Hindawi
Discrete Dynamics in Nature and Society
Volume 2022, Article ID 2171305, 15 pages
https://doi.org/10.1155/2022/2171305

Research Article

A Multiobjective Mathematical Model for Truck Scheduling Problem in Multidoor Cross-Docking System

Mahziar Taghizadeh, Amir Abbas Shojaie, Amir Homayoun Sarfaraz, and Sadigh Raissi

Department of Industrial Engineering, South Tehran Branch, Islamic Azad University, Tehran, Iran

Correspondence should be addressed to Amir Abbas Shojaie; a.shojaie@azad.ac.ir

Received 20 April 2022; Revised 3 June 2022; Accepted 7 June 2022; Published 31 July 2022

Academic Editor: Reza Lotfi

Cross-docking is the main operation of unloading products from incoming trucks, regrouping products in relation to their destination, and loading directly onto shipping trucks, reducing warehousing, picking, transportation costs, and delivery times. This is the intended logistics technology. In this paper, we present a new bi-objective mixed-integer mathematical model for truck scheduling problems in cross-docking systems. The goal of the proposed mixed-integer mathematical model is to minimize the total operation time (makespan) and cost of moving cargo within the terminal. The performance of the proposed model is compared with that of the available model to solve small instances. The results showed that in solving small size of problem, the proposed model in this study is more efficient and we found better solutions. An evolutionary algorithm called the nondominated sorting genetic algorithm (NSGA-II) has been proposed to solve larger instances due to computational complexity. To evaluate the proposed algorithm, a comparative analysis of benchmark instances was performed and the efficiency of the above algorithm was compared to the nondominated ranked algorithm (NRGA) based on the index designed in the literature. The statistical hypothesis testing (*t*-test) is used for determining the best algorithm based on the average runtime and average number of Pareto solutions. Using the Taguchi method, the proposed algorithms are tuned. Considering a temporary storage space and the multiple receiving and shipping docks is the main contribution of the paper. Finally, for evaluating algorithms, multicriteria decision-making (MCDM) technique and statistical method are used. The results show the suitable performance of presented model.

1. Introduction

Logistics costs have been the focus of all manufacturing and distribution companies for the past decade [1]. Companies are facing increasing pressure to reduce inventory and lead times and improve global efficiency. Logistics costs can be divided into three categories: inventory (including warehousing), transportation, and management costs, but transportation costs are the more influential part [2]. However, cross-docking is an approach that eliminates the two most costly processing operations of storage and picking [3]. Moreover, since approximately 30% of costs of each product are related to distribution process, numerous firms are attempting to develop their distribution strategies to achieve an effective flow management [4]. This paper is concerned with the introduction and modeling of a novel method in distribution system management that has attracted increasing attention in today's world. Cross-docking is a relatively new technique in supply chain operations that consists of transferring cargo directly from inbound trucks to outbound trucks without intermediate storage [5]. The main objectives of implementing such a strategy are to reduce inventory levels and associated processing costs and integrate truck loading into the total truck loading, especially by reducing lead times for service levels and customer satisfaction. It is to improve the degree. Finding the best sequence of inbound and outbound of trucks reduces system operation and costs, and it is blindingly obvious that this primary issue happening continuously in daily operation in cross-docking has a huge impact on the fast-moving process. Solving the problem of truck scheduling in cross-docking, which is one of the most important extent issues in cross-docking system, is the issue of this research. In cross-docking, if the goods are to be stored, this will be possible for a very short time and up to 24 hours. This will reduce the time required to meet customer demand, inventory maintenance costs, and required space for storage. Generally, cross-docking is used when goods cannot be shipped directly. Operations generally performed in a cross-docking include [6]the following:

(i) Scheduling shipments to deliver goods from producers to cross-dock. It is required that goods deliver to cross-dock in accordance with specific time in scheduling, which is linked to shipping time.

(ii) Incoming goods are immediately sorted by demands of destinations. Outbound trucks can load and transport a combination of inbound goods and goods in a temporary storage location. A high degree of cooperation and coordination is needed to prevent any unwanted delays.

(iii) Orders (goods) move quickly to the shipping dock.

Compared with traditional docking, activities such as receiving inspection, storing, assembly, and ordering have been eliminated. Figure 1 shows the general operation of a cross-docking.

The following criteria can be considered as the cross-docking performance criteria [8]:

(i) The number of receiving and shipping docks required

(ii) Dock utilization

(iii) Average time of unloading and loading of trucks

(iv) Total time spent moving materials from receiving docks to shipping docks

(v) Total time required to perform cross-docking operations

(vi) Cost of moving and maintaining inventory

Depending on what type of strategy is being adopted concerning the facility and operating conditions, it is possible to define different models of cross-docking. Deciding on the quantity and quality of the following factors produces different combinations of models:

(i) The number of available docks in site

(ii) Pattern of entry and exit of trucks to docks (dock holding pattern)

(iii) The presence or absence of temporary storage

The cross-docking model scrutinized in this paper is one of the 32 models presented in [8] with separate receiving and shipping docks along with a temporary storage. The dock holding pattern of the trucks is also static and does not include the assumed model of cross-docking operation or distribution center such as scanning, weighing, labeling, and sorting. In addition, it is assumed that the temporary storage place is close to the receiving docks (Figure 2).

The practical applications of truck scheduling are vast and varied and are applicable in a variety of areas, such as software development, planning in major transportation organizations, airlines, post offices, chain stores, and many other areas. From a theoretical point of view, truck scheduling is a very attractive research field for researchers, especially planners. The well-known problem of truck scheduling in cross-dock is one of the problems of hybrid optimization with computational complexity of $O(mn2^m)$ (m number of targets and n population size) [9]. In recent years, researchers' interest and attempt in scheduling trucks in cross-docking have greatly increased, and many new modeling concepts and algorithms have been designed and implemented in this area, but according to expert researchers, there are still many shortcomings in this area, which are being from two aspects [10].

(i) Developing models closer to real issues

(ii) Improving problem-solving methods to enhance the quality of the solution and the problem-solving time

Although the issue of truck scheduling in cross-docking is very important from the practical point of view, perhaps the main reason for these shortcomings is the difficulty of problem-solving and improving the solution methods in enhancing the quality of the solution and improving the time of solving such problems. There are only few attempts to mathematically model the truck scheduling problem with respect to real constraints, and our model is more effective due to its size complexity. Therefore, efforts to address these shortcomings and simultaneously reduce the time and cost of operations by using new method make it necessary to conduct this research.

The goal of this paper was to present a model and study the problem of truck scheduling. When it comes to scheduling issues, total operation time is often referred to as makespan. In this study, makespan is defined as the total uptime for cross-docking operations. Total uptime is the time between the first product of the first scheduled inbound truck being unloaded at the receiving dock and the last product of the last scheduled outbound truck being loaded at the shipping dock. The purpose of this study was to find the best track docking sequence for both inbound and outbound tracks to minimize the total cross-docking uptime (equivalent to maximizing the throughput rate) of the cross-docking process. Product assignments from inbound trucks to outbound trucks are determined at the same time as the inbound and outbound truck docking sequences. The purpose of the problem is to reduce the total time to complete the operation and minimize the total costs of transshipment in the cross-docking. One of the most important advantages that has attracted a lot of attention to cross-docking is the characteristic of this method to reduce costs in the distribution system. In this study, minimizing the cost of transshipping goods is considered as one of the objectives of the model.

The rest of this paper is organized as follows. Section 2 summarizes some proposed papers applied in the case of truck scheduling in cross-docking systems. Section 3 briefly describes the mathematical model. This model serves as a

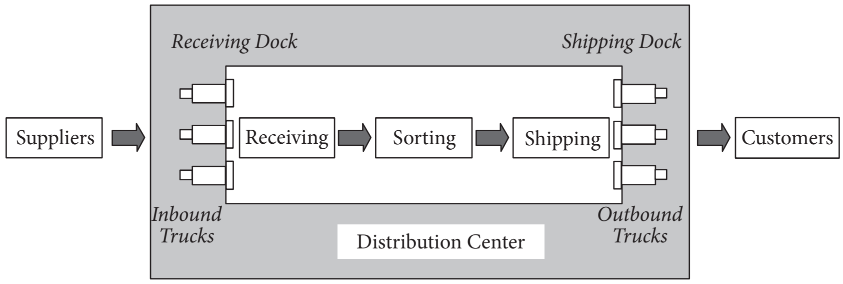

Figure 1: General cross-docking operation [7].

Receiving area		Temporary storage	Shipping area	
Number of docks	Dock holding pattern		Number of docks	Dock holding pattern
Multiple	Stay	Yes	Multiple	Stay

Figure 2: Studied cross-docking model [8].

foundation for the heuristics and is also used to evaluate their performance to the best solution. Section 4 presents the heuristics used for the resolution of the problem. Section 5 addresses parameter setting and a method called the Taguchi plan in this case. Section 6 deals with the computational results and implementation of the algorithms, and finally, Section 7 is the conclusion and trends for future work.

2. Literature Review

The objective of this section is to analyze the existing literature in order to understand the problems and try to find the respective proposed approaches. Reference [10] reviewed and classified the literature of scheduling trucks in cross-docking. An important point is the strategic issues and operations that need to be paid attention and addressed in the cross-docking system life cycle, such as cross-docking location, design and layout of warehouse, transshipping routing, and warehouse resource planning, which, to further study on this area, one can refer to [3]. Since the issue of cross-stocking has attracted increasing attention in recent years, [11] undertook a wide-ranging study to identify the research gap between theoretical issues and real-world application challenges that reveal these differences. The most famous model for truck scheduling in cross-docking system presented by [7]investigated a cross-docking system in which a temporary storage buffer is located beside the shipping dock. The purpose of this study was finding the best scheduling sequence for both receiving and shipping trucks in receiving and shipping docks to minimize total operation time or increase the efficiency of cross-docking system. Some studies such as [12–14] try to develop the [7] mathematical model by considering different objectives such as earliness and tardiness or with different solving methods such as metaheuristic. There are few studies in the literature that have introduced the mathematical model for truck scheduling in multi-door cross-docking system. For instance, [15] presented a new mixed-integer programming model that is more efficient than the model presented by [7] and to demonstrate the efficiency of their model for large-scale problems used the hybrid heuristic algorithm for collective optimization of birds with a refrigeration simulation algorithm. Reference [16] describes a Lagrangian heuristic algorithm for a transit problem, where certain quantities of certain products must be transferred directly from a certain group of incoming trucks to a certain group of outgoing trucks. The goal is to plan activities and design transit plans, while minimizing the end time of the entire process. The main contribution of the paper is the Lagrangian decay diagram for the structured integer linear model of the problem. Reference [17] studied the problem of sequencing multiterminal trucks in a cross-connected hub with the aim of minimizing production time, and they came up with a parallel machine scenario. Instead of the traditional stream stores setup and proposes a polynomial parallel machine-based heuristic method that outperforms time-indexed math formulas and modern heuristics for small, medium, and large cases big (Shahmardan and Sajadieh [18], they proposed simulated annealing as a solution method. Reference [19] first proposed a mixed-integer linear programming model to optimally solve small instances. Next, two heuristics are proposed to solve the two problems in an integrated manner. These heuristics are as follows: vehicle routing cross-docking heuristic (VRCDH) and cross-docking vehicle routing heuristic (CDVRH) each focuses on one of the issues. On the other hand, among the recent studies, [20] can be mentioned that they assumed that freight trucks during their operations fail and the number of truck failures in a given period follows the Poisson distribution. They also set a deadline for each truck and used three heuristic algorithms to solve their two-objective model with the goal of reducing the number of delayed trucks and completing them and finally comparing the results of the three algorithms. Reference [21] introduced eight mixed-integer mathematical programming models for modeling the problem of door (dock) allocation to destinations in cross-docking environments and compared and introduced the best and most efficient models based on the standard examples available in the problem literature. Rashidi Komijan et al. [22] presented a school bus cross-dock and routing problem. The main contribution of their paper was considering gender separation. Minimizing the transportation costs was the main objectives of their research. Khanchehzarrin et al. [23] presented a model for the time-dependent vehicle routing problem. Considering traffic condition is the main contribution of their paper. Reference [24] also presented two complex integer mathematical models for allocation door (dock) problem with the purpose of reducing displacement costs they used the generation columns algorithm to solve the models. The manner of waiting trucks to arrive the docks is one of the important issues studied by [25], and using the M/M/1 queueing theory model, remaining time for trucks was minimized; also, a two-objective model with the goals of reducing the cost of goods storage and reducing energy consumption in-warehouse transporters was presented and solved by two competing algorithms, Marguerite and gray wolf optimizer. Reference [26] presented a Tabu search approach to the truck scheduling problem with multiple docks. They considered minimizing the total travel time and the total tardiness as an objective [27]. Through a low-cost scheduling strategy, they addressed the issue of scheduling inbound and outbound trucks at the cross-dock facility when the arrival time of the vehicle was unknown. Two metaheuristics, MODE and NSGA-II, were used to solve the designed sampling problem and compare it to the random search-based genetic algorithms present in the literature. Khalili-Damghani et al. [28] presented a model for disaster hub location-allocation problem. The location problem was solved using GIS method, and the allocation problem was solved using the metaheuristic method. Shafipour-Omrani et al. [29] presented the simulation-optimization model for liquefied natural gas transportation. The main contributions of the presented model were considering hub location using the simulation method. The results of their paper show the suitable performance of their model. Reference [30] presented a mathematical model of mixed-integer programming for door assignments and track sequences in multidoor cross-docking systems. The goal of this model was to minimize total uptime or turnaround. Next, modified particle swarm optimization (so-called GLNPSO) with special encoding and decoding schemes was proposed to solve the track scheduling problem in multidoor cross-docking systems. Among the studies that are closely related to the model studied in this paper is [31] that introduced a multi-periodic cross-docking model considering the variable capacity of shipping and varied delivery time for shipping trucks by a complex integer programming and solved the model using an evolutionary computational approach based on a genetic algorithm whose results were compared to branch and case algorithm to evaluate the efficacy of the method. The difference between the above study and the model presented in this paper is to consider the temporary storage location in the mathematical model, as well as the multiple receiving and shipping docks of the trucks. Moreover, a multiobjective mathematical model presented in this paper includes reducing total operational time and costs of transporting inside the terminal. To solve the problem, nondominated storing genetic algorithm (NSGA-II) and nondominant ranked genetic algorithms (NRGAs) are applied and the results of two algorithms were compared and analyzed to identify a more effective algorithm. According to studies in the literature, considering a temporary storage space and the multiple receiving and shipping docks has a great effect on the efficiency of the model; therefore, it is necessary to address these shortcomings and bring the issue closer to the real situation. The literature review is shown in Table 1.

3. The Model

3.1. Indices

i Receiving truck indices

j Shipping truck counter

k Merchandise counter

m Receiving dock counter

n Shipping dock counter

R The number of receiving trucks

S The number of shipping trucks

M The number of receiving docks

N The number of shipping docks

P Types of goods

3.1.1. Parameters

$\mathbf{p}^{\mathbf{r}}_{\mathbf{ik}}$ The number of k-type goods loaded into the truck i by default

$\mathbf{p}^{s}_{jk}$ The number of k-type goods must be loaded into the truck j

h_k Time of loading (unloading) for the k-type good

W_{mn} Time of transshipping of goods from the receiving dock m to the shipping dock n (for any quantity of goods of any kind)

w^{fs}_n Time of transshipping the goods from temporary storage to shipping dock n

C^D_k Cost of shipping the k-type good from receiving dock to shipping dock directly

C^{TS}_k Cost of shipping k-type good from the receiving dock to the temporary storage place

C^{FS}_k The cost of moving k-type good from a temporary storage place to a shipping dock

D Replacement time of trucks on docks

Q Very large positive number

x^D_{ijk} The number of k-type goods being transported directly from the receiving truck i to the shipping truck J

x^{TS}_{ik} The number of k-type goods moved from the receiving truck i to the temporary storage location

x^{FS}_{jk} The number of k-type goods moved from the temporary storage location to the shipping truck j

Table 1: Literature review.

Author	Temporary storage space	Multiple receiving and shipping docks	Multiproduct	Time windows	Metaheuristic algorithm
Khalili-Damghani et al. [28]			*		*
Shafipour-Omrani et al. [29]		*		*	
Khanchehzarrin et al. [23]	*			*	
Rashidi Komijan et al. [22]				*	*
Gaudioso et al. [16]		*	*		
Fard and Vahdani [25]	*	*			
Shahmardan and Sajadieh [18]					
Nassief et al. [24]	*		*	*	
Khalili-Damghani et al. [31]	*				*
Wisittipanich and Hengmeechai [30]		*	*		
Heidari et al. [27]		*	*	*	
This research	*	*	*	*	*

3.1.2. Variables

$\mathbf{t_{ij}} = \begin{cases} 1 \\ 0 \end{cases}$ If the good from the receiving truck i is transported to the sipping truck j

otherwise

$\mathbf{p_{ij}} = \begin{cases} 1 \\ 0 \end{cases}$ If the receiving truck i overrides the receiving truck j in the sequence of receiving trucks

otherwise

$\mathbf{q_{ij}} = \begin{cases} 1 \\ 0 \end{cases}$ If the shipping truck i overrides the shipping truck j in the sequence of the shipping trucks

otherwise

$\mathbf{A^r_{im}} = \begin{cases} 1 \\ 0 \end{cases}$ If the receiving truck i is assigned to the receiving dock m

otherwise

$\mathbf{A^s_{jn}} = \begin{cases} 1 \\ 0 \end{cases}$ If the shipping truck j is assigned to the shipping dock ns

otherwise

$\mathbf{Z_j} = \begin{cases} 1 \\ 0 \end{cases}$ If the product is transported from the temporary storage to the shipping truck J

otherwise

$\mathbf{d^r_{im}}$ The time the receiving truck i enters the receiving dock m

$\mathbf{l^r_{im}}$ The time the receiving truck i leaves the receiving dock m

$\mathbf{d^s_{jn}}$ The time the shipping truck j enters the shipping dock n

$\mathbf{l^s_{jn}}$ The time the shipping truck j leaves the shipping dock n

3.2. Mathematical Model

$$\operatorname{Min} T, \tag{1}$$

$$\operatorname{Min}\mathbf{C_T} = \sum_{i=1}^{R}\sum_{j=1}^{S}\sum_{k=1}^{P}\left(C_k^D x_{ijk}^D + C_k^{TS} x_{ik}^{TS} + C_k^{FS} x_{jk}^{FS}\right). \tag{2}$$

Subject to:

$$T \geq l^s_{\text{jn}}, \quad \forall j = 1, 2, \dots S, n = 1, 2, \dots N, \tag{3}$$

$$\sum_{m=1}^{M} A^r_{im} = 1, \quad \forall i = 1, 2, \dots R, \tag{4}$$

$$\sum_{i=1}^{R} A^r_{im} \geq 1, \quad \forall m = 1, 2, \dots M, \tag{5}$$

$$\sum_{n=1}^{N} A^s_{jn} = 1 \quad , \forall j = 1, 2, \dots S, \tag{6}$$

$$\sum_{j=1}^{S} A^s_{jn} \geq 1, \quad \forall n = 1, 2, \dots N, \tag{7}$$

$$\sum_{i=1}^{R} x^D_{ijk} + x^{FS}_{jk} = p^s_{jk}, \quad \forall j = 1, 2, \dots S, k = 1, 2, \dots P, \tag{8}$$

$$\sum_{j=1}^{S} x^D_{ijk} + x^{TS}_{ik} = p^r_{ik}, \forall i = 1, 2, \dots R, k = 1, 2, \dots P, \tag{9}$$

$$\sum_{i=1}^{R} x^{TS}_{ik} = \sum_{j=1}^{S} x^{FS}_{jk}, \quad \forall k = 1, 2, \dots P, \tag{10}$$

$$x^D_{ijk} \leq Qt_{ij}, \quad \forall i = 1, 2, \dots R, j = 1, 2, | \dots S, k = 1, 2, \dots P, \tag{11}$$

$$l_{im}^{r} \geq d_{im}^{r} + A_{im}^{r}.\sum_{k=1}^{p} p_{ik}^{r}.h_k, \quad \forall i = 1,2,\ldots R, m = 1,2,\ldots M, \tag{12}$$

$$d_{jm}^{r} \geq l_{im}^{r} + D - Q\left(1 - p_{\mathrm{ij}}\right), \quad \forall i,j = 1,2,\ldots R, m = 1,2,\ldots M, i \neq j, \tag{13}$$

$$d_{im}^{r} \geq l_{jm}^{r} + D - Qp_{ij}, \quad \forall i,j = 1,2,\ldots R, m = 1,2,\ldots M, i \neq j, \tag{14}$$

$$\begin{gathered} d_{im}^{r} \geq d_{jn}^{r} - Qp_{ij} - Q\left(1 - A_{im}^{r}\right) - Q\left(1 - A_{jn}^{r}\right), \\ \forall i,j = 1,2,\ldots R, m,n = 1,2,\ldots M, i \neq j, m \neq n, \end{gathered} \tag{15}$$

$$\mathbf{p_{ii}} = 0, \quad \forall i = 1,2,\ldots R, \tag{16}$$

$$l_{jn}^{s} \geq d_{jn}^{s} + A_{jn}^{s}.\sum_{k=1}^{p} p_{jk}^{s}.h_k, \quad \forall i = 1,2,\ldots R, m = 1,2,\ldots M, \tag{17}$$

$$d_{jn}^{s} \geq l_{in}^{s} + D - Q\left(1 - q_{ij}\right), \quad \forall i,j = 1,2,\ldots S, n = 1,2,\ldots N, i \neq j, \tag{18}$$

$$d_{in}^{s} \geq l_{jn}^{s} + D - Qq_{ij}, \quad \forall i,j = 1,2,\ldots S, n = 1,2,\ldots N, i \neq j, \tag{19}$$

$$\begin{gathered} d_{im}^{s} \geq d_{jn}^{s} - Qq_{ij} - Q\left(1 - A_{im}^{s}\right) - Q\left(1 - A_{jn}^{s}\right), \\ \forall i,j = 1,2,\ldots S, m,n = 1,2,\ldots N, i \neq j, m \neq n, \end{gathered} \tag{20}$$

$$q_{ii} = 0, \quad \forall j = 1,2,\ldots S, \tag{21}$$

$$\begin{aligned} & l_{\mathrm{jn}}^{\mathrm{s}} + \mathrm{Q}\left(1 - A_{jn}^{s}\right) \geq d_{im}^{\mathrm{r}} + W_{mn} + \sum_{k=1}^{p} x_{ijk}^{D}.h_k + w_n^{fs} \\ & \quad + \sum_{k=1}^{p} x_{jk}^{FS}.h_k - \mathrm{Q}\left(1 - t_{ij}\right) - \mathrm{Q}\left(1 - z_j\right) - Q\left(1 - A_{im}^{r}\right) l_{jn}^{s} \\ & \quad = \mathrm{Max}\left\{d_{jn}^{s}, \mathrm{Max}\, t_{ij}.d_{im}^{r}\right\} + \mathrm{Max}\left\{A_{jn}^{s} A_{im}^{r} W_{mn}\right\} \\ & \quad + Z_j.w_n^{fs} + 2\sum_{k=1}^{p} p_{jk}^{s}.h_k \\ & \quad \forall i = 1,2,\ldots R, j = 1,2,\ldots S, m = 1,2,\ldots M, \\ & \quad n = 1,2,\ldots N, i \neq j, m \neq n, \end{aligned} \tag{22}$$

$$\begin{aligned} & l_{jn}^{s} + \mathrm{Q}\left(1 - A_{jn}^{s}\right) \geq l_{im}^{r} - \mathrm{Q}\left(1 - t_{ij}\right) - Q\left(1 - A_{im}^{r}\right) l_{jn}^{s} \\ & \quad = \mathrm{Max}\left\{d_{jn}^{s}, \mathrm{Max}\, t_{ij}.d_{im}^{r}\right\} + \mathrm{Max}\left\{A_{jn}^{s} A_{im}^{r} W_{mn}\right\} \quad p_{jk}^{s}.h_k, \\ & \quad + Z_j.w_n^{fs} + 2\sum_{k=1}^{p} \end{aligned} \tag{23}$$

$$\text{all variable} \geq 0. \tag{24}$$

Constraint equation (1) represents the model's initial goal of minimizing manufacturing margins. Second objective function equation (2). The second purpose is to minimize the total cost of transshipment in the warehouse. Makespan equalizes condition equation (3) with the time the last transport truck leaves the transport dock. Condition equation (4) ensures that each receiving track is associated with only one receiving dock. Condition equation (5) assigns each receive dock to at least one receives track to utilize all receive docks. This constraint applies if the number of receiving docks does not exceed the number of receiving tracks. This is part of the mathematical model assumptions. Similarly, constraints equations (6) and (7) control the allocation of transport trucks to the transport dock. Condition equation (8) specifies the relationship between the products transferred from all receiving trucks and the temporary storage on each shipping truck. In addition, this constraint makes the total of all products shipped from all receiving trucks and temporary storage to shipping trucks equal to the number of products initially required for that shipping truck. Similarly, condition equation (9) specifies the relationship between the products transferred from each receiving truck and the temporary storage on all shipping trucks. This is done by setting the total number of products transferred from each receiving truck and temporary storage to all shipping trucks equal to the total number of products initially loaded on each receiving truck. Constraint equation (10) ensures that the total number of products transferred to the intermediate vault is equal to the total number of products transferred from the intermediate vault. Constraint equation (11) sets the relationship between the product transfer variable and the decision variable *t_ij*. Condition equation (12) sets the time for receiving truck i to leave receiving dock m to be greater than or equal to the time for receiving truck i to enter receiving dock m plus the time it takes to unload all products. This equation is valid only if the receiving track i is associated with the receiving dock m. Constraint equations (13) and (14) adjust the time of entry and exit of different receiving trucks to the same receiving dock based on the order of the receiving trucks. Constraint equation (15) adjusts the arrival times of different receive tracks to different receive docks based on the order of the receive tracks. Condition equation (16) guarantees that the receiving track does not precede in the receiving track order. Constraint equation (17) sets the time it takes for transport truck j to leave transport dock n to be greater than or equal to the time it takes for transport truck j to load all the required products in time to enter transport dock n. This equation is valid only if transport truck j is associated with transport dock n. Constraint equations (18) and (19) adjust the time of entry and exit of different transport trucks to the same transport dock based on the order of the transport trucks. Constraint equation (20) adjusts the admission time of different transport trucks to different transport docks based on the order on the transport truck.

4. Solution Method

Different approaches have been applied to model and solve this problem. These approaches include mixed-integer

Table 2: Makespan obtained by mathematical model for the test problems.

Problem set	Problem size				Exact solution (makespan)	
	Number of receiving trucks	Number of shipping trucks	Number of product types	Total number of products	Optimal [7]	Optimal this study
1	4	5	4	990	1557	1483
2	5	4	6	1030	1577	1412
3	3	3	8	890	1372	1300
4	5	5	8	1000	1749	1503
5	5	3	8	960	1579	1355
6	4	4	5	1020	1546	1370
7	5	4	6	980	1535	1330
8	3	5	7	890	1525	1451
9	4	4	8	900	1473	1334
10	3	4	9	930	1452	1363
11	5	4	6	1620	2232	1791
12	6	4	8	1950	2833	2140
13	5	6	8	1610	2386	1554
14	5	5	8	1680	2385	1831
15	6	5	4	2030	2745	2069
16	5	6	6	1690	2407	2001
17	4	4	7	1180	1867	1397
18	6	6	7	1770	2502	1989
19	5	5	10	1720	2553	2359
20	6	6	9	2020	2732	2392

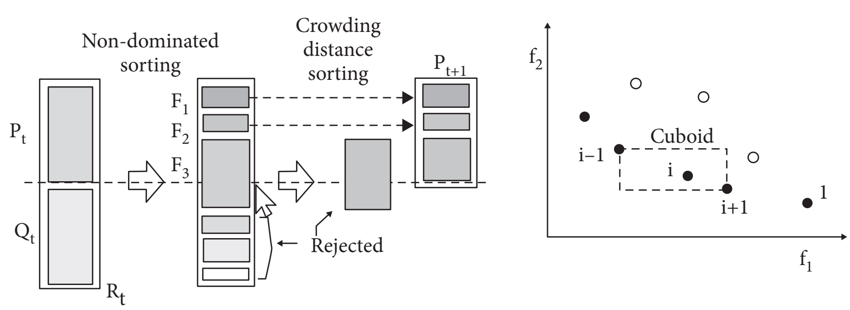

Figure 3: Nondominated sorting genetic algorithm II (NSGA-II).

programming, branch and boundary techniques, search algorithms, full enumeration methods, and heuristic and metaheuristic algorithms. Full enumeration methods and mixed-integer programming have been used as the basic approaches to generate exact solutions, and metaheuristic algorithms have used these solutions to obtain the optimal responses. In the following, we will discuss in detail the different approaches to solve the problem of truck scheduling and studies in the field of cross-docking.

In this study, it is attempted to introduce an effective model that meets the needs of the day, by considering as far as possible the multiple objectives and considering constraints in real circumstance of truck scheduling problem. Twenty sets of test problems were randomly generated to test the performances of the mathematical model. Details on the test problems are presented in [8]. To validate the presented model, it was considered as the single-objective model with the aim of minimizing the total operation time, in a cross-docking warehouse with one receiving, and one shipping dock is coded and solved through GAMS software on a computer with 2 GB RAM and 2.53 GHz central processor and optimal solutions obtained by the proposed model have been compared with the model presented by [7] in Table 2. Data in Table 2 show that in small and medium size of problem our model is more efficient. In addition, to solve the two-objective problem, nondominated storing genetic algorithm (NSGA-II) and nondominated ranking genetic algorithm (NRGA) have been used. Optimization of multiobjective is different from single-objective issues because it contains several goals that must pay attention simultaneously to all goals in optimization. In this paper, we use two nondominated storing genetic algorithm and nondominated ranking genetic algorithm for large size of problem.

4.1. Controlled NSGA-II. Nondominated storing genetic algorithm is one of the most efficient and well-known multiobjective optimization algorithms presented by [32]. However, controlled NSGA-II presented by [33] is the same as NSGA-II, but here you use the concept of controlled elitism to create the next generation. The method of solving

Table 3: Numerical examples of different sizes.

Problem	Receiving truck	Shipping truck	Receiving dock	Shipping dock	Products types
1	10	13	6	5	5
2	16	15	11	8	6
3	20	17	15	8	11
4	20	28	16	9	19
5	23	30	18	10	25
6	25	31	19	14	27
7	36	35	19	17	31
8	47	41	23	17	33
9	48	43	23	21	35
10	97	88	25	25	40

the above model is based on the nondominated storing genetic algorithm according to Figure 3.

4.2. Nondominated Ranking Genetic Algorithm (NRGA). A new population-based multiobjective evolutionary algorithm called genetic algorithm based on nondominated ranking nondominatedhas been successfully developed by [34] to optimize non-convex, nonlinear, and discrete functions. They studied multiobjective algorithms that worked on nondominated sorting. They noticed three problems in these algorithms.

(i) The computational complexity was $O(mn2^m)$ (M: the number of targets and N: the population size)

(ii) Lack of efficient elitism

(iii) The need to specify parameters in the division process

Based on the problems in their previous approaches, they developed a new approach by combining the roulette wheeling algorithm based on ranking and the Pareto-based population ranking algorithm, which was named NRGA (nondominated ranking genetic algorithm). Their proposed algorithm solves the three problems in previous approaches. In this combination, a two-layer ranking based on the selection operator of roulette wheeling is offered, which randomly selects the new generation from the parent generation based on the selection of the best solutions (in terms of fit and extent). This algorithm is in most cases capable of achieving better scalability of the solutions at the Pareto boundary and the earlier convergence at the Pareto optimal boundary, compared with other multiobjective evolutionary algorithms. However, the difference between the NRGA and the controlled NSGA-II is in the strategy selection section and the population sorting and selection for the next generation.

4.3. Numerical Example. To illustrate the performance of the proposed strategy of the model, ten sets of problems were randomly generated, in medium and large size. Table 3 represents the size of the test problem sets. The number of product units unloaded from inbound trucks, or loaded onto outbound trucks, receiving and shipping trucks, and receiving and shipping docks are randomly generated from a uniform distribution over (5, 100). The data generated for medium and large size instances follow the restriction of a cross-docking system in which the inbound flow should be equal to the outbound flow. Each example is run 10 times by NSGA-II and NRGA in MATLAB software (R2009a) on a computer with 2 GB RAM and 2.53 GHz central processor. For one of the examples, an experimental design is employed to quickly converge and more accurately answer for the parameters of the two proposed algorithms. The Taguchi method is used here to set parameters.

Table 4: Parameters for NSGA-II and NRGA.

NSGA-II				NRGA			
Parameters	1	2	3	Parameters	1	2	3
Pc	0.7	0.8	0.85	Pc	0.7	0.85	0.9
Pm	0.2	0.25	0.3	Pm	0.1	0.2	0.3
NPop	25	50	150	NPop	25	50	150
Max Gen	50	75	100	Max Gen	75	100	150

5. Taguchi Method

There are several statistical methods for designing experiments to adjust the parameters of the algorithms. Taguchi improved a family of matrices of partial factorial experiments, so that after many experiments, he could design experiments in a way that the number of experiments for one problem reduced. In the Taguchi method, orthogonal arrays are used to study a large number of decision variables with a small number of experiments. Taguchi divides the factors into two main classes: controllable factors and sound factors. Sound factors are those that cannot be controlled directly. When removing sound factors is impossible, the Taguchi method seeks to minimize the impact of the sounds and determine the optimal level of controllable factors. The purpose of this study was to find the parameters of NSGA-II and NRGA as receiving variables to obtain the optimal response (Y). To set the problem parameter with 10 receiving trucks, 13 shipping trucks, 6 receiving docks, 5 shipping docks, and 5 different product types are reviewed. The Taguchi method has been used to adjust parameters of population size (Npop), probability of crossover (Pc), probability of mutation (Pm), and reproduction (Max Gen) in NSGA-II and NRGA. The Taguchi method here is applied for four factors at three levels, so that the factors are the same parameters of the two algorithms and each factor is at three

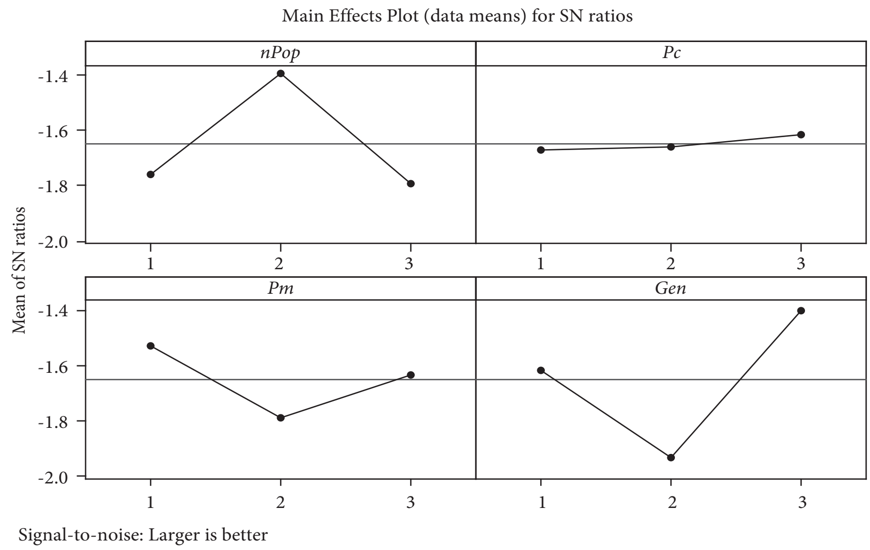

Figure 4: Values of different levels of parameters in S/N ratio for NSGA-II.

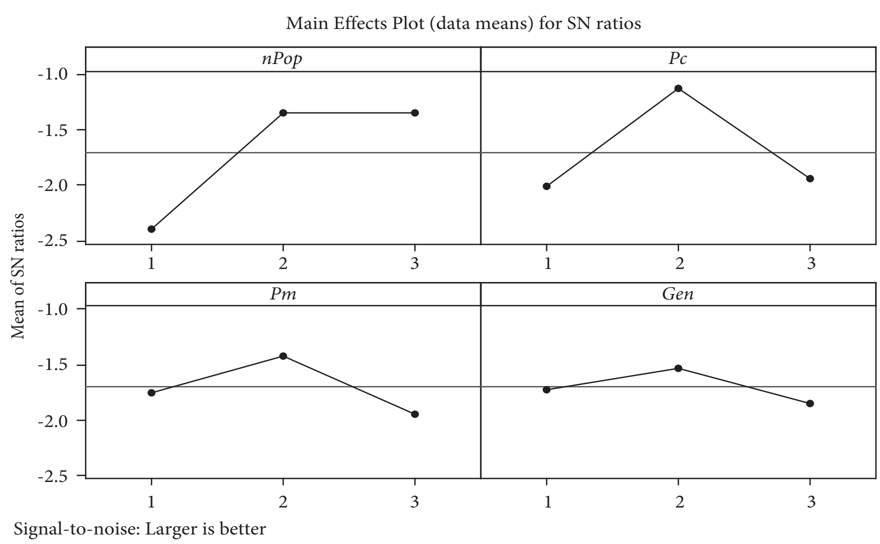

Figure 5: Values of different levels of parameters in the S/N ratio for NRGA.

Table 5: Best value of parameters for NSGA-II and NRGA.

NSGA-II		NRGA	
Parameter	Value	Parameter	Value
Pc	0.85	Pc	0.85
Pm	0.2	Pm	0.2
Gen	100	Gen	100
NPop	50	NPop	50

levels. Table 4 shows the values of the factors at each level for NSGA-II and NRGA so that the numbers 1, 2, and 3 are the levels of each factor. The numbers in Table 4 are based on the trial and error method and the researchers' suggestion.

Given the dual purpose of the model, the Taguchi parameters must be adjusted in the two-objective space. For this purpose, for the mentioned problem with 3 receiving trucks, 2 receiving docks, 4 shipping docks, 4 shipping trucks, and 6 different product types, at each level, the normalized weighted sum of the time algorithm performance criteria (CPU time), number of Pareto solutions (NOS), first objective function (completion time), second objective function (cost), and generational distance (GD) were calculated, so that the values obtained for each criterion from 10 times of the algorithm's execution, based on nature of the positive or negative criteria, are normalized using a method according to the SAW principles. According to this method, the sum of the weighted values of the criteria is calculated at each level and the maximum value is used as the main parameter to calculate S/N ratios (here, it is assumed that the weight of the criteria is equal to 0.2). Now, considering the calculated values after 10 run times for each case and the S/N ratios for the different parameters of the problem for NSGA-II and NRGA, the average graphs of parameters for S/N rates at different levels are shown in

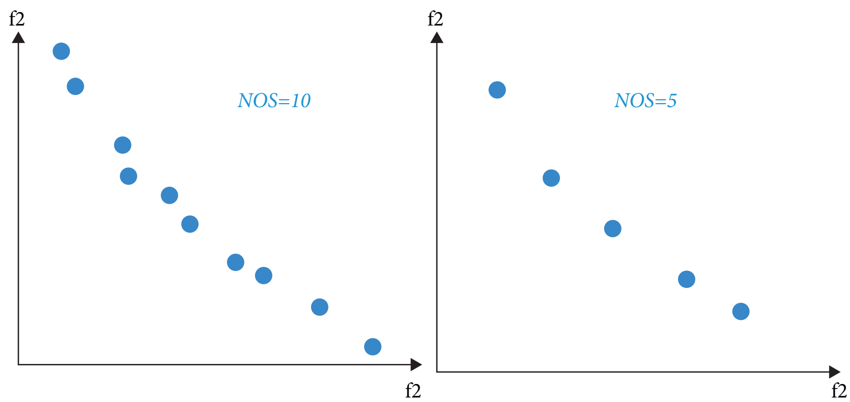

Figure 6: Method to calculate the number of Pareto solutions.

Figures 4 and 5. Given equation (1), the lower the S/N ratio, the better the answers of algorithm. According to Figure 5, the optimal values of appropriate parameters for NSGA-II and NRGA are in accordance with Table 5.

$$\frac{S}{N_S} = -10 \log\left(\frac{1}{n}\sum_{i=1}^{n} y_i^2\right). \tag{25}$$

6. Computational Result

In this section, five benchmarks are presented to evaluate multiobjective optimization algorithms:

6.1. Most Expansion. The below criterion measures the length of the spatial cube diameter applied by an ultimate measure of the objectives, for the set of nondominated solutions. Equation (26) illustrates the computational procedures of this index.

$$D = \sqrt{\sum_{J=1}^{M} \max_i f_i^j - \min_i f_i^j 2}. \tag{26}$$

6.2. Spacing. This following criterion calculates the relative distance of successive solutions using equations (27)–(29).

$$S = \sqrt{\frac{1}{|n|}\sum_{i=1}^{n}\left(d_{i-}\bar{d}\right)^2}, \tag{27}$$

$$d_i = \min \sum_{m=1}^{2} |f_m^i - f_m^k| \tag{28}$$

$$\bar{d} = \sum_{i}^{n} \frac{d_i}{|n|}. \tag{29}$$

The measured distance is equal to the lowest value of the sum of the absolute values of the difference in the values of the objective functions between the ith answer and the solutions in the final nondominated set. It is noteworthy that this distance criterion is different from the criterion of the lowest elucidation distance among the solutions.

Table 6: Comparative criteria value for NSGA-II algorithm.

Problem	$\overline{D}$	$\overline{S}$	$\overline{\text{NOS}}$	$\overline{\text{GD}}$	$\overline{T}$
1	0.4283	4110.72	3	18.132	37740
2	0.7345	2800.82	7	19.44	173656
3	0.6532	2619.86	24	18.61	5172159
4	0.9821	5445.06	17	24.23	587126
5	0.8763	5701.82	14	24.93	331846
6	0.4553	5367.43	18	26.06	1759341
7	0.9234	4112.76	18	19.01	1378814
8	0.8766	5723.18	23	22.13	3333969
9	0.8661	4598.12	20	27.43	19109557
10	0.9012	3892.74	24	23.19	59399282

Table 7: Comparative criteria value for NRGA.

Problem	$\overline{D}$	$\overline{S}$	$\overline{\text{NOS}}$	$\overline{\text{GD}}$	$\overline{T}$
1	0.7802	4554.22	12	17.66	174211
2	0.9871	3442.12	3	18.92	38861
3	0.8993	3032.11	32	16.23	5503859
4	0.9887	1790.21	20	21.63	481018
5	0.7864	3309.28	14	27.19	328979
6	0.7602	5466.09	22	25.22	1765051
7	0.9103	5990.66	23	24.93	1380413
8	0.8872	3354.88	28	32.11	3344819
9	0.7898	4909.31	35	19.87	19125443
10	0.9821	5891.01	32	17.14	59388502

6.3. Number of Pareto Solutions (NOSs). The NOS benchmark represents the number of optimal Pareto solutions that can be found in any algorithm. Figure 6 provides an example for calculating NOS.

6.4. Generational Distance (GD). This criterion finds the average distance of Q solutions from p^*, instead of finding answers from the set of nondominated Q solutions belonging or not to the optimal Pareto solutions.

Table 8: Values of RPD criteria for NSGA-II.

Problem	$\overline{T}$	$\overline{P}$	Best $\overline{T}$	Best $\overline{P}$	RPD $\overline{T}$	RPD $\overline{P}$
1	0.4283	3	0.4185	3	2.35	0
2	0.4982	7	0.4282	9	16.35	17.77
3	0.7226	14	0.4416	30	63.62	52.33
4	0.4946	18	0.4209	31	17.52	42.90
5	0.9645	18	0.9470	27	1.85	32.60
6	0.9080	19	0.4482	30	102.58	37
7	0.5622	24	0.4500	37	24.94	35.67
8	0.9301	24	0.4988	36	86.43	33.05
9	1.1138	20	0.9744	38	14.31	42.84
10	1.4798	24	1.3758	41	7.55	40.48

Table 9: Values of RPD criteria for NRGA.

Problem	$\overline{T}$	$\overline{P}$	Best $\overline{T}$	Best $\overline{P}$	RPD $\overline{T}$	RPD $\overline{P}$
1	0.5235	4	0.4170	6	25.54	38.33
2	0.5211	13	0.4017	19	29.71	32.63
3	0.5279	15	0.4074	28	40.25	45.92
4	0.5355	21	0.4209	33	27.23	36.96
5	1.0174	24	0.9306	38	9.32	37.90
6	0.9381	23	0.9104	39	30.3	41.53
7	0.8109	28	0.4398	40	84.38	29
8	0.7452	32	0.4447	39	65.57	17.94
9	1.0331	36	0.9926	40	4.07	11
10	1.5206	32	1.4012	44	8.51	27.27

$$\mathrm{GD} = \frac{\left(\sum_i^Q d_i^p\right)^{1/p}}{|Q|}. \tag{30}$$

For $p = 2$, the d_i parameter is equal to the Euclidean distance (in the target space) between the solutions of i belonging to q and the closest member of p^*.

$$d_i = \min_{k=1} \sqrt{\sum_{m=1}^{M} \left(f_m^{(i)} - f_m^{*\,(k)}\right)^2}. \tag{31}$$

6.5. Algorithm Run Time (CPU Time). Another standard criterion for comparing multiobjective algorithms is the use of the algorithm's runtime criterion, which is the lower this time, the better the algorithm's performance.

After defining standard benchmarks for comparing Pareto-based multiobjective algorithms in Tables 6 and 7, these criteria are calculated for each of the experimental production problems, and then, based on the results, algorithms are studied statistically and using analytical methods. Since comparing the performance of algorithms on the basis of the values of one of the criteria does not provide a clear solution, therefore, the combination and synthetic methods are used to compare the algorithms and select the most efficient algorithm. One of these methods is the percentage of relative deviation. To measure algorithms, residual prediction deviation (RPD) is used whose computing method is based on

$$\mathrm{RPD} = \frac{\mathrm{Alg}_{sol} - \mathrm{Best}_{sol}}{\mathrm{Best}_{sol}} 100. \tag{32}$$

In this equation, $\mathrm{Alg}_{\mathrm{sol}}$ is the value obtained for each problem by the algorithm. $\mathrm{Best}_{\mathrm{sol}}$ is the best value among the solved sample issues. The lowest the average values of RPD, the better solutions obtained from the algorithm. The above criterion is calculated for two factors, the running time of the program (T) and the number of Pareto solutions (P). Moreover, it was implemented ten times for ten different problems that in Tables 8 and 9, the average values for desired criteria for NSGA-II and NRGA.

As Tables 8 and 9 illustrate, it is not easy to decide accurately which one of the two algorithms is more efficient than the other in averages of the number of solutions RPD ($\overline{T}$) and runtime RPD ($\overline{P}$). Therefore, two methods were used to evaluate the results of the two algorithms. Applying SAW method is one of the multiple-criteria decision-making methods or using statistical methods, which used one-way statistical hypothesis testing for runtime and number of solution averages.

6.6. Investigation of Results Using Multicriteria Decision-Making (MADM). To decide different problems, there are a large number of models. In general, these models are divided into two main categories, multicriteria decision-making models (MADMs) and multiobjective decision-making models (MODMs). By adopting MADM method, the decision-maker must select one or more of a limited set of alternatives so that each alternative was evaluated by at least 2 criteria. The simple additive weighting method (SAW) is the most popular method of MADM methods. SAW method is defined as follows: assume that F is a decision matrix. First, a numerical scaling system, for example, normalization, is used to obtain the score for each alternative. A score in SAW method is the sum of the scores of all the criteria for each alternative in the decision matrix. In decision matrix F equation (34) A_r is alternative r, B_j is jth criterion, and X_{rj} is the value of alternative r for jth criterion. In general, the value of an alternative in SAW method is calculated as follows:

$$\mathbf{V}(\mathbf{A_r}) = \mathbf{V_r} = \overset{\mathbf{n}}{\underset{\mathbf{j}=1}{\text{å}}} \mathbf{W_j V_j}\left(\mathbf{X_{rj}}\right)\mathbf{r} = 1.2\ldots.\mathbf{L}. \tag{33}$$

Table 10: Superior performance of each problem based on SAW method for NSGA-II.

Problems	NSGA-II			
	CPU time (second)	Total cost	Makespan (second)	Pareto solution
1	0.440915	741	36055	3
2	0.431867	26531	175532	6
3	0.497491	41031	324173	29
4	0.431391	48770	573148	21
5	0.946947	87931	1406232	13
6	0.463434	103839	1756427	29
7	0.463434	185443	3287332	29
8	0.498891	140617	2181641	19
9	0.979835	1433406	19106634	13
10	1.50751	6382844	59333435	29
Average	0.6661608	845115.3	8818060.9	19.1

Table 11: Superior performance of each problem based on SAW method for NRGA.

Problems	NRGA			
	CPU time (second)	Total cost	Makespan (second)	Pareto solution
1	0.417008	741	36015	4
2	0.423161	26530	173208	15
3	0.427635	41032	323804	27
4	0.454585	131655	63312	33
5	0.979052	79483	1370871	10
6	0.914421	172774	1784343	9
7	0.952752	185856	3334967	33
8	0.523281	278420	5508685	35
9	0.992697	1592228	19135640	40
10	1.544602	7600860	59414621	44
Average	0.7629194	10110957.9	9114546.6	25

Table 12: Comparison of results for all issues.

	Average makespan (second)	Average total cost
NSGA-II	881806.09	84511.3
NRGA	9114546.6	1010957.9

In the above equation, L is the number of alternatives, n is the number of criteria, $V_j(x_{i,j})$ is the value of ith criterion under the jth alternative, and w_j is the weight of jth alterative.

$$\begin{array}{cc} & \begin{array}{ccc} \mathrm{B}_1 & \cdots & \mathrm{B}_n \end{array} \\ F = \begin{array}{c} \mathrm{A}_1 \\ \vdots \\ \mathrm{A}_l \end{array} & \begin{bmatrix} \mathrm{x}_{11} & \cdots & \mathrm{x}_{1n} \\ \vdots & \ddots & \vdots \\ \mathrm{x}_{l1} & \cdots & \mathrm{x}_{ln} \end{bmatrix}. \end{array} \tag{34}$$

In this study, NSGA-II and NRGA, alternatives (choices), makespan, and total cost are also criteria. Here, the criteria were weighted after normalization (the criteria weight is considered to be 0.5) and the best execution of each problem is selected by SAW method. Tables 10 and 11 show the results for NSGA-II and NRGA.

The results of Table 12 show that, in general, considering two criteria makespan and total cost, NSGA-II is more efficient than NRGA from SAW perspective.

6.7. Result Analysis Using Statistical Method. To compare the results of NSGA-II and NRGA retained in this method, a statistical method was applied. Here, two one-way assumption tests for values of RPD(P) and RPD(T) for NRGA and NSGA-II were considered. In this example, the confidence coefficient is equal to 0.95. It means $(1-\alpha = 0.95)$.

Equations (35)–(38) show one-way statistical tests for $RPD\,(\overline{P})$ and $RPD\,(\overline{T})$ and values of t-distribution for $RPD\,(\overline{P})$ and $RPD\,(\overline{T})$, respectively, so that $\overline{T}$ is defined as the runtime average and $\overline{P}$ is equal to the average of the number of solutions. This test is performed assuming that variances are known.

$$\begin{aligned} H_0&: \ \mu_{\overline{T}_{\mathrm{NRGA}}} \geq \mu_{\overline{T}_{\mathrm{NSGA}}}, \\ H_1&: \ \mu_{\overline{T}_{\mathrm{NRGA}}} < \mu_{\overline{T}_{\mathrm{NSGA}}}, \end{aligned} \tag{35}$$

$$\begin{aligned} H_0&: \ \mu_{\overline{P}_{\mathrm{NRGA}}} \geq \mu_{\overline{P}_{\mathrm{NSGA}}}, \\ H_1&: \ \mu_{\overline{P}_{\mathrm{NRGA}}} < \mu_{\overline{P}_{\mathrm{NSGA}}}, \end{aligned} \tag{36}$$

$$t_{\mathrm{Distribution}} = \frac{\overline{T}_{\mathrm{NRGA}} - \overline{T}_{\mathrm{NSGA}}}{S_p^2\sqrt{1/n_{\mathrm{NRGA}} + 1/n_{\mathrm{NSGA}}}}, \tag{37}$$

$$t_{\mathrm{Distribution}} = \frac{\overline{P}_{\mathrm{NRGA}} - \overline{P}_{\mathrm{NSGA}}}{S_p^2\sqrt{1/n_{\mathrm{NRGA}} + 1/n_{\mathrm{NSGA}}}}. \tag{38}$$

In the above equation, S_p^2 is defined as follows in which S_{NRGA}^2 and S_{NSGA}^2 are equal to sample variance for NSGA-II and NRGA. If $t_{distribution} > t_{1-\propto}$, thus, H_0 is rejected and H_1 is accepted; otherwise, H_1 is rejected and H_0 is accepted.

$$S_p^2 = \frac{(n_{\mathrm{NRGA}} - 1)S_{\mathrm{NRGA}}^2 + (n_{\mathrm{NSGA}} - 1)S_{\mathrm{NSGA}}^2}{n_{\mathrm{NRGA}} + n_{\mathrm{NSGA}} - 2}. \tag{39}$$

The results of RPD $(\overline{P})$ values for ten examples made here, after solving by presented algorithms, are given in Tables 11 and 12. The calculation is as follows:

$$\begin{aligned} t_{\mathrm{Distribution}} &= \frac{29.96 - 33.74}{1050.47\sqrt{1/10 + 1/10}} = -0.008, \\ t_{0.95,18} &= 1.73. \end{aligned} \tag{40}$$

According to the above calculations, $t_{\mathrm{distribution}} > t_{0.95,18}$ is not established; thus, H_1 assumption is rejected and H_0 is accepted. Therefore, given the lower the average number of solutions, the better, then, NSGA-II is better than NRGA regarding RPD $(\overline{P})$ criterion. The study of results with statistical method showed that NSGA-II is better than NRGA in terms of two criteria RPD $(\overline{P})$ and RPD $(\overline{T})$. The results of RPD $(\overline{T})$ values for ten examples made here, after solving by presented algorithms, are given in Tables 8 and 9. The calculation is as follows:

$$\begin{aligned} t_{\mathrm{Distribution}} &= \frac{31.84 - 33.86}{172.78\sqrt{1/10 + 1/10}} = -0.026, \\ t_{0.95,\,18} &= 1.73. \end{aligned} \tag{41}$$

According to the above calculations, $t_{\mathrm{distribution}} > t_{0.95,18}$ is not established; thus, H_1 assumption is rejected and H_0 is accepted. Therefore, given the lower the average runtime, the better, then, NSGA-II is better than NRGA regarding RPD $(\overline{T})$ criterion. The study of results with statistical method showed that NSGA-II is better than NRGA in terms of two criteria RPD $(\overline{P})$ and RPD $(\overline{T})$.

6.8. Managerial Insights and Practical Implications. The results of this study can be useful for organizations such as municipalities, transportation organizations, and organizations that are somehow related to traffic. One of the advantages of the presented methods is that NSGA-II and NRGA use only the values of the objective function to perform the optimization process and do not require additional information such as the function derivative. Also, the disadvantages of the proposed methods are that the final solution in NSGA-II and NRGA depends on the coder's skill in defining chromosomes and the initial value of its parameters.

7. Conclusion and Future Research

In this study, the problem of scheduling trucks in a cross-docking system, to minimize time of the whole process and cost of handling inside the terminal, has been investigated. To be more realistic, the cross-docking problem was considered with multiple receiving and shipping docks. Also, we assumed that there is a temporary storage facility near the shipping docks with limited capacity. The developed model was solved by GAMS software, and the obtained solutions were compared with the model presented in [7]. The results showed that in solving small size of problem, the proposed model in this study is more efficient and we found better solutions for objective function (makespan).

Due to the complexity of multiobjective mathematical model, two different metaheuristic algorithms (NSGA-II and NRGA) were applied to solve the medium and large size of problem. Due to getting better result, the proposed algorithms were tuned by applying the Taguchi method. To decide which algorithms are more effective, two methods were used to compare the results of the two algorithms: the two metaheuristic algorithms (NSGA-II and NRGA) were compared based on 4 criteria (CPU time, total cost, makespan, and number of Pareto solution) by means of SAW method, which is one of the multicriteria decision-making methods. The statistical hypothesis testing (t-test) is used for determining the best algorithm based on the average runtime and average number of Pareto solutions. Finally, both methods showed that NSGA-II metaheuristic algorithm was more effective than NRGA metaheuristic algorithm and provided better solutions. As there was no official database for some parts of cost elements, the driver's estimations were asked to help. The questions about the shipping costs for each route have been categorized, and the estimated costs have been entered into the mathematical model.

The future research suggestions of this paper can be divided into two parts:

(i) Development of methods such as Tabu search algorithm, ant colony optimization, and particle swarm optimization for the problem and comparison with the proposed methods

(ii) Exploring the feasibility of utilizing intelligent combination systems and hybrid heuristic methods for model development

(iii) Using other methods, for tuning problem parameters

(iv) Changes in the structure of the problem

In the model presented in this paper, the dock holding pattern was considered static, so one of the topics for future research could be different dock holding patterns. In this research, it is assumed that trucks are available at the start time of scheduling, so considering uncertainty in the arrival time of receiving trucks is suggested. Clearly, considering this assumption adds complexity to the problem.

Data Availability

The data that support the findings of this study are available from the corresponding author, upon reasonable request.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

References

[1] I. J. J. Bartholdi and K. R. Gue, "Reducing labor costs in an LTL crossdocking terminal," *Operations Research*, vol. 48, no. 6, pp. 823–832, 2000.

[2] R. Lotfi, Z. Sheikhi, M. Amra, M. AliBakhshi, and G. W. Weber, "Robust optimization of risk-aware, resilient and sustainable closed-loop supply chain network design with Lagrange relaxation and fix-and-optimize," *International Journal of Logistics Research and Applications*, pp. 1–41, 2021.

[3] B. J. Van, P. Valckenaers, and D. Cattrysse, "Cross-docking: state of the art," *Omega*, vol. 40, pp. 827–846, 2012.

[4] R. Lotfi, H. Nazarpour, A. Gharehbaghi, S. M. H. Sarkhosh, and A. Khanbaba, "Viable closed-loop supply chain network by considering robustness and risk as a circular economy," *Environmental Science and Pollution Research*, pp. 1–20, 2022.

[5] A. Shuib and W. N. Fatthi, "A review on quantitative approaches for dock door assignment in cross-docking," *International Journal of Advanced Science, Engineering and Information Technology*, vol. 2, pp. 31–34, 2012.

[6] S. Sharabiani, *Obtaining Optimal and Approximate Solutions to the Problem of Scheduling Inbound and Outbound Trucks in Cross Docking Operations", Master Thesis*, School of Business & Economics, Wilfrid Laurier University Waterloo, Ontario N2L3C5, Canada, 2009.

[7] Y. Wooyeon and P. J. Egbelu, "Scheduling of inbound and outbound trucks in crossdocking systems with temporary storage," *European Journal of Operational Research*, vol. 184, pp. 377–396, 2008.

[8] W. Yu, *Operational Strategies for Cross-Docking Systems"*, Ph.D. dissertation. Iowa State University, 2002, https://dr.lib.iastate.edu/entities/publication/6a39db4b-2384-478d-9b4d-e27288d53dd1.

[9] DY. Ma and F. Chen, "Dynamic programming algorithm on two machines cross docking scheduling," *Journal of Shanghai Jiao Tong University*, vol. 41, no. 5, pp. 852–856, 2007.

[10] N. Boysen and M. Fliedner, "Cross dock scheduling: classification, literature review and research agenda," *Omega*, vol. 38, no. 6, pp. 413–422, 2010.

[11] A. Ladier and G. Alpan, "Cross-docking operations: current research versus industry practice," *Omega*, vol. 62, 2015.

[12] B. Vahdani and M. Zandieh, "Scheduling trucks in cross-docking systems: robust meta-heuristics," *Computers & Industrial Engineering*, vol. 58, 2009.

[13] A. R. B. Arabani, S. M. T. F. Ghomi, and M. Zandieh, "A multi-criteria cross-docking scheduling with just-in-time approach," *International Journal of Advanced Manufacturing Technology*, vol. 49, pp. 741–756, 2010.

[14] F. Chen and C. Y. Lee, "Minimizing the makespan in a two-machine cross-docking flow shop problem," *European Journal of Operational Research*, vol. 193, no. 1, pp. 59–72, 2009.

[15] M. Keshtzari, B. Naderi, and E. Mehdizadeh, *An Improved Mathematical Model and a Hybrid Metaheuristic for Truck Scheduling in Cross-Dock Problems*, Computers & Industrial Engineering, vol. 91, pp. 197–204, 2015.

[16] M. Gaudioso, M. Flavia, and M. Sammarra, "A Lagrangian heuristics for the truck scheduling problem in multi-door, multi-product Cross-Docking with constant processingtime," *Omega*, vol. 110, 2020.

[17] T. H. Nogueira, F. P. Coutinho, R. P. Ribeiro, and M. G. Ravetti, "Parallel-machine scheduling methodology for a multi-dock truck sequencing problem in a cross-docking center," *Computers & Industrial Engineering*, vol. 143, 2020.

[18] A. Shahmardan and M. S. Sajadieh, "Truck scheduling in A multi-door cross-docking center with partial unloading - reinforcement learning-based simulated annealing approaches," *Computers & Industrial Engineering*, vol. 139, 2019.

[19] P. Cota, T. Nogueira, A. Juan, and M. Ravetti, "Integrating vehicle scheduling and open routing decisions in a cross-docking center with multiple docks," *Computers & Industrial Engineering*, vol. 164, Article ID 107869, 2022.

[20] A. Amini and R. Tavakkoli-Moghaddam, "A bi-objective truck scheduling problem in a cross-docking center with probability of breakdown for trucks," *Computers & Industrial Engineering*, vol. 96, pp. 180–191, 2016.

[21] G. Shahin, G. Fred, G. Oualid, H. Saïd, N. Placide, and T. Raca, "A comparative study of formulations for a cross-dock door assignment problem," *Omega*, vol. 91, 2018.

[22] A. Rashidi Komijan, P. Ghasemi, K. Khalili-Damghani, and F. HashemiYazdi, "A new school bus routing problem considering gender separation, special students and mix loading: a genetic algorithm approach," *Journal of Optimization in Industrial Engineering*, vol. 14, no. 2, pp. 23–39, 2021.

[23] S. Khanchehzarrin, M. Shahmizad, I. Mahdavi, N. Mahdavi-Amiri, and P. Ghasemi, "A model for the time dependent vehicle routing problem with time windows under traffic conditions with intelligent travel times," *RAIRO - Operations Research*, 2021.

[24] W. Nassief, I. Contreras, and B. Jaumard, "A comparison of formulations and relaxations for cross-dock door assignment problems," *Computers & Operations Research*, vol. 94, 2018.

[25] S. S. Fard and B. Vahdani, "Assignment and scheduling trucks in crossdocking system with energy consumption consideration and trucks queuing," *Journal of Cleaner Production*, vol. 213, 2019.

[26] V. B. Jan, V. Paul, V. B. Greet, and C. Dirk, "A tabu search approach to the truck scheduling problem with multiple docks and time windows," *Computers & Industrial Engineering*, vol. 66, pp. 818–826, 2013.

[27] F. Heidari, SH. Zegordi, and R. Tavakkoli-Moghaddam, "Modeling truck scheduling problem at a cross-dock facility through a bi-objective bi-level optimization approach," *Journal of intellectual manufacturing*, 2015.

[28] K. Khalili-Damghani, M. Tavana, and P. Ghasemi, "A stochastic bi-objective simulation–optimization model for cascade disaster location-allocation-distribution problems," *Annals of Operations Research*, vol. 309, no. 1, pp. 103–141, 2022.

[29] B. Shafipour-Omrani, A. Rashidi Komijan, P. Ghasemi, E. Ghasemzadeh, and A. Babaeinesami, "A simulation-optimization model for liquefied natural gas transportation considering product variety," *International Journal of Management Science and Engineering Management*, vol. 16, no. 4, pp. 279–289, 2021.

[30] W. Wisittipanich and P. Hengmeechai, "Truck scheduling in multi door cross docking terminal by modified particle swarm optimization," *Computers & Industrial Engineering*, vol. 113, pp. 793–802, 2017.

[31] K. Khalili-Damghani, M. Tavana, F. Santos-Arteaga, and M. Ghanbarzad-Dashti, "A customized genetic algorithm for solving multi-period cross-dock truck scheduling problem," *Measurement*, vol. 108, pp. 101–118, 2017.

[32] K. Deb, S. Agrawal, A. Pratap, and T. Meyarivan, "A fast elitist nondominated sorting genetic algorithm for multi- Objective optimization NSGA-II," in *Proceedings of the parallel problem*

solving from nature", VI (PPSN-VI) conference, pp. 849–858, Springer, Berlin, Heidelberg, 2000.

[33] K. Deb and T. Goel, "Controlled elitist nondominated sorting genetic algorithms for better convergence," in *Proceedings of the first international conference on evolutionary multi-criterion optimization (EMO-2001)*, pp. 67–81, 2001.

[34] O. Al Jadaan, C. R. Rao, and L. Rajamani, "Nondominated ranked genetic algorithm forsolving multiobjective optimization problems, NRGA," *Journal of Theoretical and Applied Information Technology*, pp. 60–67, 2008.