International Journal of Future Generation Communication and Networking
Vol. 13, No. 2, 2020 pp.624-642

Modeling A Truck Scheduling Problem In Cross Docking System With Multiple Dock Door

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Abstract

A cross docking facility is a type of warehouse in supply chain management that dealing with the process of receiving and shipping goods without storing them more than 24 hours. In this research, the issue of modeling the multi objective truck scheduling problem will be addressed. The objectives for proposed mixed integer mathematical model consist of minimizing total operation time (makespan) and cost of moving freight inside the terminal. For validating the model, the developed single-objective mathematical model is coded in GAMS software and the solutions obtained are compared with the basic model answers in the literature. Due to multiple objective of the model, it seems impossible to reach the local or global optimized solution by using classical optimization method. Therefore, as a result of computational complexity an evolutionary algorithm called non-dominated sorting Genetic algorithm (NSGA-II) is proposed for finding optimized schedule. In order to evaluating proposed algorithm a comparative analysis on benchmark instances from the literature were conducted and Efficiency of above algorithm has been compared with non-dominated ranked algorithm (NRGA) based on designed indexes in literature. For setting parameter of tow algorithms Taguchi method has been used. Finally, for analyzing the results of tow algorithms and identifying better algorithm, multi criteria decision making (MCDM) technique and statistical method are used.

Keywords: *Cross Dock, mathematical modeling, truck scheduling problem*

1. Introduction

There has long been a strong desire to optimize the distribution grid to reduce logistics costs that this purpose includes finding optimal location of facilities, reducing inventory, and declining transporting costs, therefore, supply and distribution chain management is very challenging. Effective control of physical flow of goods in the supply chain is considered as the most important factor in reducing the overall costs of the supply chain. Moreover, since approximately 3o% 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.

This paper is concerned with introduction and modeling of a novel method in distribution system management that has attracted increasing attention in today's world. Scheduling inbound and outbound trucks into cross-docking in order to find the optimal sequence of trucks is known as the truck scheduling problem. Depending upon the scheduling of trucks, any inbound or outbound truck entering the warehouse is allocated to a specific dock for cargo processing (loading or unloading). Finding the best sequence of inbound and outbound of trucks reduces system operation and costs, 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.

1.1. Cross Docking

Cross docking is a creative and innovative docking strategy to control the flow of materials, logistics costs, distribution and regulation of customer service. Cross-docking is the process of shipping - merchandises from distribution centers without storing them; In other words, the direct flow of goods from the receiving process to the ship process with minimal movement and storage. Cross docking is a practical approach to reduce the amount and cost of inventory, through the material flow lines between the manufacturer and the distributor, this strategy can help reduce inventory storage. Cross docking is a distribution and docking management method. If the goods are to be stored, this will be possible for

ISSN: 2233-7857 IJFGCN

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.

1.1.1. General Operation of Cross Docking: Cross docking is used when goods cannot be shipped directly. Operations generally performed in a cross docking include (Sharabiani, 2009):

- 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.
- 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.
- 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.

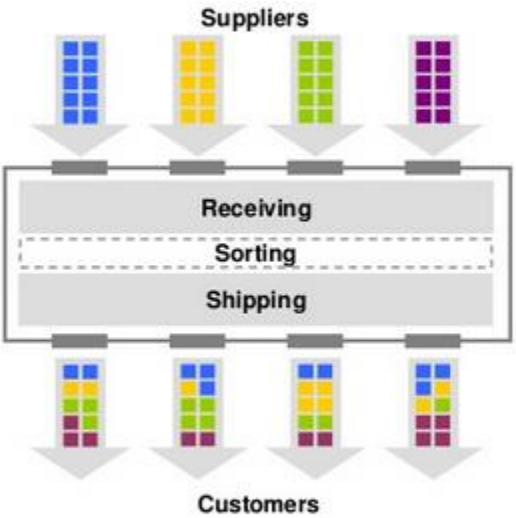

Fig 1. General cross docking operation

1.1.2. Cross Docking Performance: The following criteria can be considered as the Cross-docking Performance Criteria (Yu, 2002):

- The number of receiving and shipping dock required
- Docks utilization
- Average time of unloading and loading of trucks
- Total time spent moving materials from receiving docks to shipping docks
- Total time required to perform cross docking operations
- Cost of moving and maintaining inventory

1.2. Scheduling Trucks

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:

- The number of available docks in site
- dock holding pattern
- The presence or absence of temporary storage

ISSN: 2233-7857 IJFGCN

The cross-docking model scrutinized in this paper is one of the 32 models presented in the dissertation of (Yu, 2002) with separate receiving and shipping docks along with a temporary storage. dock holding pattern of the trucks are also static and do 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.

The main purpose of cross docking is to stabilize cargoes of different sizes and the same destinations in the full capacity of the truck (consolidation of goods) to reduce and economize the freight costs. To achieve this goal, several scheduling methods have been introduced in recent years whose goal is to solve the truck scheduling problem. This issue decides the sequence of receiving and shipping trucks to cross docking for a set of inbound and outbound docks.

1.3. Necessity of research

The practical applications of car 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 $\boldsymbol{O(mn2^{m})}$ (m number of targets and n population size) (Ma and Chen, 2007). In recent years, researchers' interest and attempt in scheduling trucks in cross-docking has 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 (Boysen and Fliedner, 2010).

- Developing models closer to real issues
- Improving problem solving methods to enhance the quality of the solution and the timing of problem solving of truck scheduling.

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. Therefore, efforts to address these shortcomings and simultaneously reduce the time and cost of operations by using heuristic algorithms make it necessary to conduct this research.

1.4. Research purposes: The purpose of this paper is to present a model and study the problem of truck scheduling. A set of specific trucks which transport goods from suppliers to retailers through a cross-docking, and the entire process must be completed in this planning. During the planning period, each supplier and retailer can only meet once and the total number of goods in a truck should be less than its capacity. The purpose of the problem is to reduce the total time to complete the operation and minimize the total costs of transshipping in the cross-docking.

1.4.1. Operation Completion Time: The operation time is defined as follows:

From the moment the first product is discharged from the first timed inbound truck to the receiving dock until the last product is loaded onto the last scheduled outbound truck on the shipping dock. The factors influencing the completion time in the cross-docking system are as follows:

1. Design and layout of receiving and shipping docks
2. Number of receiving and shipping docks
3. Composition and number of products for each receiving and shipping truck
4. Product turnover path in cross-docking
5. Method of transportation of materials inside the warehouse
6. Availability of freight trucks in required time

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7. Delay time or interval created between loads or unloads

8. Required storage space for temporary storage

9. Pattern of entry and exit of trucks (Unloading and loading in whole or in part, or in partial or multiple times)

10. Sequence of inbound and outbound trucks

11. The amount of unloaded and loaded products of one type per truck

In this study, it is assumed that the 7 elementary factors are predetermined. Also, we will have several different models based on how factors 8 and 9 are taken into account. In addition, they are considered factors 10 and 11 as decision variables to minimize the completion time.

1.4.2. Costs: 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.

2. Literature Review

(Yu and Egbelu, 2008) investigated a cross-docking system in which a temporary storage buffer is located besides 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 shipping of cross-docking system. (Larbi, ALpan and Penz, 2009) modeled a similar problem using a dynamic planning and suggested two creative algorithms to solve it. (Alpan et al, 2010) studied a transshipment scheduling in a multiple inbound and outbound dock configuration, so that goods could be transshipped directly between inbound and outbound trucks or be placed temporarily on temporary storage dock till the appropriate truck is sent to the dock or a proper truck is directed to the dock by the warehouse supervisor in order to transship directly which led to charging the cost of replacing the trucks to the system. The objective of this study was to find the best transship scheduling to minimize the sum of inventory holding and truck replacement costs. Transship Scheduling in cross-docking concerning with determining the sequence of outbound and inbound trucks, has major influences on granting a fast workflow and timely delivery of goods. (Boysen and Fliender, 2010), reviewed and classified the literature of scheduling trucks in cross-docking. Another important point is the important strategic issues and operations that need to be payed attention and addressed in the cross-docking system life cycle, such as cross-docking locating, design and layout of warehouse, transshipping routing, warehouse resource planning, etc. which to further study on this area, one can refer to (Van Belle, Valckenaers, and Cattrysse, 2012). (Konur, Mihalis and Golias, 2013) Provided a two-step approach to solve the problem of assignment of distinations to docks and determine the optimal sequence of freight trucks in situations in which the arrival time of trucks was uncertain and used a genetic algorithm to solve both cases .1) Specific and certain arrival time 2) Uncertain and pessimistic arrival time. Since the issue of cross-stocking has attracted increasing attention in recent years, (Ladier and Alpan, 2015), undertook a wide-ranging study to identify the research gap between theoretical issues and real-world application challenges that reveal these differences. (Keshtazi, Naderi, and Mehdizadeh, 2013) presented a new mixed integer programming model that is more efficient than the model presented by (Yu and Egbelu, 2008) and to demonstrate the efficiency of their model for large-scale problems used the hybrid heuristic algorithm for collective optimization of birds with refrigeration simulation algorithm.

On the other hand, among the recent studies, (Amini and Tavakkoli-Moghaddam, 2016) 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. (Gelareh, et al. 2018) introduced eight mixed integers mathematical programming model for modeling the problem of door (dock) allocation to destinations in cross-docking environments, and compared and

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introduced the best and most efficient models based on the standard examples available in the problem literature. (Nassief, Contreras, and Jaumard ,2018) also presented two complex integer mathematical models in order to modeling the allocation doors (docks) problem for the purpose of reducing displacement costs and using the generation columns algorithm solved the models.

The manner of waiting trucks to arrive the docks is one of the important issues studied by (Shahram fard and Vahdani ,2018) and by 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. Among the studies that are closely related to the model studied in this dissertation is (Khalili-Damghani, et al,2017) 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 by using an evolutionary computational approach based on genetic algorithm whose results were compared to branch and case algorithm in order to evaluate 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, mathematical 2-obgectives complex integer model presented in this paper includes reducing the cost of operational total time and costs of in-warehouse transporting to solve which, two non-dominated storing genetic and more dominant ranked genetic algorithms was used and the results of two algorithms were compared and analyzed to identify a more effective algorithm. According to studies in the literature of the issue, it is of great importance to consider the temporary storage space and the multiple receiving and shipping docks for the efficient management of cross-warehouse operations, therefore, it is necessary to try to address these shortcomings and bring the issue closer to the real situation.

3. The Model

3.1. Variables, Parameters, Indices and mathematical model

i	Receiving truck indices
j	Shipping truck counter
k	Merchandise counter
m	Receiving dock counter
n	Shipping dock counter
R	The number of receiving truck
S	The number of shipping truck
M	The number of receiving dock
N	The number of Shipping dock
P	Types of goods
$\mathbf{p_{ik}^r}$	The number of k-type goods loaded into the truck i by default
p_{jk}^s	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)

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w_n^{fs}	Time of transshipping the goods form temporary storage to shipping dock n
C_k^D	Cost of shipping the K-type good from receiving dock to shipping dock directly
C_k^{TS}	Cost of shipping K-type good from the receiving dock to the temporary storage place
C_k^{FS}	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_{ijk}^D	The number of k-type goods being transported directly from the receiving truck i to the shipping truck J
x_{ik}^{TS}	The number of k-type goods moved from the receiving truck i to the temporary storage location
x_{jk}^{FS}	The number of k-type goods moved from the temporary storage location to the shipping truck j
$\boldsymbol{t_{ij}} = \begin{cases} \mathbf{1} \\ \mathbf{0} \end{cases}$	If the good from the receiving truck i is transported to the sipping truck j otherwise
$\boldsymbol{p_{ij}} = \begin{cases} \mathbf{1} \\ \mathbf{0} \end{cases}$	If the receiving truck i overrides the receiving truck j in the sequence of receiving trucks otherwise
$\boldsymbol{q_{ij}} = \begin{cases} \mathbf{1} \\ \mathbf{0} \end{cases}$	If the shipping truck i overrides the shipping truck j in the sequence of the shipping trucks otherwise
$\mathbf{A_{im}^r} = \begin{cases} \mathbf{1} \\ \mathbf{0} \end{cases}$	If the receiving truck i is assigned to the receiving dock m otherwise
$\mathbf{A_{jn}^s} = \begin{cases} \mathbf{1} \\ \mathbf{0} \end{cases}$	If the shipping truck j is assigned to the shipping dock n otherwise
$\mathbf{Z_j} = \begin{cases} \mathbf{1} \\ \mathbf{0} \end{cases}$	If the product is transported from the temporary storage to the shipping truck J otherwise
$\boldsymbol{d_{im}^r}$	The time the receiving truck i enters the receiving dock m
$\boldsymbol{l_{im}^r}$	The time the receiving truck i leaves the receiving dock m
$\boldsymbol{d_{jn}^s}$	The time the shipping truck j enters the shipping dock n
$\boldsymbol{l_{jn}^s}$	The time the shipping truck j leaves the shipping dock n

$$\text{Min} \quad T \tag{1}$$

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$$\text{Min } \boldsymbol{C_T} = \sum_{i=1}^{R}\sum_{j=1}^{S}\sum_{k=1}^{P}(C_k^D x_{ijk}^D + C_k^{TS} x_{ik}^{TS} + C_k^{FS} x_{jk}^{FS}) \quad (2)$$

Subject to:

$T \geq l_{\mathrm{jn}}^{\mathrm{s}}$,∀ j=1,2,…S , n =1,2,…N (3)

$\sum_{m=1}^{M} A_{im}^r = 1$,∀ i =1,2,…R (4)

$\sum_{i=1}^{R} A_{im}^r \geq 1$,∀ m =1,2,…M (5)

$\sum_{n=1}^{N} A_{jn}^s = 1$,∀ j =1,2,…S (6)

$\sum_{j=1}^{S} A_{jn}^s \geq 1$,∀ n=1,2,…N (7)

$\sum_{i=1}^{R} x_{\mathrm{ijk}}^{\mathrm{D}} + \mathrm{x}_{\mathrm{jk}}^{\mathrm{FS}} = \mathrm{p}_{\mathrm{jk}}^{\mathrm{s}}$, ∀ j=1,2,…S , k =1,2,…P (8)

$\sum_{j=1}^{S} x_{\mathrm{ijk}}^{D} + \mathrm{x}_{\mathrm{ik}}^{\mathrm{TS}} = \mathrm{p}_{\mathrm{ik}}^{\mathrm{r}}$, ∀ i =1,2,…R, k =1,2,…P (9)

$\sum_{i=1}^{R} x_{\mathrm{ik}}^{\mathrm{TS}} = \sum_{j=1}^{S} x_{\mathrm{jk}}^{\mathrm{FS}}$, ∀ k =1,2,…P (10)

$x_{\mathrm{ijk}}^{\mathrm{D}} \leq \mathrm{Q}\ \mathrm{t_{ij}}$, ∀ i =1,2,…R, j=1,2,…S , k =1,2,…P (11)

$l_{\mathrm{im}}^{\mathrm{r}} \geq d_{\mathrm{im}}^{\mathrm{r}} + A_{im}^r . \sum_{k=1}^{p} p_{ik}^r . h_k$, ∀ i =1,2,…R, m =1,2,…M (12)

$d_{jm}^{\mathrm{r}} \geq l_{\mathrm{im}}^{\mathrm{r}} + D - Q(1 - p_{\mathrm{ij}})$, ∀ i , j =1,2,…R, m =1,2,…M, i≠j (13)

$d_{im}^{\mathrm{r}} \geq l_{\mathrm{jm}}^{\mathrm{r}} + D - Qp_{\mathrm{ij}}$, ∀ i , j =1,2,…R, m =1,2,…M, i≠j (14)

$d_{im}^{\mathrm{r}} \geq d_{jn}^{\mathrm{r}} - Qp_{\mathrm{ij}} - Q(1 - A_{im}^r) - Q\left(1 - A_{jn}^r\right)$, ∀ i , j =1,2,…R, m ,n =1,2,…M, i≠j, m≠n (15)

$p_{\mathrm{ii}} = 0$, ∀ i =1,2,…R (16)

$d_{\mathrm{jn}}^{\mathrm{s}} \geq l_{\mathrm{in}}^{\mathrm{s}} + D - Q(1 - \mathrm{q_{ij}})$, ∀ i , j =1,2,…S, n=1,2,…N, i≠j (17)

$d_{\mathrm{in}}^{s} \geq l_{\mathrm{jn}}^{\mathrm{s}} + D - Q\mathrm{q_{ij}}$, ∀ i , j =1,2,…S, n=1,2,…N, i≠j (18)

$d_{\mathrm{im}}^{\mathrm{s}} \geq d_{jn}^{\mathrm{s}} - Q\mathrm{q_{ij}} - Q(1 - A_{im}^s) - Q\left(1 - A_{jn}^s\right)$,∀ i , j =1,2,… S, m,n=1,2,…N, i≠j, m≠n (19)

$\mathrm{q_{ii}} = 0$, ∀ j=1,2,…S (20)

$l_{\mathrm{jn}}^{\mathrm{s}} = \mathrm{Max}\left\{d_{\mathrm{jn}}^{\mathrm{s}}\ \mathrm{Max}\ t_{ij} . d_{\mathrm{im}}^{\mathrm{r}}\right\} + \mathrm{Max}\left\{A_{jn}^s A_{im}^r t_{ij} . W_{\mathrm{mn}}\right\} + \mathrm{Z_j} . \mathrm{w}_{\mathrm{n}}^{fs} + 2\sum_{k=1}^{p} p_{jk}^s . h_{\mathrm{k}}$ (21)

∀ i =1,2,…R, j=1,2,…S, m =1,2,…M, n=1,2,…N, i≠j, m≠n

all variable ≥0 (22)

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4. Solution Method

Different approaches have been applied to model and solve this problem. These approaches include mixed integer programming, branch and boundary techniques, search algorithms, full counting methods, and heuristic and metaheuristic algorithms.

Full enumeration methods and mixed integer programming have been used as the basic approaches to generate justified responses that search and meta-heuristic algorithms have used these responses to obtain the optimal response. 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 constraints facing the truck scheduling problem. To validate the presented model, it was considered as the single-objective model with the aim of minimizing the total time of operation, with one receiving and one shipping dock, 4 types of goods, 4 receiving trucks and 5 shipping trucks according to Table 1 (according to experimental problem in the literature) in coded and solved through GAMS Software and optimal response obtained by the model Proposed in the paper (Yu and Egbelu, 2008) was compared (Table 2). In addition, to solve the two-objective problem, non-dominated storing genetic algorithm (NSGA-II) and non-dominated ranking genetic algorithm (NRGA) have been used. Optimization of multi-purpose is different from single-purpose issues because it contains several goals that must pay attention simultaneously to all goals in optimization. In this paper, we use two non-dominated storing genetic algorithm and non-dominated ranking genetic algorithm.

Table 1. Experimental Problem

Receiving truck			Shipping truck		
truck	product	quantity	truck	product	quantity
1	1	48	1	1	151
	2	36		4	87
	3	84	2	2	106
	4	72		3	33
2	1	89	3	2	264
	2	127	4	1	61
	3	64		2	132
3	1	75	5	2	26
	2	105			
	3	15		3	130
	4	15			
4	2	260			

Table 2: Comparison of the experimental problem response

	makspan		
	optimal	worst	average
(Yu and Egbelu,2008)	1557	2260	1923/27
This paper	1606	2405	2005/5

4.1. Controlled NSGA-II Genetic Algorithm

non-dominated storing genetic algorithm is one of the most efficient and well-known multi-objective optimization algorithms presented by (Deb, et al. 2000). However, Controlled NSGA-II presented by

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(Deb and Goel, 2001), which is the same as NSGA-II algorithm, but here you use the concept of controlled elitism to create the next generation. The method of solving the above model is based on the non-dominated storing genetic algorithm according to Figure 2.

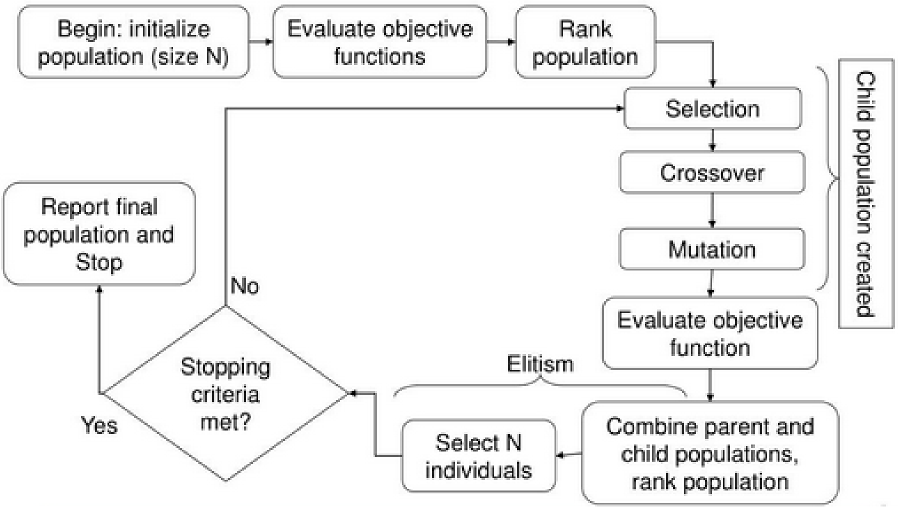

Fig 2. Flowchart of Controlled NSGA-II Algorithm

4.2. Non-Dominated Ranking Genetic Algorithm (NRGA)

A new population-based multi-objective evolutionary algorithm called Genetic Algorithm Based on ranking non-dominated has been successfully developed by (Al Jadaan, Rao and Rajamani, 2008) to optimize non-convex, nonlinear and discrete functions. They studied multi-objective algorithms that worked on non-dominated sorting. They noticed three problems in these algorithms.

1. The computational complexity Was $\boldsymbol{O}(\boldsymbol{mn2^m})$ (M: the number of targets and N: the population size)
2. Lack of efficient elitism
3. 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 (non-dominated 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 as well as the earlier convergence at the Pareto optimal boundary, compared to other multi-objective evolutionary algorithms. However, the difference between the NRGA algorithm and the Controlled NSGA-II algorithm is in the strategy selection section and the population sorting and selection for the next generation.

4.3. Numerical Issues

To illustrate the performance of the proposed strategy of the model, 10 numerical examples with the number sizes of small, medium and large are reviewed in accordance with Table 3. Each example is run 10 times by NSGA-II and NRGA algorithms 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.

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Table 3: Numerical examples of different sizes

Problem	Receiving Truck	Shipping Truck	Receiving Dock	Shipping Dock	Products Types
1	3	2	2	2	3
2	6	4	4	4	6
3	8	6	6	6	8
4	11	9	9	9	11
5	15	14	14	14	15
6	18	12	12	12	18
7	24	9	9	9	24
8	30	10	10	10	30
9	55	15	15	15	55
10	100	35	35	35	100

4.4. Taguchi Method

There are several statistical methods for designing experiments in order 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 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, 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 algorithms as receiving variables to obtain the optimal response (Y). To set the problem parameter with 2 receiving trucks, 4 receiving docks, 4 shipping docks, 4 shipping trucks and 6 different product types are reviewed. 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 algorithms. 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 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.

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

Given the dual purpose of the model, 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,

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(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, the S / N ratios for the different parameters of the problem for NSGA-II and NRGA algorithms, the average graphs of parameters for S / N rates at different levels are shown in Figures 3 and 4. Given the equation 1, the lower the S / N ratio, the better the answers of algorithm. According to Figures 3 and 4, the optimal values of appropriate parameters for NSGA-II and NRGA algorithms are in accordance with table 5.

$$S/N_S = -10\log\left(\frac{1}{n}\sum_{i=1}^{n} y_i^2\right) \tag{23}$$

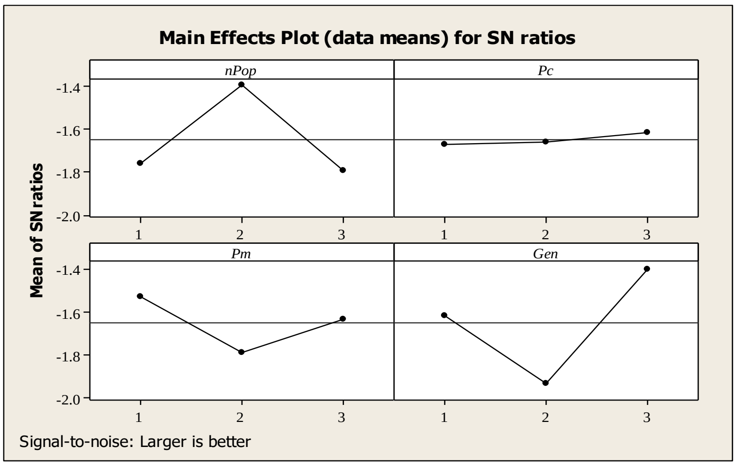

Figure 3: Values of different levels of parameters in S/N ratio for NSGA-II algorithm

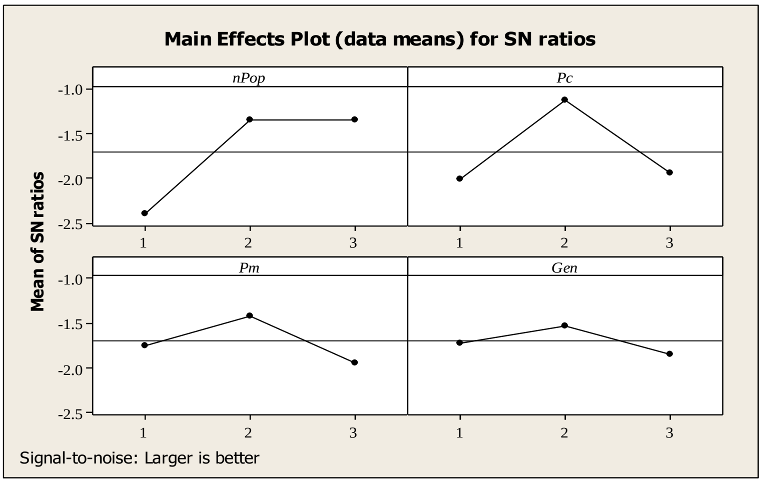

Figure 4: The values of different levels of parameters in the S/N ratio for NRGA algorithm

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

NSGA-II		NRGA	
Parameter	Value	Parameter	Value
Pc	0/85	*Pc*	0/85

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Pm	0/2	*Pm*	0/2
Gen	100	*Gen*	100
nPop	50	*nPop*	50

5. Comparison of Proposed Algorithms

In this section, five benchmarks are presented to evaluate multi-objective optimization algorithms:

5.1. Most Expansion

The criterion presented by ZITLER (1999), measures the length of the spatial cube diameter applied by ultimate measure of the objectives, for the set of non-dominated solutions. The equation (24) illustrates computational procedures of this index.

$$D=\sqrt{\sum_{j=1}^{M}(\max_{i} f_i^j - \min_{i} f_i^j)^2} \tag{24}$$

5.2. Spacing

This criterion presented by Scott (1999), calculates the relative distance of successive solutions using the equations (25), (26), and (27).

$$S = \sqrt{\frac{1}{|n|}\sum_{i=1}^{n}(d_i - \bar{d})^2} \tag{25}$$

$$d_i = min \sum_{m=1}^{2} |f_m^i - f_m^k| \tag{26}$$

$$\bar{d} = \sum_{i}^{n} \frac{d_i}{|n|} \tag{27}$$

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 i-th answer and the solutions in the final non-dominated set. It is noteworthy that this distance criterion is different from the criterion of the lowest elucidation distance among the solutions.

5.3. Number of Pareto Solutions (NOS)

The NOS benchmark represents the number of optimal Pareto solutions that can be found in any algorithm. Figure 5 provides an example for calculating NOS.

5.4. Generational Distance (GD)

This criterion finds the average distance of Q solutions from $\boldsymbol{p}^*$, instead of finding answers from the set of non-dominated Q solutions belonging or not to the optimal Pareto solutions.

$$GD = \frac{\left(\sum_i^Q d_i^p\right)^{1/p}}{|Q|} \tag{27}$$

For p = 2, the $\boldsymbol{d_i}$ parameter is equal to the Euclidean distance (in the target space) between the

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solutions of i belonging to q and the closest member of $\boldsymbol{p}^*$

$$d_i = \min_{k=1} \sqrt{\sum_{m=1}^{M} \left(f_m^{(i)} - f_m^{*(k)}\right)^2} \tag{28}$$

5.5. Algorithm Run Time (Cpu Time)

Another standard criterion for comparing multi-objective algorithms is the use of the algorithm's runtime criterion which the lower this time, the better the algorithm's performance.

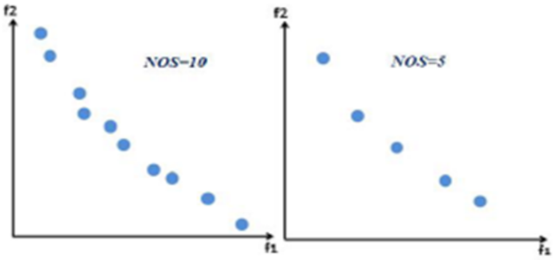

Figure 5. The method to calculate the number of Pareto solutions

Table 6. Comparative Criteria Value for NSGA-II Algorithm

Problem	$\overline{D}$	$\overline{S}$	$\overline{NOS}$	$\overline{GD}$	$\overline{T}$
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 the Algorithm NRGA

Problem	$\overline{D}$	$\overline{S}$	$\overline{NOS}$	$\overline{GD}$	$\overline{T}$
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

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10	0/9821	5891/01	32	17/14	59388502

After defining standard benchmarks for comparing Pareto-based multi-objective algorithms in Tables 6 and 7, these criteria are calculated for each of the experimental production problems, and then, based on 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, relative deviation percentage (RPD) is used whose computing method is based on equation (29).

$$\boldsymbol{RPD = \frac{Alg_{sol} - Best_{sol}}{Best_{sol}} 100} \quad (29)$$

In this equation, Alg_{sol} is the value obtained for each problem by the algorithm. $Best_{sol}$ 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 algorithms.

Table 8. The values of RPD criteria for NSGA-II algorithm

Problem	$\bar{T}$	$\bar{P}$	$Best\bar{T}$	$Best\bar{P}$	$RPD\bar{T}$	$RPD\bar{P}$
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. The values of RPD criteria for NRGA algorithm

Problem	$\bar{T}$	$\bar{P}$	$Best\bar{T}$	$Best\bar{P}$	$RPD\bar{T}$	$RPD\bar{P}$
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

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10	1/5206	32	1/4012	44	8/51	27/27

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 $\boldsymbol{RPD}(\overline{\boldsymbol{T}})$ and runtime $\boldsymbol{RPD}(\overline{\boldsymbol{P}})$. Therefore, two methods were used to evaluate the results of the two algorithms. applying SAW method which 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 solutions averages.

5.6. Investigation of Results Using Multi Criteria Decision Making (MADM)

To decide in different problems, there are a large number of models. In general, these models are divided into two main categories, multi-criteria decision-making models (MADM) and multi-objective decision-making models (MODM). 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. 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 31), Ar is alternative r, Bj is j-th criterion, Xrj is the value of alternative r for j-th criterion. In general, the value of an alternative in SAW method is calculated as follows:

$$V(A_r) = V_r = \sum_{j=1}^{n} W_j V_j\left(X_{rj}\right) \quad r = 1.2 \dots . L \tag{30}$$

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 i-th criterion under the j-th alternative and wj is the weight of j-th alterative.

$$\boldsymbol{F} = \begin{array}{cc} & \begin{array}{ccc} \boldsymbol{B_1} & \dots & \boldsymbol{B_n} \end{array} \\ \begin{array}{c} \boldsymbol{A_1} \\ \vdots \\ \boldsymbol{A_l} \end{array} & \begin{bmatrix} \boldsymbol{x_{11}} & \cdots & \boldsymbol{x_{1n}} \\ \vdots & \ddots & \vdots \\ \boldsymbol{x_{l1}} & \cdots & \boldsymbol{x_{ln}} \end{bmatrix} \end{array} \tag{31}$$

In this study, NSGA-II and NRGA algorithms, alternatives (choices), make span 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.

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

Problems	NSGA-II			
	CpuTime (second)	Total Cost (Toman)	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	0/463327	103839	1756427	29
7	0/463434	185443	3287332	29

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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			
	CpuTime (second)	Total Cost (Toman)	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 (Toman)
NSGA-II	8818060/9	845115/3
NRGA	9114546/6	1010957/9

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.

5.7. Results 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, confidence coefficient is equal to 0.95. it means (1-α=0.95)

Equations 32, 33, 34, and 35 show one-way statistical tests for $\boldsymbol{RPD}(\overline{\boldsymbol{P}})$and $\boldsymbol{RPD}(\overline{\boldsymbol{T}})$and values of t-distribution for $\boldsymbol{RPD}(\overline{\boldsymbol{P}})$and $\boldsymbol{RPD}(\overline{\boldsymbol{T}})$, respectively, so that $\overline{\boldsymbol{T}}$ is defined as the runtimes average and $\overline{\boldsymbol{F}}$ is equal to the average of the number of solutions. This test is performed assuming that variances are known.

$$\mathbf{H_0}:\ \mu_{\overline{T}_{NRGA}} \geq \mu_{\overline{T}_{NSGA}} \tag{32}$$

$$\mathbf{H_1}:\ \mu_{\overline{T}_{NRGA}} < \mu_{\overline{T}_{NSGA}}$$

$$\mathbf{H_0}:\ \mu_{\overline{P}_{NRGA}} \geq \mu_{\overline{P}_{NSGA}} \tag{33}$$

$$\mathbf{H_1}:\ \mu_{\overline{P}_{NRGA}} < \mu_{\overline{P}_{NSGA}}$$

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$$t_{Distribution} = \frac{\overline{T}_{NRGA} - \overline{T}_{NSGA}}{S_p^2\sqrt{1/n_{NRGA} + 1/n_{NSGA}}} \tag{34}$$

$$t_{Distribution} = \frac{\overline{P}_{NRGA} - \overline{P}_{NSGA}}{S_p^2\sqrt{1/n_{NRGA} + 1/n_{NSGA}}} \tag{35}$$

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.

$$S_p^2 = \frac{(n_{NRGA} - 1)S_{NRGA}^2 + (n_{NSGA} - 1)S_{NSGA}^2}{n_{NRGA} + n_{NSGA} - 2} \tag{36}$$

The results of $RPD(\overline{P})$ values for ten examples made here, after solving by presented algorithms, are given in tables 8 and 9. The calculation is as followed:

$$t_{Distribution} = \frac{29.96 - 33.74}{1050.47\sqrt{1/10 + 1/10}} = -0.008 \tag{37}$$

$t_{0.95,\ 18}=1.73$

According to above calculations, $t_{distribution} > t_{0.95,18}$ 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 algorithm is better than NRGA regarding $RPD(\overline{P})$ criterion. The study of results with statistical method showed that NSGA-II is better than NRGA algorithm 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 followed:

$$t_{Distribution} = \frac{31.84 - 33.86}{172.78\sqrt{1/10 + 1/10}} = -0.026 \tag{38}$$

$t_{0.95,\ 18}=1.73$

According to above calculations, $t_{distribution} > t_{0.95,18}$ 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 algorithm is better than NRGA regarding $RPD(\overline{T})$ criterion. The study of results with statistical method showed that NSGA-II is better than NRGA algorithm in terms of two criteria $RPD(\overline{P})$ and $RPD(\overline{T})$.

6. Conclusion

In this paper the issue of minimizing total operation time and finding optimum cost of moving fright

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inside the cross dock terminal were considered. the cross-docking problem was studied with multiple receiving and shipping and a static service pattern in the receiving and shipping docks. We assumed that a temporary storage facility was located near to the shipping docks with limited capacity. To illustrate the validity of the developed model, the problem was solved and developed as a one-objective, by GAMS software and the definite solution was compared to the present solutions in the problem literature. Because of the complexity of two-objective model, NSGA-II and NRGA meta-heuristic algorithms were used to solve the problem. For quick convergence of the proposed algorithms to the best solution, Taguchi method was also proposed, and the Residual Prediction Deviation (RPD) was used to measure the algorithms. It is not easy to decide exactly which one of the two algorithms is more effective than the other. Therefore, two methods were used to compare the results of the two algorithms: the SAW, which is one of the multi-criteria decision-making methods. and the other is the statistical test using the one-way test used for determining runtime and number of solutions. Finally, it was showed that NSGA-II meta-heuristic algorithm is more effective than NRGA meta-heuristic algorithm and provides better solutions.

6.1. Future research

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

- Change in problem solving approach
- Development of methods such as Tabu search algorithm, Ant colony algorithm, Particle swarm optimization, etc. for the problem and comparison with the proposed methods.
- Exploring the feasibility of utilizing intelligent combination systems as well as hybrid heuristics methods for model development
- Using other methods, to adjust problem parameters such as RSM or…
- 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 pattern.
- 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.

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ISSN: 2233-7857 IJFGCN