques can solve this nonlinear problem satisfactorily. Second, traditional methods are incapable of dealing with large and unstructured data that come from different areas of the supply chain, where ML techniques precisely have been developed to deal with big and unstructured data. Third, ML techniques are far stronger than traditional statistical methods in recognizing and predicting the most effective factors on supply chain performance. Thus, ML can be considered as an important tool to help companies to analyze the big data in their SCM.

Seeking new information and knowledge using big data analytics can help to predict future trends, which can lead to informed decisions in various parts of SCM, making a worthy paradigm for companies. Emerging technologies such as the Internet of things (IoT), blockchain, and advanced deep learning (ADL) techniques can equip supply chains with a self-aware mechanism in which different operating objects are connected simultaneously. SCM is really in need of such a self-adaptive smart system to manage the fluctuations in customer demand. Increasing the transparency and connectivity of the supply chain via IoT and blockchain technologies can be a good sign to face the customers' ever-changing demands. This can provide a stream of real-time data and information between various parts of supply chains anywhere in the world.

There is a strong need in the literature to investigate various applications of ML techniques in different parts of supply chains as the majority of the works have considered one, two, or limited areas of the supply chain. For instance, Piramuthu [9] applied ML techniques to design an automated SCM framework. Cavalcante et al. [10] proposed a supervised ML technique for resilient supplier selection. Zhu et al. [11] used China's SME to implement ML techniques in predicting financial risks in supply chains. Priore et al. [12] applied ML techniques to find appropriate replenishment policies in SCM. Baryannis et al. [13] employed ML to predict supply chain risks. Darvazeh et al. [5] conducted a review on ML in SCM. Bai et al. [14] used a multicriteria decision-making (MCDM) and ML hybrid approach to segment suppliers based on environmental factors. However, there is less attention to accomplish a comprehensive study to consider ML applications in different related aspects of the supply chain, which can affect the understanding of how these valuable techniques can be effectively used in managing different aspects of SCM. Therefore, this paper develops a framework in which the most commonly used ML algorithms in managing different areas of the supply chain will be discussed. The main contributions of the paper are outlined as follows:

(i) By comparing the efficiency of traditional and AI methods in facing big data

(ii) By reviewing, summarizing, and classifying the most frequently used AI methods in SCM

(iii) By providing a detailed framework to explain the outputs of the application of ML techniques in supplier selection and segmentation, predicting supply chain risks, and estimating demand and sales, production, inventory management, transportation and distribution, sustainable development (SD), and circular economy (CE)

In this regard, Section 2illustrates a review of ML techniques. The applications of ML techniques in different parts of supply chain are presented in Section 3. Finally, conclusions, managerial insights, and future directions are presented in Section 4.

2. Machine Learning

ML techniques are used to teach machines how to automatically handle a large volume of data more efficiently. Sometimes the extraction of patterns or information from the large volume of data and interpreting them are impossible by traditional techniques [15]. The abundance of datasets available has caused a rising demand for ML techniques. ML techniques are widely applied in different industries from medicine to the military to discover and extract knowledge and information from the data. Many studies have been done by mathematicians and programmers that resulted in the development of various ML algorithms [16]. In this paper, a review of the application of machine learning in SCM was considered. Several studies have mentioned advantages of application of ML techniques in demand and sales estimation [17–19], transportation and distribution [20–22], production [23–25], inventory control [22, 26], supplier selection and segmentation [27–30], and so on. Some of the most famous learning algorithms with a brief description are shown in Table 1.

3. Machine Learning in Supply Chain Management

Despite a large number of publications in the field of ML and SCM separately, the number of publications that have paid to the applications of ML algorithms in managing a supply chain is not adequate [38]. On the other hand, there is no enough connection between researchers and practitioners in this field. It might be caused by inadequate knowledge of practitioners about the power and advantages of ML algorithms in solving SCM problems. In this section, a review of the application of the most famous ML algorithms in managing supply chain-related issues including supplier selection, supplier segmentation, supply chain risk

Table 1: Frequently used ML algorithms.

Type of learning	Algorithm	Description
Supervised learning	Decision tree	Using related values, decision trees (DTs) will categorize attributes in different groups which can be applied for classification purposes [31].
	Naïve Bayes	Naïve Bayes can be best applied to cluster and classify objects [32].
	Support vector machine	Working on the margin calculations, support vector machine (SVM) can be best applied for classification purposes [33].
	K-nearest neighbor	In *K*-nearest neighbor (KNN), the learner usually uses the training data. When the test data are introduced to the learner, it compares both the data. Here, *K* most correlated data are taken from a training set. The majority of K is taken which serves as the new class for the test data [34].
	Supervised neural network	Using supervised neural network (SNN), the predicted output and actual output will be compared, and according to the identified error, the parameters will be modified and considered as the input into the neural network again [15].
Unsupervised learning	*K*-means clustering	Using similarity of the clusters of data,*K*-means (KM) clustering algorithm defines*K* clusters in which the center of the clusters is the mean of the values [35].
	Principal component analysis	Principal component analysis (PCA) can provide faster and easier computations as it reduces the dimension of the data [34].
	Unsupervised neural network	Unsupervised neural network (UNN) categorizes data based on their similarities. Since the output is unknown, UNN considers the correlations between different inputs and categorizes them into different groups [15].
Semisupervised learning	Self-training	Self-training first classifies using labeled data, and then unlabeled data are used as inputs [15].
	Transductive support vector machine	Being an extension of SVM, transductive support vector machine (TSVM) considers both labeled and unlabeled data to make sure the margin is maximized between them [15].
Ensemble learning	Boosting	Boosting uses two sorts of variables, namely, weak learners and strong learners. By grouping weak learners and converting them to strong learners, it aims to decrease bias and variances [36].
	Bagging	Bagging is another tool which can be applied to decrease variances and increase the accuracy and stability of ML [37].

prediction, demand and sales estimation, production, inventory management, and transportation is provided.

3.1. Application of Machine Learning Algorithms in Supplier Selection. Supplier selection can be considered as the main activity in the purchasing function [39]. Due to the important role of suppliers on time, cost, and quality, supply chain managers have put much effort into the supplier selection process. The selection process can be covered by MCDM techniques which include different conflicting factors. Therefore, finding the right balance between those factors is an important task for purchasing managers. MCDM techniques support the decision-makers in evaluating a set of alternatives [27]. The MCDM techniques support decision-makers in evaluating and selecting a set of alternatives. In some cases, the number of potential suppliers and the number of criteria are significantly larger than those that MCDM techniques can cope with them satisfactorily. On the other hand, MCDM methods are categorized into descriptive and static methods like most of the other traditional methods, while in today's competitive marketplace, predictive analytics methods are definitely more useful than descriptive methods. In such an era, ML algorithms have much better performance than the mentioned methods. Among the ML techniques, DT and SVM technique as a supervised learning technique and the Q-learning technique as a reinforcement learning (RL) technique have been applied many times by researchers to solve the supplier selection problem. In the following, how to apply some of the ML techniques to solve the supplier selection problem is discussed.

3.1.1. Supplier Selection Using DT and P-SVM Combined Technique. DT is one of the ML techniques that is used in classification problems where the dataset is not large and can be modeled by a similar model. Moreover, this classifier can be used when only a few features are available or a model is needed that can be visualized and explained in simpler. DT provides an effective and rapid method of classifying datasets. Recently, DT has been applied in various domains [40–42]. In addition, DTs can be used as alternatives to find solutions for a multiclass problem that has binary predictors as it has a hierarchical structure [27]. The hierarchical structure includes ramifications and nodes.

Baryannis et al. [13] compared the outputs of SVM and DT techniques in the supply chain area. The results of their study showed that SVM prediction models analyze data for classification and regression analysis. Considering the lower result for different metrics, SVM models achieve good results across various metrics. The results also indicate how accuracy can be a misleading metric in different scenarios. In the case of DT results, it can be seen that the outcomes were quite similar when it was solved via SVM.

In this subsection, the potential support vector machine (P-SVM) is introduced as a novel approach to the original SVM proposed by Hochreiter and Obermayer [43], which is combined with DT to solve the supplier selection problem. P-SVM can be used to construct binary classifiers and select various features at the same time. The hybrid technique developed by Guo et al. [27] (based on P-SVM and DT) evaluates and selects a supplier based on three steps:

Step 1. Using training samples, it generates DT via the adapted Kruskal algorithm (for more information about the Kruskal algorithm, refer to Guo, Yuan, Tian [27], page 6984)

Step 2. P-SVM is used to construct the binary classifiers and select the features of related nodes

Step 3. Using the values of new samples as input to binary classifiers, P-SVM evaluates the suppliers and selects the best one based on DT

In the procedure of DT and P-SVM combined techniques as shown in Figure 1, at the nodes of A, B, and C, the binary classifiers are defined using the selected features. For instance, class 2 samples are separated from classes 1, 3, and 4 samples which are classified at nodes B and C. Therefore, new samples only should be defined at each of the nodes as a subset of the initial features. Moreover, to form a hierarchical system, some subsets are achieved using P-SVM. For instance, class 2 samples should be defined with a subset signed with A when they are separated from classes 1, 3, and 4 samples. Furthermore, the samples from class 3 should be described with a subset of features marked with B when they are separated from samples from classes 1 and 4. Thus, at each of the related nodes, those subsets signed with A, B, and C shape a hierarchical system that can be used to classify samples [27].

As mentioned, the supplier selection problem is an MCDM problem in which suppliers must be evaluated with respect to many criteria. The number of criteria makes it hard for decision-makers to accomplish consistent compression in order to determine the weights of criteria and then makes it too complex to evaluate the performance of each potential supplier with respect to each weighted criteria by the traditional method. The P-SVM-DT combined technique leads to much better results than traditional MCDM and original SVM methods in solving the supplier selection problem because of the three following reasons [27]:

(I) Introducing the hierarchical structure of the P-SVM-DT combined technique reduces the number of binary classifiers

(II) Combined with the Kruskal algorithm, the hierarchical structure of P-SVM-DT is designed to increase the accuracy and decrease the computation time in different classifications

(III) To promote the generalization performance, P-SVM selects the most "informative" features to develop classifiers

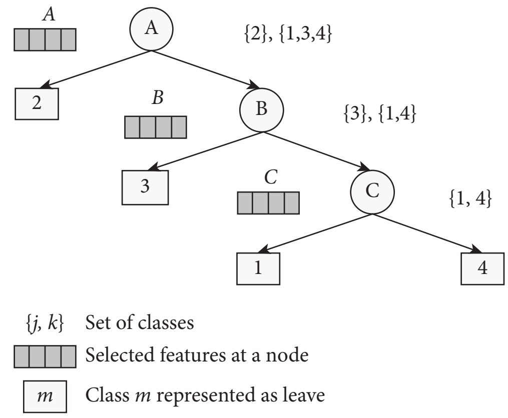

Figure 1: Structure of P-SVM and DT combined technique [27].

3.1.2. Supplier Selection Using Reinforcement Learning. RL, in contrast to other ML methods, does not need a model of the environment and is capable of online learning. In this subsection, Q-learning technique as one of the most widely pursued RL techniques is introduced to solve the supplier selection problem. Valluri and Croson [28] have proposed a modified Q-learning technique to evaluate and select suppliers. Q-learning is a model-free RL algorithm that rewards actions with positive outcomes and penalizes actions with negative outcomes. In this regard, $Q_t(a_i)$indicates the supplier's value at a quality level a_i, at time t. Supplier's value at a quality level a_i, at the time $t+1$, is updated with the following equation:

$$Q_{t+1}(a_i) = Q_t(a_i) + \alpha[P_{t+1}(a_i) + Q_t(a_i)]. \quad (1)$$

The Q-learning equation is illustrated by equation (1) where the assumption of discount factor is 1 and between periods is assumed to be 1. Here, $P_{t+1}(a_i)$is the suppliers' profits at the quality level of a_i. Various states of Markov decision process include different levels of quality which suppliers can achieve. Considering the increment of 0.1, suppliers can produce the level of quality level ranging from 0 to 1. The modified Q-learning algorithms have been used to obtain faster convergence. In the initial algorithm, if supplier agents meet the requirement to reach "Grade I goods," the level of quality $a_i$will be selected to be rewarded; however, in the modified algorithm, all levels of quality higher than the chosen level will be rewarded and the ones lower than the chosen level of quality will be penalized (as in Figure 2(a), the 0.5 is the specific level of quality and all other levels higher than 0.5 will be rewarded). This is illustrated in Figure 2(b), where 0.5 is the chosen level of quality, and it can be seen that all other levels of quality lower than 0.5 are penalized.

The logic behind using penalty or reward actions is related to the supplier's ability to meet the requirements defined at the chosen level of quality. This means that if suppliers reach the chosen level of quality, it is highly likely

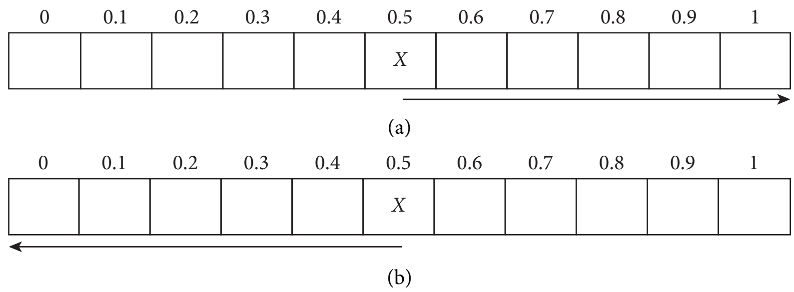

Figure 2: RL under the modified learning algorithm [28].

to reach a higher level in the next periods, which can be rewarded by more profits. However, if suppliers fail to satisfy the requirement at the chosen level of quality, it is highly possible that the suppliers fail in the lower level of quality.

3.2. Application of Machine Learning Algorithms in Supplier Segmentation. Supplier segmentation is one of the strategic activities of any organization through which suppliers are categorized into groups based on their similarities. Contracts, managing, and handling suppliers' affairs are similar within each group and different from the suppliers in other groups. Supplier segmentation promotes the efficiency and effectiveness of relationships with suppliers and leads to the development and improvement of the organization's performance [29, 44]. A review of the literature on segmentation shows that supplier segmentation has received little attention in comparison to customer segmentation and is still in its initial stages. While customer segmentation is one of the targets of the market demand side, supplier segmentation focuses on the objectives of the market supply side [30].

Generally, market segmentation can be divided into three categories as follows:

(a) Segmentation of customers or end consumers
(b) Segmentation of industrial customers or demand side of B2B2 market
(c) Segmentation of suppliers or supplied side of B2B market

While the research literature is relatively rich for the first two cases, the third case—supplier segmentation—has rather been neglected, and few studies have been conducted in order to provide a practical tool that can be applied and implemented in real-world conditions [45]. A review on supplier segmentation indicates that in most of the research studies in this area, MCDM methods under fuzzy conditions have been used to evaluate and segment the suppliers. Some of these studies are presented in Table 2.

Most of the MCDM methods that are mentioned in Table 2are expert-based and/or pairwise comparison-based methods. An important disadvantage of these methods is that the weaknesses in dealing with big data. Therefore, researchers have drawn attention to the use of ML methods in evaluating and managing suppliers [51–53] which are even more efficient than traditional methods. In this section, the application of ML in supplier segmentation has been considered. Bai et al. [14] proposed an MCDM-ML method to evaluate and segment the suppliers. In the following, the steps of MCDM-ML proposed to evaluate and segment the suppliers are presented:

Step 1. Identify a set of criteria to evaluate suppliers

Step 2. Evaluate and score the suppliers with respect to each of the weighted criteria using an outranking MCDM method (e.g., Entropy, PROMETHEE, and TOPSIS (Technique for order of preference by similarity to ideal solution (TOPSIS)))

Step 3. Determine the importance/weight of each criterion using a weighted MCDM method (e.g., Entropy, AHP, and BWM)

Step 4. Segment the suppliers based on their score using a supervised/unsupervised ML method (e.g., K-means, fuzzy C-means, SVM, and DT)

3.3. Application of Machine Learning Algorithms in Managing Supply Chain Risks. Supply chain risk management (SCRM) refers to the coordinated and collaborative efforts of all parties involved in a supply chain to assess, identify, monitor, and mitigate risks aiming at increasing robustness and resilience, reducing the vulnerability of the supply chain, and guaranteeing continuity and profitability [54, 55]. SCRM encompasses a wide range of actions and decisions that have resulted in an equally wide spectrum of solutions pursued by many scholars.

(1) *Multiplecriteria Decision Analysis (MCDA).* This category encompasses well-established approaches to assess various risk-related criteria that affect supply chain performance, as well as the efficacy of potential solutions, such as a hybrid AHP, PROMETHEE approach [56], and an integrated fuzzy TOPSIS-CRITIC approach [57, 58].
(2) *Mathematical Modeling and Optimization.* This category is by far the most common one and encompasses approaches based on fuzzy programming or stochastic and robust optimization [51, 54, 59, 60].
(3) AI techniques have received relatively little attention in the field of SCRM or typically supply chain research [61]. Recently, because of the availability of large amounts of data and increased computing

Table 2: The widely used methods in supplier segmentation.

Authors	Method used for supplier segmentation
Rezaei and Ortt [46]	Supplier segmentation using two general criteria of suppliers' capability and willingness using fuzzy logic
Rezaei and Ortt [45]	Supplier segmentation using two general criteria of suppliers' capability and willingness using fuzzy AHP[3]
Rezaei et al. [47]	Supplier segmentation using two general criteria of suppliers' capability and willingness, using BWM(Best-worst method (BWM)) technique
Segura and Maroto [48]	Supplier segmentation using two strategic and vital dimensions using MAUT (Multi-attribute utility theory (MAUT)) and PROMETHEE (Preference ranking organization method for enrichment of evaluations (PROMETHEE)) techniques
Rezaei et al. [44]	Supplier segmentation based on environmental criteria using ELECTRE (Elimination and choice translating reality (ELECTRE)) TRI-rC techniques
Rezaei and Fallah lajimi [49]	Supplier segmentation based on the hybrid approach of PPM (Purchasing portfolio matrix (PPM)) and SPP (Supplier potential matrix (SPM)) matrices using BWM technique
Parkouhi et al. [50]	Selection and segmentation of suppliers based on their resilience using DEMATEL (Decision-making trial and evaluation laboratory (DEMATEL)) and gray SAW (Simple additive weighting (SAW)) techniques

power, as well as the success of ML techniques, AI has been a resurgence. It has also led to apply the potential of AI techniques in SCRM by researchers in processes such as prediction, risk identification, assessment, and response [62–69].

A data-driven framework for managing supply chain risks includes two general phases:

(i) *Risk Identification*. Risk identification is the first activity in SCRM. Different researchers have used different algorithms and methods to identify risks. Classification and clustering techniques such as SVM and DT are widely employed techniques to identify risks. After identifying SCR, it is the time to assess the risks and propose some appropriate activities to mitigate the risks.

(ii) *Risk Assessment and Response*. ML and big data analytics have also been utilized to deal with risk assessment. Artificial neural networks (ANNs) and Bayesian networks are the two most used ML techniques that have shown acceptable potential in modeling for risk assessment [70, 71].

In the following, a framework to integrate AI techniques within the SCRM process has been proposed that can enhance supply chain risk prediction. The aim of this two-way framework is the creation of synergy and interactivity between AI and supply chain experts: any decision that should be made by the AI experts always depends on the specific inputs by the supply chain, while the developed models and produced results have to be interpretable so that decision-making is based on them or they can affect SCRM decision-making. Figure 3represents the flow of the framework's process. On the left-hand side of the figure, the focal point is on the major tasks involved in a data-driven AI methodology. The right-hand side contains the traditional tasks that are involved in a standard SCRM process. As can be perceived, this framework is built upon effective synergies between a team of experts of data-driven AI and a team of experts of risk management within a supply chain.

3.4. Application of Machine Learning Algorithms in Demand/Sales Estimation. In SCM, planning is based on sales/demand estimation. By introducing nonlinear analyses, ML techniques have been used to accurately predict and forecast demand, sales, and inventory, leading to optimization of supply chain performance. An intelligent forecasting system leads to optimize performance, reduce costs, and increase sales and profit. In this case, it is required to relate the parameters associated with multiple explanatory variables to their dependent variables in a highly nonlinear manner. Being different from those traditional methods like exponential smoothing, moving average, time-series method, and Box–Jenkins method, ML techniques usually do not heavily rely on the accuracy of historical data so that ML techniques have been promoted as great alternatives for demand forecasting and planning in SCM [72]. For instance, Thomassey [73] proposed a forecasting model by advanced methods such as data mining and fuzzy logic for sale. Their model performance is more reliable than traditional models. This model worked well under situations such as strong seasonality of sales, volatile demand, and a wide number of items with a short life cycle or the lack of historical data background. Figure 4indicates the principles of a fuzzy forecasting system. This system makes it possible to generate a model which automatically recreates the expert approach when they carry out intuitive predictions with respect to explanatory variables. Three stages are needed to implement this fuzzy forecasting system as follows:

(1) Removing the impact of explanatory variables from historical sales

(2) Using the baseline sales as a resulting data to forecast the baseline of the next year, for example, applying a basic forecasting technique according to the seasonality average

(3) Adding the impact of explanatory variables regarding the next year to this baseline forecast

3.5. Application of Machine Learning Algorithms in Inventory Management. Storage incurs important costs in SCM. For instance, the annual costs of storage in supply chains are about 15%–35% of their total business value [74]. Supply chain inventory management seeks to decrease costs, increase product variety, and improve customer service as well. However, precisely estimating, predicting, and

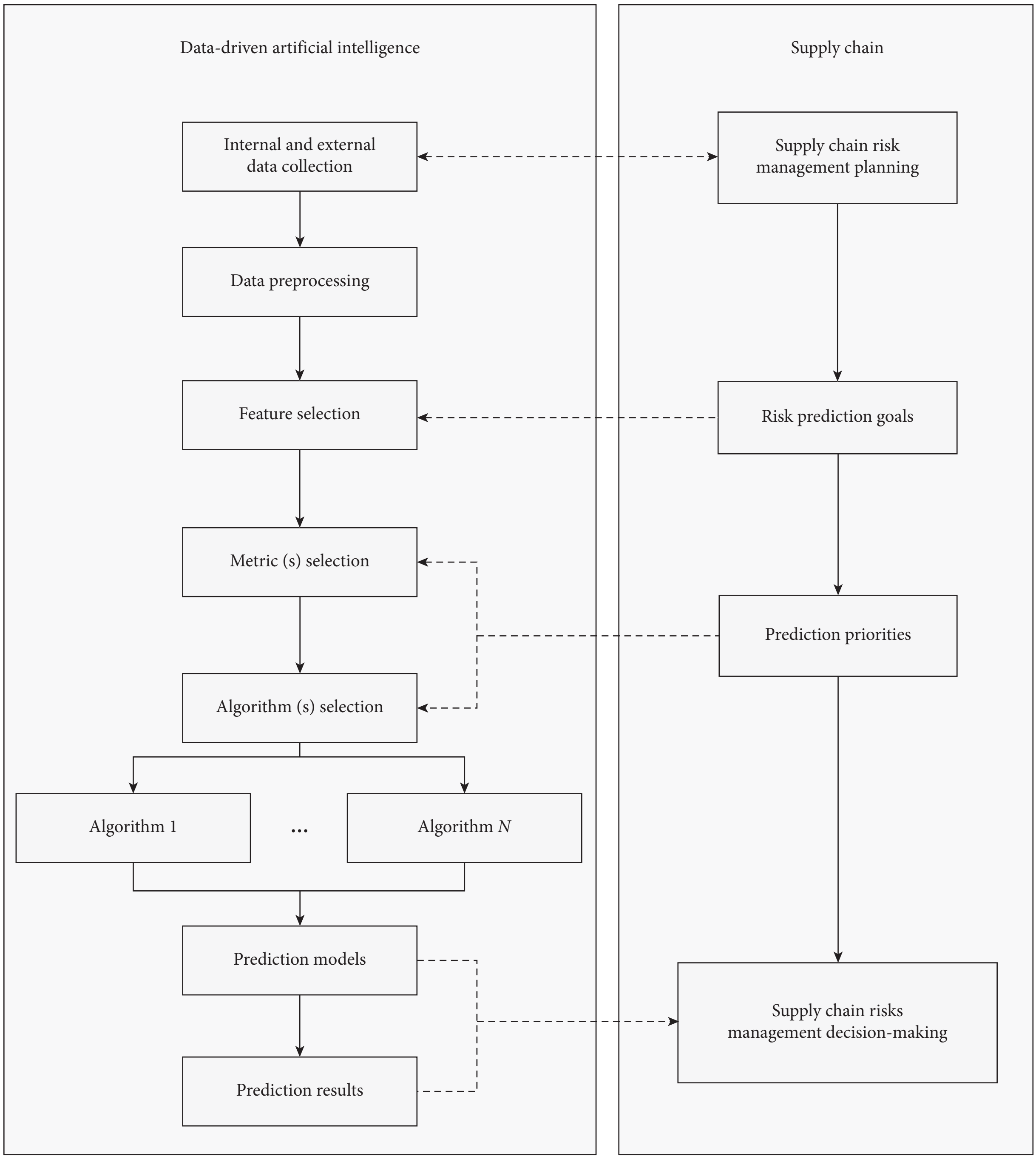

Figure 3: Data-driven risk prediction framework [54].

accessing the concerned information of all these goals by traditional decision rules are hard because this information usually is high according to the experience and judgment of inventory managers themselves. Hence, the inventory input is an uncertain parameter. In recent years, the inefficiency of traditional methods in facing uncertainty has led researchers to apply AI. ML tools can explore quick input comparable patterns on warehouse datasets. Gumus et al. [26] applied neural networks to lead-time forecasting. They employed neuro-fuzzy demand in a multi-echelon supply chain. The results showed that their proposed model efficiently improved the inventory management performance. Furthermore, ML has demonstrated an efficient performance for in-house delivery or automating inspecting the damage inside logistics hubs. As a result, the ML tools are able to find the hidden inventory patterns that have never been unfolded in decreasing and saving costs.

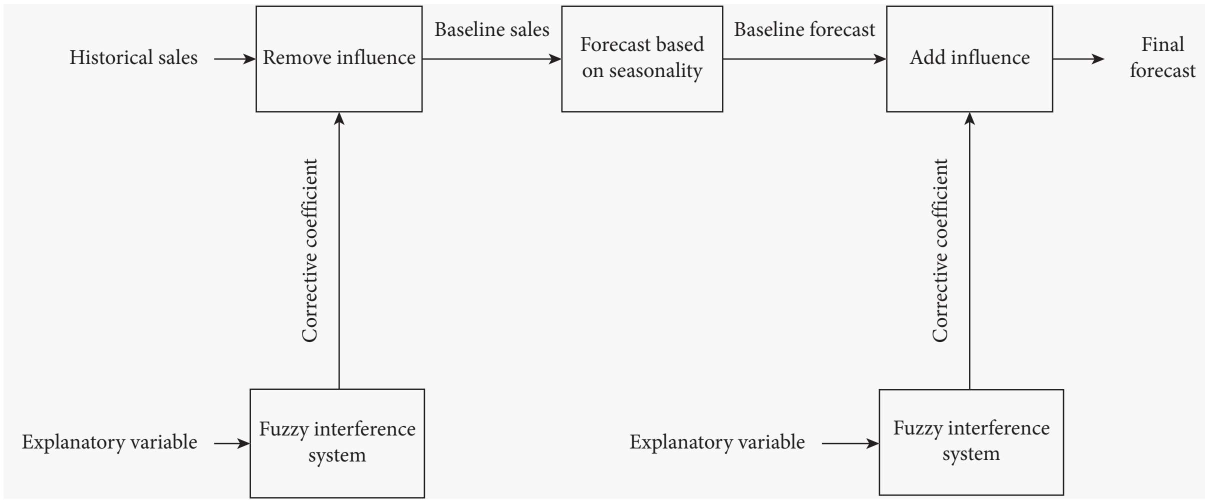

Figure 4: Fuzzy forecasting system [73].

3.6. Application of Machine Learning Algorithms in Transportation and Distribution. Vehicle routing problems (VRPs) are categorized as one of the most applicable issues in SCM [75–80]. Solving VRPs is one of the high and well-known applications of ML in SCM. The optimal route for transporting vehicles is an important issue in SCM to deliver products and services on time to customers; in most cases, routing is beyond the ability of a human brain. ML tools have excellent performance for analyzing large and diverse datasets and accurate forecasting of parameters. Ćirović et al. [81] developed a model for the routing of light delivery vehicles through logistics operators in which an adaptive neural network was trained by a simulated annealing algorithm. This model assesses the performance of the distribution network routes. ML algorithms are able to generate better delivery routes by objectively and timely exploring the pattern of transportation, consumers' behavior, infrastructures, and vehicles.

3.7. Application of Machine Learning Algorithms in Production. ML tools will improve the production planning and factory scheduling accuracy by taking into account multiple constraints. ML tools will also make it possible to balance the constraints more effectively than those that were manually done in the past, particularly for manufacturers who rely on build-to-order and make-to-stock production workflows. Manufacturers can apply ML tools to reduce supply chain latency for components and parts used in their most heavily customized products. For example, faced with the different production regulations and customization requirements of each country, Chen et al. [82] applied NNs to group similar customization needs. Then, they used the existing inventory information to select the parts for production managers, which hugely reduced the cost during the supply chain compared with human decision. As a whole, the ML tools can yield the lead-time prediction in production with a shorter response time.

3.8. Application of Machine Learning Algorithms in Sustainable Development. In different industries, the emergence of decentralization in the level of organizational structure restricts the SCM scope whereas concentrating on sustainable performance [83–87]. In terms of quantity and time, ML has real-time capability inputs related to activities and resources [88]. Accordingly, ML gathers and employs the data, conducts analysis, and renders the required inputs to decide on coping with the dealt affairs. ML permits industries to minimize human intervention and maximize the effectiveness and efficiency of work processes simultaneously.

Focusing on customer demand and production planning in traditional SCM is not an effective way, and that is why the concept of sustainable SCM is brought up [89]. Furthermore, the lack of objectivity in human experts limits the research works on the data analysis on demand forecast in the traditional SCM. In fact, the SCM literature shows that analysis in the traditional supply chain is highly affected by the biases of decision-makers and unreasonable market conjectures. Due to this, the inclusion of ML is the best choice. For example, ML provides better production planning since it helps managers identify consumers' requirements and their purchase patterns under different scenarios. On the other hand, for a sustainable SCM, ML can play a vital role due to its high potential to tackle the uncertainty and conserve industries for efficiently encountering the approaching challenges. As a real case, Sharma et al. [89] performed a comprehensive review on the application of ML techniques in sustainable agriculture SCM, where 93 papers were surveyed.

3.9. Application of Machine Learning Algorithms in Circular Economy. A CE is a systemic procedure that contributes to maintain the activities related to reverse flows in supply chains including resource usage, recovery, recycling, reuse, repair, remanufacturing, and refurbishment [90]. It motivates the perpetual reuse of materials to reduce waste, as well as directing demand toward natural resource consumption

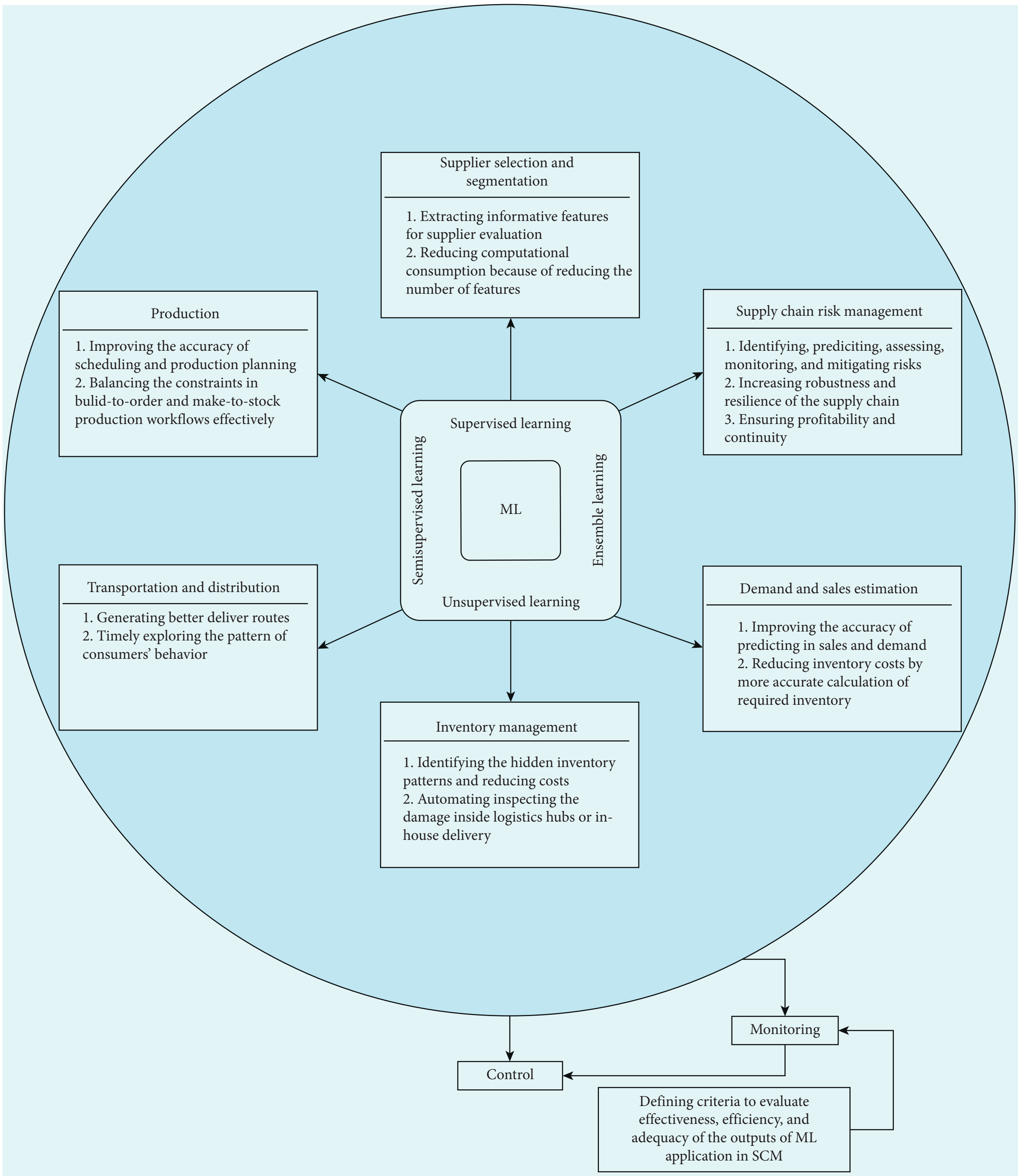

Figure 5: Conceptual framework for ML application in SCM.

[86]. AI and ML algorithms can serve as efficient platforms for a quick transformation to the CE. There are three key factors of CE where ML techniques can be applied as follows:

(i) *Design Circular Materials, Components, and Products*. It is obvious that ML tools can facilitate the development of new materials and products, such as rapid ML-driven prototyping and testing

(ii) *Operate Circular Business Models*. ML can improve product circulation through intelligent demand prediction, pricing, inventory management, predictive maintenance, and so on

(iii) *Optimize Circular Infrastructure*. ML can enhance components remanufacturing, products sorting and disassembling, and materials recycling which can provide the reverse logistics infrastructure

As a recent study, Wilts et al. [91] investigated the application of AI in sorting of municipal solid waste (MSW) according to the CE principles. ML was discussed as one of the most efficient technologies for automatic waste sorting.

4. A Framework for ML Application in SCM

In the previous sections, the application of ML techniques in different areas of SCM was discussed. In this section, a conceptual framework was presented to give a broad overview of the outputs of the application of ML in each area of SCM, which cannot be achieved by applying traditional methods. Moreover, some useful information about the necessary and sufficient conditions to use ML in SCM effectively was provided. As it is clear in Figure 5, one of the most important outputs of applying ML techniques such as SVM in supplier evaluation is to extract some seminal features which could have a significant effect on supplier selection and segmentation processes. Moreover, using ML techniques can reduce the time of evaluating suppliers based on criteria by reducing the number of features applied to classification. The outputs of applying ML in SCRM are predicting, assessing, and mitigating risks intelligently. Furthermore, applying ML in SCRM can make it possible to cultivate a robust and resilient supply chain and ensure the continuity and profitability of the organization. One of the outputs of applying ML in demand and sales estimation is to predict demand and sales more accurately than traditional methods, and this leads to lower inventory costs by an accurate required inventory estimation. ML techniques can recognize the hidden inventory patterns that have a significant impact on reducing costs. Using AI makes it possible to establish an automated inspecting system to mitigate the damage inside logistics hubs or in-house delivery. Transportation and distribution is an important activity in SCM that loads heavy costs on organizations. The results of applying ML in transportation and distribution systems can lead to timely delivery of a product to the corresponding customers by generating better delivery routes and exploring the consumer behavior. The other activity in SCM that has faced multiple constraints is production planning. An appropriate production planning system should be dealt with these constraints effectively. ML techniques can balance the constraints in build-to-order and make-to-stock production workflows and effectively improve the accuracy of scheduling and production planning.

As mentioned earlier, traditional methods are weak in dealing with big data problems. Therefore, recently, researchers have drawn attention to the use of ML techniques in managing the supply chain [13, 14, 52, 53] which are even more efficient than traditional techniques in dealing with a large number of data. On the other hand, there are two criticisms about ML methods as follows:

(I) The nature of most of the AI-based techniques is learning historical data, and then they make a decision about new samples. These techniques are not capable of dealing with big changes and revolutions in problem situations. For example, the COVID-19 outbreak has made large and unpredictable changes in the business environments that ML techniques could not have acceptable performance in dealing with. In such a condition that the problem situation is undergoing big and unpredictable changes, AI is faced with a condition that has no resemblance to what it has learned and faced in the past, and the effectiveness and efficiency of AI methods could be dramatically reduced.

(II) There is a doubt about the validity and fairness of ML techniques in some cases. At the heart of the problem is the fact that ML techniques calculate optimal models from the data they are given. Meaning they can end up replicating the problems they are meant to correct [92].

Therefore, as mentioned at the bottom of Figure 5, the outputs of ML techniques in SCM must be monitored, evaluated, and controlled based on their logical desirability and cultural feasibility. In other words, the outputs of AI-based methods must be evaluated by the human agent (SCM expert) to ensure that the outputs and gained strategies from them are logically desirable and culturally feasible or not, or the outputs of ML application in SCM are effective, efficient, and adequate.

5. Conclusion and Managerial Implication and Future Research Direction

This paper aimed to provide an overview of the application of ML techniques in different areas of the supply chain. In this regard, after a brief review of widely used supervised, unsupervised, and semisupervised ML techniques, the application of each one in managing different areas of the supply chain was presented. Accordingly, supplier selection, supplier segmentation, supply chain risk prediction, demand estimation, inventory management, transportation, sustainable development, and circular economy in SCM were discussed as the most significant areas. In the section on supplier selection, two different machine learning methods were explained. First, how the use of DT and P-SVM combined method in evaluating and selecting suppliers was explained. Second, the Q-learning technique as an RL technique was introduced in order to solve the supplier selection problem. In the next section, the procedure of supplier segmentation using an MCDM-FCM combined method and based on environmental criteria was described. Third, the stages of designing a data-driven framework for predicting supply chain risks were introduced. Fourth, the application of a fuzzy forecasting system as one of the widely used machine learning techniques in demand/sales estimation was explained. Finally, a summary of ML algorithms' applications in inventory management, transportation, and production was introduced. Although the main goal of this paper was addressed as expected and the advantages of applying ML in managing supply chains were concluded, there are some limitations. For instance, considering the target audience of this paper (beginners and industry managers), providing the details of ML algorithms was not possible and just general explanation and sometimes drawing some flowcharts to acquaint the beginners and managers with the process of implementing and utilizing the power of ML algorithms in the SCM area were provided. In this paper, without any concentration on a specific industry, the application of ML generally in different SCs was considered; it is obvious that the nature of the industry and the type and the volume of data have a significant effect on selecting a suitable algorithm. Therefore, it is suggested that managers should be careful in using different algorithms and consider the suitability of the selected algorithm with the nature of the data and its interpretability for the industry. There are some industries that are in the early stages of using ML techniques to improve their various supply chain processes. For example, there is a great space in the renewable energy supply chain to cover and fruitful research contents to see in this domain in the future. There is also a great gap in leveraging the power of the mathematical optimizing model and machine learning in order to design and optimize SC, which can be considered in future research studies. Furthermore, the presented framework can be tested using structural equation modeling in some industries in future research studies. Despite the presence of AI for the last half-century and its recent emergence in the SCM area, there is still a lack of research regarding the specific topics of artificial intelligence for different areas of the supply chain. Based on projected AI research trends, we suggest further exploration in the application of RL techniques in real-time pricing. Most AI techniques applications in the SCM area remain limited to relatively well-structured (well-defined), operational, and tactical SCM problems. Future research can address the application of AI techniques (especially agent-based systems) to solve a variety of soft but strategic SCM issues. The main reason is that providing efficient solutions for SCM problem is either too expensive or difficult due to the inherent complexity and ill-structured nature of the problem, such as outsourcing relationships, supplier relationship management, supply chain coordination, and strategic alliances among supply chain partners.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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