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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

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

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

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

$y\ dr^k_{dr}$ 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.

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

xr^k_{lr} 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.

$y\ dd^k_{d_1 d_2}$ 1 if vehicle k goes from d1 to d2.

$yll^k_{l_1 l_2}$ 1 if vehicle k goes from retailer L1 to L2.

$ymm^k_{m_1 m_2}$ 1 if the vehicle k goes from the production center m1 to m2.

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

$yrd^k_{r\ d}$ 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.

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

xr^k_{rm} 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.

$$\begin{aligned}
\operatorname{Min} OBJ1 = {} & \sum_{m\in M} OC_m y_m + \sum_{d\in D} OC_d y_d + \sum_{l\in L} FC_1 \\
& + \sum_{k\epsilon k_1} FVF_k \left(\sum_{m\in M}\sum_{d\in D}\sum_{p\in P} ymd^k_{m\ dp} \right) + \sum_{k\epsilon k_2} FVS_k \left(\sum_{d\in D}\sum_{l\in L}\sum_{p\in P} y\ dl^k_{dl\ p} \right) \\
& + \sum_{m\in M}\sum_{p\in P} VC_{mp} h_{mp} + \sum_{m\in M}\sum_{p\in P} VCR_{mp} hr_{mp} \\
& + \sum_{d\in D}\sum_{p\in P} VC_{dp} \left(\sum_{m\in M}\sum_{k\epsilon k_1} x^k_{m\ dp} \right) \\
& + \sum_{r\in R} VCR_R \left(\sum_{k\epsilon k_2}\sum_{l\in L} xr^k_{lr} \right) + \sum_{k\epsilon k_1}\sum_{a,b\in M} C_{ab} ymm^k{}_{ab} \\
& + \sum_{k\epsilon k_1}\sum_{i,j\in N_1} C_{ij} ymd^k_{ij} + \sum_{k\epsilon k_2}\sum_{i,j\in N_2} C_{ij} y\ dl^k_{ij} + \sum_{k\epsilon k_2}\sum_{i,j\in N_3} C_{ij} ylr^k_{ij} \\
& \cdot \sum_{k\epsilon k_1}\sum_{j\in R,M} C_{ij} yrm^k_{ij} + \sum_{k\epsilon k_1}\sum_{a,b\in D} C_{ab} y\ dd^k_{ab} + \sum_{k\epsilon k_2}\sum_{a,b\in L} C_{AB} yll^k_{ab} + \sum_{k\epsilon k_1}\sum_{i,j\in D,R} C_{ij} y\ dr^k_{ij} + \sum_{k\epsilon k_2}\sum_{i,j\in D,R} C_{ij} yrd^k_{ij}.
\end{aligned} \tag{1}$$

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

Subject to the following:

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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.

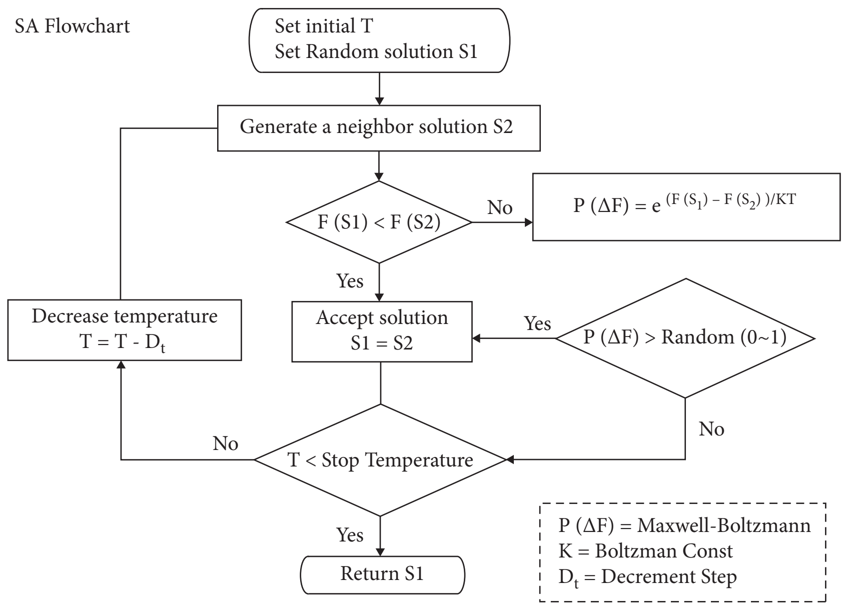

FIGURE 2: Proposed MOSA algorithm.

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

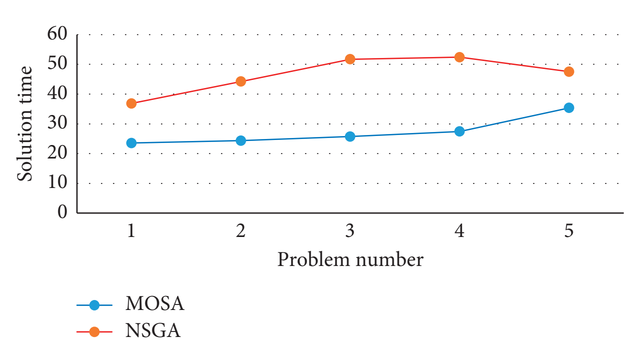

FIGURE 3: Comparison of computation time in proposed algorithms.

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

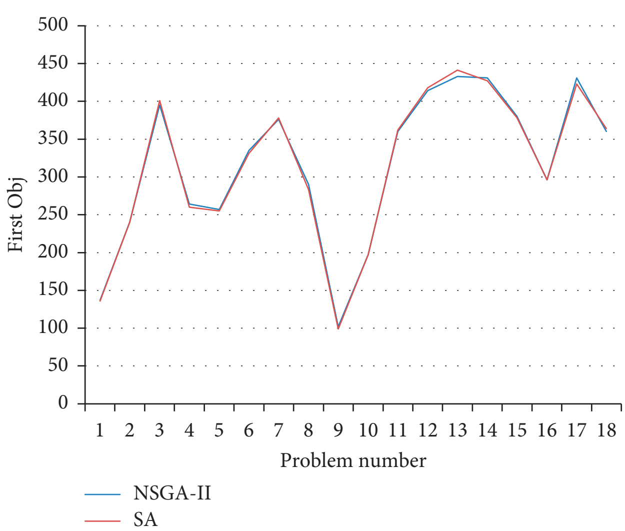

Figure 4: Comparison of the first objective based on problem number.

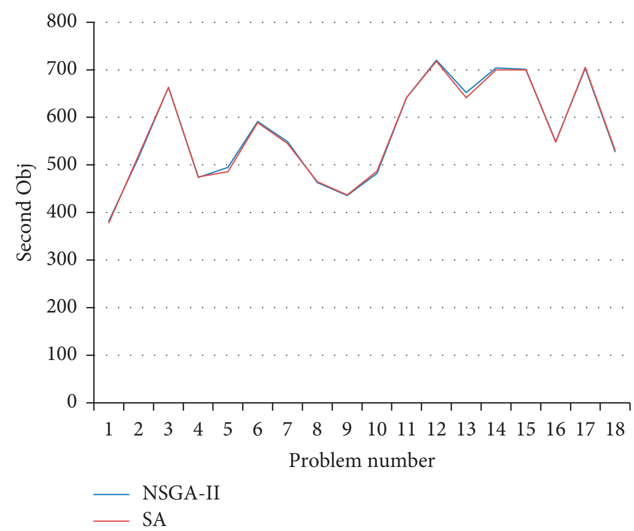

Figure 5: Comparison of the second objective based on problem number.

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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