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MODELING THE ROBUTS FACILITY LAYOUT PROBLEM FOR UNEQUAL SPACECONSIDERING HEALTH AND ENVIRONMENTAL SAFETY CRITERIA UNDER UNCERTAIN PARAMETERS

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Abstract: *This study examines the robust facility layout problem (RFLP) while taking into account unpredictable health and environmental safety standards. This problem's major goal is to arrange the departments in various departments of a hall, allot each department the appropriate amount of space, and identify the kind of amenities and equipment needed for each chosen sector. To accomplish the aforementioned objective, five criteria were taken into account: the total cost of department transfer and selection; access to more facilities and equipment; access to firefighting equipment; access to favorable climatic conditions; and the separation of noisy departments from one another. The fuzzy programming approach is utilized in this research to regulate the uncertainty parameters due to the uncertainty of the transfer cost and transfer time parameters. Additionally, by supplying an appropriate chromosome, the precise Epsilon constraint approach, NSGA II, and MOPSO have been employed to tackle the issue. The computational sizes of larger-sized sample problems solved demonstrate the strong performance of the NSGA II in quickly finding effective solutions.*

Key words: *Multiple objective programming, robust facility layout problem, meta-heuristics algorithm, fuzzy programming, health and environmental safety.*

1. Introduction

FLP plays an important role in production and service processes and has many effects on the efficiency and effectiveness of organizations and companies. The FLP is actually

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defined by determining the most effective departmental layout in a hall. Lack of proper layout of departments according to different criteria can have huge costs for the company or organization (Tavakkoli-Moghaddam et al., 2007). The layout plan chosen for a unit identifies the relationships between the activities associated with the transfer of materials / services. Therefore, the FLP and activities related to material handling are completely related to each other and have a direct effect on each other. What is important in this regard is the relationship between the facilities or departments of a production unit that should be considered far or close to each other (Anjos & Vieira, 2017).

If two facilities or departments are more closely related to each other, it is obvious that these two facilities should be placed next to each other to reduce the costs of transferring materials / services. An appropriate layout can minimize the total cost of moving materials and the distances between facilities where materials / services are exchanged, as well as our production cycle. Therefore, in order to create a new layout, it is absolutely inevitable to consider material handling (Kumar et al., 2020). An appropriate layout should not be considered solely on the basis of cost or distance reduction criteria. In most layout problems, distance and proximity of departments and facilities from each other, considering the access of departments to firefighting equipment, considering the optimal lighting for the facilities, etc. should also be considered. Because manpower as the most important factor of productivity must be working in optimal conditions in the production / service unit. Therefore, health and environmental safety issues along with cost and time factors should be considered in the new FLP (Anjos & Vieira, 2021). Production units must be able to work effectively in the modern global economy and react swiftly to changes in the product range as well as in demand. The transportation of materials between various departments and industrial facilities is altered as a result of these changes. The layout and design of facilities may change as a result of variations in the flow of materials throughout time (Pourvaziri et al., 2022).

Therefore, it is not possible to change the layout of the design in every period of time. Therefore, this problem is presented as a strategic issue that should be considered in all aspects and principles of the FLP (Allahyari & Azab, 2018). By anticipating changes in the cost and time of material transfer between facilities in different time periods, different layout plans can be planned for several time periods. Then, based on the importance of cost and health and environmental safety criteria, the most efficient plan was selected. Because the costs of changing the layout of the facility in each time period account for a large portion of the total cost of the layout plan. Therefore, it is necessary to find an optimal plan to avoid wasting resources and costs incurred in this way. Considering the importance of the FLP and also the importance of considering health and environmental safety criteria in this paper, the RFLP for unequal space has been modeled by considering health and environmental safety criteria under uncertain parameters. Uncertain consideration of cost and transfer parameters as well as environmental criteria such as access to firefighting equipment, access to favorable climatic conditions (adequate light, sufficient wind, etc.) Remote noise departments from departments Silence has led to the creation of a novel, integrated FLP.

Therefore, the most important factor in this problem is the allocation of departments to each part of the hall, taking into account the different levels of facilities and equipment, provided that the logical limitations of the issue are taken into account. Also, the NP-Hard nature of the RFLP has led to the use of multi-objective algorithms to solve the problem in much larger sizes. In this paper, in addition to presenting a new RFLP by considering health and environmental safety criteria, a suitable chromosome is designed to solve the problem in very large sizes with high efficiency.

The article's primary structure is as follows; in the second section, the literature is evaluated and the problem's research need is identified. The fuzzy parameters of the issue are managed using the fuzzy programming approach after an indefinite model of the RFLP is supplied in the third section. The crossover and mutation operators utilized in the method are identified in the fourth section, along with the chromosomes connected to the RFLP. The performance of the NSGA II and Epsilon constraint techniques are examined in the fifth part, which also evaluates the experiments. The paper's conclusion is then explored in the sixth part.

2. Literature Review

In this section, the literature review related to the FLP is examined. The literature studied is from articles published in the prestigious journals Elsevier, Springer, Science Direct, and other reputable publications between 2005 and 2022.

Numerous scholars have provided mathematical models and solutions as a result of FLP's significance in production units and businesses. Four factors—material handling cost, proximity rate, material handling time, and hazardous material handling rate—were taken into account by (Chen & Sha, 2005) while designing an FLP for handling hazardous materials. Aiello et al. (2006) utilized GA to develop the multi-objective FLP employing a number of criteria. In order to solve an RFLP, Baykasoglu et al. (2006) took into account instances with restricted and unlimited budgets and employed the ant colony solution approach. In three separate FLP scenarios—time-limited, solution-limited, and unrestricted—Arostegui et al. (2006) assessed the effectiveness of TS, SA, and GA. They discovered the TS to be the finest in every situation (Arostegui et al., 2006). A RFLP via approximation dynamic planning has been presented by El-Rayes and Said (2009) as a method for addressing issues by dissecting them into smaller ones. This technique aims to present judgments linked to the location and location of the complete facility using the planning mentioned above as well as a number of decisions, etc.

A TS was used by Samarghandi and Eshghi (2010) to resolve a single-row layout issue with facilities of different sizes. An approach for resolving dynamic two-stage FLPs that combines the SA and mathematical programming was put out by Wang et al. (2015). Finally, it was discovered that this approach has the capacity to identify the true method for issues with real sizes as well as the ideal solution for problems of modest size. At order to address the RFLP, Ulutas and Islier (2015) performed a research in a shoe factory, taking into account various working schedules and aiming to reduce both the total amount of material transported as well as the recycling expenses. As a consequence, an ACO was suggested as a solution to the RFLP, and it eventually outperformed both the tests and the numerical findings. Based on the strong links between the facilities, Neghabi and Tari (2016) developed a novel strategy for the FLP. According to this method, the plan receives more credit because of how close the facility is. The distance of certain installations is also seen as an advantage in order to apply safety indications. They suggested a mathematical solution to the issue and evaluated its effectiveness using computer trials. The computing results demonstrated the suggested model's effectiveness in simultaneously taking economic and safety factors into account and coming up with several layout solutions. To improve the FLP, Guan and Lin (2016) suggested a hybrid approach. The suggested technique was built using two neighborhood search algorithms combined with an ant colony. They suggested three effective neighborhood architectures in addition to a fresh method for shortening the computation required to calculate the goal function. On the other hand, the ACO's pheromones were updated using a novel technique. They evaluated the algorithm using common issues from the literature and showed that it was better than earlier approaches.

Zhang et al. (2022) designed a multi objective facility location problem. They proposed a solution approach to yield a set of solutions that can represent the trade-offs among conflicting objectives. The applicability and validation of the presented model and performance of the proposed optimization approach evaluated using a real case. Esmikhani et al. (2022) designed a facility layout problem by the facility dimensions and the materials flow between facilities. In this paper uncertain as fuzzy random variables and the plant region was equipped with the wall mounted jib cranes and the small gate cranes and there were some forbidden areas in the plant region where the placement of facilities was forbidden. Pourvaziri et al. (2022) proposed a practical approach to mitigate the effects and repercussions of changing environments and avoid rearranging the layout. A robust layout approach is presented, where changes in product demand and mix are absorbed by altering product routes and not rearranging the layout. Guo et al. (2022) designed the typical UA-FLP in an air-conditioner production shop floor, and developed a modified NSGA-II to identify the optimal layout plan considering the material handling cost (MHC) and the closeness rating score (CRS). Mohapatra et al. (2022) modeled and solved a route selection problem between the facility center and the consumer by considering different criteria. The simulation result shows that the proposed MCDM-based routing protocol outperforms both MCDM-based and non-MCDM-based routing schemes.

In Table 1, some of the researches conducted in the field of RFLP have been reviewed and compared.

Table 1. Studies conducted in the field of RFLP

Ref	Objective Function	Deterministic/ Uncertainty	Parameter Control Method	Solution Method	Unequal Department	Health And Environmental Safety
Paes et al. (2017)	min distance	deterministic	-	GA	*	-
Turanoğlu & Akkaya (2018)	min cost	deterministic		BFO	-	-
Liu & Liu (2019)	min cost	deterministic	-	ACO	*	-
Garcia-Hernandez et al. (2020)	min distance	deterministic	--	hybrid algorithm	*	-
Ahmadi-Javid & Ardestani-Jaafari (2021)	min distance	deterministic	-	SA	*	-
Dahlbeck (2021)	min distance	deterministic	-	cplex	-	-
Liu et al. (2021)	min distance	deterministic	-	firework	-	-
Zhang et al.(2022)	min distance-cost	deterministic	-	tabu search	*	-
Esmikhani et al. (2022)	min cost-max usability	uncertainty (cost)	fuzzy programming	MPS-MNSGA II	*	-
Guo et al. (2022)	min cost	deterministic	-	NSGA II	*	-
This paper	min cost max the number of equipment close access to firefighting equipment close access to favorable climatic conditions keeping noisy departments away from each other	uncertainty (cost-transportation time)	fuzzy programming	NSGA II MOPSO Epsilon Constraint	*	*

According to the literature on the subject under study, it can be said that so far, a comprehensive RFLP has not been modeled and solved considering health and environmental safety criteria under conditions of uncertainty. Therefore, in the third section, a comprehensive model of the stated cases is presented and a suitable chromosome is presented to solve the RFLP.

The main features of this paper can be stated in the following cases:

- Designing a RFLP based on health and environmental safety.
- Consider uncertainty in model parameters based on trapezoidal fuzzy numbers.
- Consider different types of equipment for placement in each hall.
- Suitable chromosome design with high efficiency to solve the RFLP.

Therefore, this article specifically presents a new model of RFLP, which, unlike similar models, deals with aspects of health and environmental safety, such as reducing noise pollution, access to safety equipment, etc. Also, uncertainty is considered in this model, which is not considered in similar models. Solving the problem with meta-heuristic algorithms that led to the definition of a suitable chromosome is also another important feature of this article.

3. Problem Definition and Modeling

In many cases, it is not possible to arrange the facility without changing the size of the departments due to the physical limitations of the hall. Therefore, in some departments, such as administrative departments, it is possible to change the dimensions of the department without changing the area of our department. Therefore, by changing the departments, it is possible to better arrange the facilities without increasing the transfer costs, construction costs, product backlog, and so on. Therefore, the use of a RFLP leads to the reduction of these cases.

In this paper, a RFLP is modeled in different parts of a hall under the uncertainty of cost and transfer time and considering health and environmental safety criteria. The main objective in this paper is the optimal layout of departments in potential parts of the hall with different equipment and facilities. Therefore, according to Figure 1, there are several departments with a certain level of space that should be located in one hall and in different sections. Each part of the hall has different levels of equipment and facilities that are directly related to the cost allocated to it. If a section with more equipment and facilities is selected, the costs associated with it will be higher. In this model, the layout of the departments is based on environmental and health safety criteria is done. According to Table 2, the departments that have an A relationship should be close to each other and the departments that have an X relationship should be away from each other. Since relationships A to X (A, E, I, O, U, X) are based on departmental communications and noise pollution. Therefore, relation A has the lowest level of pollution and relation X has the highest level of pollution. Also, two criteria of access to firefighting equipment and access to favorable climatic conditions (optimal light, optimal wind direction, etc.) are considered in the designed model. Therefore, the departments that have the greatest need for access to firefighting equipment and favorable climatic conditions should be close to these points. Therefore, considering the 5 different aspects of the RFLP have been modeled (transfer and section selection costs, more access to equipment and facilities, distance and proximity of departments based on noise pollution criteria, more access to firefighting equipment and More access to favorable climatic conditions).

Figure 1. Schematic of RFLP

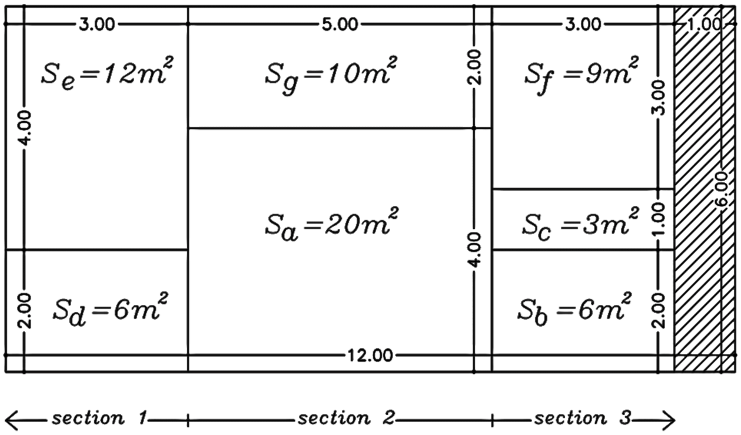

Table 2. Department's relationships based on noise pollution criteria

Department	1	2	3	4	5	6
1		A	E	X	O	O
2			A	E	E	I
3				I	I	O
4					U	X
5						O
6						

A noteworthy point in the matter of robust layout is the possibility of changing the dimensions of the departments. Therefore, the only importance is the issue of allocating the space required by each department to the relevant departments. Due to the length to width ratio assigned to each department, it is not possible to consider the level for each department outside the intended dimensions. Also, due to the uncertainty of the cost parameters and the time of material flow transfer between departments, these parameters are considered as uncertain and using trapezoidal fuzzy numbers in the model. Therefore, in order to control uncertain parameters, fuzzy programming has been used. The assumptions of the robust layout model under uncertainty conditions with respect to health and environmental safety criteria are as follows:

- The RFLP is multi-period, so the material flow in different periods has different values.
- The cost of equipment selection and facilities of each section is directly related to the type of equipment selected.
- Departments should be positioned so that the total width of the departments in each section is the same as the width of the hall.
- There is no overlap between departments.
- The starting point of the layout is (0,0) or the origin of the coordinates.

- Each department is allowed to choose a level of facilities and equipment.
- Departments should not exceed the allowed length and width.
- The cost and time of material transfer between departments are considered as trapezoidal fuzzy numbers.
- Relationships between departments with A = 6 is the least noise pollution and X = 1 is the most noise pollution.

According to the above assumptions, the multi-objective RFLP is modeled in the next section.

Sets

I	Departments $m,n = \{1,2,\dots,I\}$
J	Sections $r,s = \{1,2,\dots,J\}$
T	Period $t = \{1,2,\dots,T\}$
E	Equipment level $e = \{1,2,\dots,E\}$

Parameters

W	The total length of the hall along the x-axis
H	The total width of the hall along the y axis
A_m	The area required for the department m along the planning horizon
α_m	Length to width ratio for department m in all planning periods
S_m^{max}	Maximum length allowed for department m in all planning periods $S_m^{max} = min\{H, \sqrt{A_m\alpha_m}\}$
S_m^{min}	Minimum length for department m in all planning periods $S_m^{min} = \sqrt{\frac{A_m}{\alpha_m}}$
$\widetilde{Ti}_{mn}$	Uncertain transfer time between departments m and n in each time period
$\widetilde{Tr}_{mn}$	Uncertain transfer cost between departments m and n in each time period
F_{re}	The cost of department layout in section r with the equipment level e in all time periods
MC_{re}	Number of equipment and facilities used in section r with equipment level e in all time periods
f_{mnt}	Flow of materials transfer between departments m and n in period t
ToT	Maximum flow time between all departments
V_{mn}	Relationships between departments m and n based on noise pollution
G_m	Percentage of need for department m for faster access to firefighting equipment
P_m	Percentage required for Department m to access suitable climatic conditions
(a,b)	Coordinates of the center of the place of firefighting equipment
(c,d)	Coordinates of optimal light radiation center and suitable wind

Decision Variables

B_r	The length of section r along the planning horizon
L_{mr}	The length of the department m in section r along the planning horizon
H_m	Width of department m along the y-axis
(x_m, y_m)	Coordinates of the center of the department m in the layout
$D_{mn}^x = \lvert x_m - x_n \rvert$	The distance between the center of the department m and n along the programming horizon along the x-axis

$D^y_{mn} = \lvert y_m - y_n \rvert$	The distance between the center of the department m and n along the programming horizon along the y axis
I_{mr}	If department m is assigned to section r, it gets 1, otherwise it gets 0.
U_{re}	If part r is used with the equipment level e, it gets 1, otherwise it gets 0.
Y_{mn}	If department m is above department n in the same section, it gets 1, otherwise it gets 0.

Robust Layout Model under Uncertainty Conditions

$$min\ Z_1 = \sum_{r\in J}\sum_{e\in E} F_{re}.U_{re} + \sum_{m\in I}\sum_{\substack{n\in I\\ n>m}}\sum_{t\in T} f_{mnt}.\widetilde{Tr}_{mn}.\left(D^x_{mn} + D^y_{mn}\right) \tag{1}$$

$$max\ Z_2 = \sum_{r\in J}\sum_{e\in E} MC_{re}.U_{re} \tag{2}$$

$$min\ Z_3 = \sum_{m\in I}\sum_{\substack{n\in I\\ n>m}} V_{mn}.\left(D^x_{mn} + D^y_{mn}\right) \tag{3}$$

$$min\ Z_4 = \sum_{m\in I} G_m.(|x_m - a| + |y_m - b|) \tag{4}$$

$$min\ Z_5 = \sum_{m\in I} P_m.(|c - x_m| + |d - y_m|) \tag{5}$$

$$s.t.:$$

$$D^x_{mn} \geq x_m - x_n, \ \ \forall n > m \tag{6}$$

$$D^x_{mn} \geq x_n - x_m, \ \ \forall n > m \tag{7}$$

$$D^y_{mn} \geq y_m - y_n, \ \ \forall n > m \tag{8}$$

$$D^y_{mn} \geq y_n - y_m, \ \ \forall n > m \tag{9}$$

$$\sum_{r\in J} I_{mr} = 1, \ \ \forall m \tag{10}$$

$$B_r = \frac{1}{H}\sum_{m\in I} I_{mr}A_m, \ \ \forall r \tag{11}$$

$$S^{min}_m I_{mr} \leq B_r \leq S^{max}_m + W(1 - I_{mr}), \ \ \forall m, r \tag{12}$$

$$x_m \geq \sum_{s\leq r\in J} B_s - 0.5B_r - (W - S^{min}_m)(1 - I_{mr}), \ \ \forall m, r \tag{13}$$

$$x_m \leq \sum_{s \leq r \in J} B_s - 0.5B_r + (W - S_m^{min})(1 - I_{mr}),\ \ \forall m, r \tag{14}$$

$$\frac{L_{mr}}{A_m} - \frac{L_{nr}}{A_n} - max\left\{\frac{S_m^{max}}{A_m}, \frac{S_m^{max}}{A_n}\right\}(2 - I_{mr} - I_{nr}) \leq 0,\ \ \forall r, n > m \tag{15}$$

$$\frac{L_{mr}}{A_m} - \frac{L_{nr}}{A_n} + max\left\{\frac{S_m^{max}}{A_m}, \frac{S_m^{max}}{A_n}\right\}(2 - I_{mr} - I_{nr}) \geq 0,\ \ \forall r, n > m \tag{16}$$

$$\sum_{m \in I} L_{mr} = H. \sum_{e \in E} U_{re},\ \ \forall r \tag{17}$$

$$\sum_{e \in E} U_{re} \leq 1,\ \ \forall r \tag{18}$$

$$S_m^{min} I_{mr} \leq L_{mr} \leq S_m^{max} I_{mr},\ \ \forall l, r \tag{19}$$

$$\sum_{r \in J} L_{mr} = H_m,\ \ \forall m \tag{20}$$

$$y_m - 0.5. H_m \geq y_n + 0.5. H_n - H(1 - Y_{mn}),\ \ \forall m \neq n \tag{21}$$

$$Y_{mn} + Y_{nm} \leq 1,\ \ \forall n > m \tag{22}$$

$$Y_{mn} + Y_{nm} \geq I_{mr} + I_{nr} - 1,\ \ \forall n > m, r \tag{23}$$

$$0.5. H_m \leq y_m \leq H - 0.5. H_m,\ \ \forall m \tag{24}$$

$$\sum_{m \in I} \sum_{\substack{n \in I \\ n > m}} \widetilde{Ti}_{mn}. \left(D_{mn}^x + D_{mn}^y\right) \leq Tot \tag{25}$$

$$B_r, L_{mr}, H_m, x_m, y_m, D_{mn}^x, D_{mn}^y \geq 0 \tag{26}$$

$$I_{mr}, U_{re}, Y_{mn} \in \{0,1\} \tag{27}$$

Eq. (1) minimizes the total cost of transferring and selecting different parts to FLP. Eq. (2) seeks to maximize the equipment and facilities allocated to different parts of the hall. Eq. (3) minimize the distance between departments with relation A and seeks to increase the distance between departments with relation X. Eq. (4) Minimizes the distance between facility centers and firefighting equipment centers. Eq. (5) expresses the proximity of departments required to access favorable climatic conditions to the center. Relationships (6) to (9) linearize the broken line spacing functions in the objective function. Equation (10) ensures that each department should be assigned to only one department. Eqs. (11) and (12) specify the width of each section based on the minimum and maximum allowable length changes of the departments. Eqs. (13) and (14) specify the coordinates of the center of the departments along the X-axis.

Relationships (15) to (17) calculate the length of each department assigned to each section. Eq. (18) ensures that each department must use a maximum of one level of equipment and facilities. Eqs. (19) and (20) specify the width of each department along the y-axis. Eqs. (21) to (24) specify the center coordinates of the departments along the y-axis. Eq. (25) ensures that the transfer time between departments does not exceed the maximum time allowed. Eqs. (26) and (27) show the type of model variables.

The cost and transfer time parameters in the aforementioned model are regarded as being unknown. As a result, the model parameters have been controlled using the fuzzy programming approach. The fuzzy programming approach to managing the model's unknown parameters is discussed in the paragraphs that follow. Take into account the following fuzzy parameterized linear mathematical programming model:

$$Min\ Z = \tilde{c}^t x \tag{28}$$

$$s.t.:$$

$$x \in N(\tilde{A}, \tilde{B}) = \{x \in R^n | \tilde{a}_i x \geq \tilde{b}_i,\ \ i = 1, \dots, m \ \ x \geq 0\} \tag{29}$$

Where the fuzzy parameters used in the objective function, vector coefficient, and parameter to the right of the constraint are, respectively, $\tilde{c} = (\tilde{c}_1, \tilde{c}_2, \dots, \tilde{c}_n)$, $A = [\tilde{a}_{ij}]_{m\times n}$ and $\tilde{b} = (\tilde{b}_1, \tilde{b}_2, \dots, \tilde{b}_n)^t$. Based on the characteristics of fuzzy numbers, it is hypothesized that fuzzy parameters have a probabilistic distribution function. Finally, the decision vector is represented as $x = (x_1, x_2, \dots, x_n)$. Controlling the ambiguous parameters offered in the goal and constraint functions is required for the viability and optimization of the problem presented in the aforementioned model. As a result, the controlled model is as follows, assuming that the parameter is the lowest degree of constraint feasibility:

$$Min\ Z = EV(\tilde{c})x \tag{30}$$

$$s.t.:$$

$$[(1-\alpha)E_2^{a_i} + \alpha E_1^{a_i}]x \geq (1-\alpha)E_1^{b_i} + \alpha E_2^{b_i},\ \ i = 1, \dots, m \ \ x \geq 0,\ \ \alpha \in [0,1] \tag{31}$$

The expected value of the fuzzy number utilized in the model's objective function, $EV(\tilde{c})$, is derived as follows and is used in the relationship above:

$$EV(\tilde{c}) = \frac{E_1^c + E_2^c}{2} \tag{32}$$

The problem's indefinite parameters are seen as trapezoidal fuzzy numbers in this study, as well as a potential distribution of the fuzzy parameter $\tilde{C} = (C^1, C^2, C^3, C^4)$. The decision maker determines the level values of the 1 to 4 fuzzy numbers $\tilde{C}$, which are represented by the letters C^3, C^2, C^1, and C^4, accordingly. As a result, the following formula may be used to determine the mathematical expectation (expected value of the fuzzy parameter of the objective function):

$$EI(\tilde{c}) = [E_1^c, E_2^c] = \left[\frac{c^1 + c^2}{2}, \frac{c^3 + c^4}{2}\right] \tag{33}$$

Therefore, the controlled model of the RFLP is as follows:

$$min\ Z_1 = \sum_{r\in J}\sum_{e\in E} F_{re}.U_{re} + \sum_{m\in I}\sum_{\substack{n\in I\\ n>m}}\sum_{t\in T} f_{mnt}.\left[\frac{Tr_{mn}^1 + Tr_{mn}^2 + Tr_{mn}^3 + Tr_{mn}^4}{4}\right].\left(D_{mn}^x + D_{mn}^y\right) \tag{34}$$

$$\sum_{m\in I}\sum_{\substack{n\in I\\ n>m}}\left(\alpha\left[\frac{Tr_{mn}^1 + Tr_{mn}^2}{2}\right] + (1-\alpha)\left[\frac{Tr_{mn}^3 + Tr_{mn}^4}{2}\right]\right).\left(D_{mn}^x + D_{mn}^y\right) \le Tot \tag{35}$$

$$Eq(2) - Eq(24) \tag{36}$$

4. Design of Primary Chromosome

The precise Epsilon constraint technique has been used to solve the issue in small sizes due to the NP-Hardness and the multi-objective nature of the RFLP in uncertain situations, while the NSGA II and MOPSO have been used to solve the problem in larger sizes. As a result, this section explains the principal chromosome that should be used to address the issue as well as how mutation and crossover operators function in the NSGA II and MOPSO. The parameter of the mentioned algorithm is then tweaked using the Taguchi approach to boost its effectiveness in generating an effective solution following the introduction of the indicators utilized in the NSGA II and MOPSO.

The reason for using the above algorithms is the high search ability of these algorithms in the continuous and discrete space of the chromosome simultaneously. The proposed algorithms are among population-based algorithms and have high efficiency in achieving effective solutions. Therefore, two algorithms that have been noticed in the literature have been chosen to solve the problem.

4.1. Primary Chromosomes

The chromosome designed to solve the RFLP as shown in Figure 2 consists of three separate sections. The first part of the chromosome shows the prioritization of the departments for layout in the hall. The second part of the chromosome shows the classification of the departments to be located in each part, and finally the third part of the chromosome determines the equipment and facilities assigned to each part of the hall. Figure 2 shows a problem with the assumption of 6 departments, 3 sections and 3 types of equipment and facilities. Therefore, the first part of the chromosome is the permutation of natural numbers along the number of departments $|I|$. The second part of the chromosome is random numbers between 0 and one with length $|I| + |J| - 1$ and the third part of the chromosome is integers between 1 and | E |.

Table 3. Primary chromosome designed to solving a problem

Section 1	6		5	1	2	3	4	
Section 2	0.23	0.15	0.37	0.11	0.09	0.76	0.67	0.53
Section 3		3			2			1

As shown in Table 3, it can be seen that the order of prioritization of departments for layout starts from department 6 and ends in department 4, respectively. Also, according to the third part of the designed chromosome, it is observed that the third type of equipment is allocated to the first part of the hall, the second type of equipment is allocated to the second part of the hall and the first type of equipment is allocated to the third part of the hall. To decode the above chromosome, the chromosome in Figure 2 must first be modified according to the following steps:

Step 1. Select the largest number among the chromosomes in Section 2 and replace it with the first priority of Section 1.

Step 2. If the genes in Section 2 of the chromosome have the same numbers, a number is randomly selected and replaced by the corresponding Section 1 priority.

Step 3. After replacing all the numbers in section 1 on the chromosome in section 2, the remaining random numbers are reduced to 0.

According to the above steps, the modified shape of the problem chromosome, converts to Figure 3.

Table 4. Modified chromosome to problem solving

Section 2	3	4	2	0	0	6	5	1
Section 3		3			2		1	

According to Table 4, it can be seen that departments 3-4-2 have been allocated to the first part with the level of type 3 equipment and departments 6-5-1 have been allocated to the second part with the level of type 2 equipment. Also, according to Figure 3, it can be inferred that Department 3 should be located under Department 4 and Department 2. Also in the second section, Department 6 should be located under Department 5 and under Department 1. The numbers 0 in the second part of the modified chromosome mean that the new departments are not assigned to the previous section for arrangement in the hall. After categorizing and determining the location of each department for layout, the following two equations are used to allocate the required space of each department in each section and then the coordinate center of each department is calculated.

Step 1. The total space required for each section is divided by the specified width of the hall. In this relation, the length of each section is calculated. $B_r = B_m = \frac{\sum_{m \in I} A_m}{H}$

Step 2. The width of each department can be calculated using the following equation. $H_m = \frac{A_m}{B_m}$

Step 3. If the modified shape of the departments exceeds the interval between S_m^{min} and S_m^{max}, the penalty function is used to justify the problem. Figure 2 shows the RFLP based on the expressed chromosome.

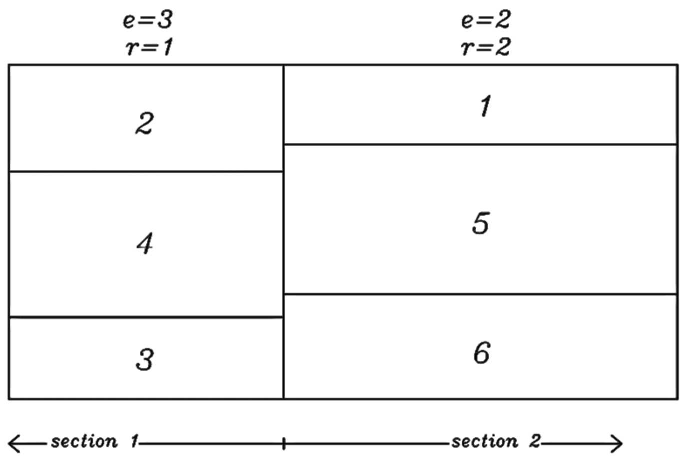

Figure 2. The RFLP based on the expressed chromosome

4.2. NSGA II Operators

Beginning with a basic population of chromosomes that satisfies the problem's boundaries or constraints, the NSGA II generates chromosomes at random. In other words, chromosomes are strings of suggested values for the problem's solution variables, each of which stands for a potential solution. From a series of reproductions known as generations, the chromosomes are determined. The optimization goal is used to assess these chromosomes throughout each generation, and those that are thought to be a better solution to the issue are more likely to replicate problem solutions. In order to speed up the convergence of calculations towards the ideal public solution, it is crucial to develop the chromosomal assessment function. Each string is given a fitness number based on the values obtained by the objective function in the population of strings because in the GA, the amount of the evaluation function for each chromosome must be calculated and because in many cases with a significant number of chromosomes, in general, the timing of the calculation of the evaluation function can actually make it impossible to use the GA on some problems. The likelihood of selection for each string will be determined by this fitness value. A collection of strings is first chosen based on this likelihood. In order to produce new chromosomes for the next generation, either two chromosomes from the present generation are transplanted using the combinatory operator, or chromosomes are modified using the mutation operator. The number of strings in the repeated calculations is then maintained by replacing strings from the starting population with new ones. More agile strings are more likely to join to form new strings and are more resistant to the other strings during the replacement phase, according to random factors that operate on the selection and removal of strings. In this way, the value of the objective function in the population of strings completes and increases the population of sequences in a competition based on the objective function over multiple generations, so that after a number of years, the algorithm converges to the best chromosome, which ideally represents an optimal or sub-optimal solution to the problem. In this algorithm, the search mechanism generally explores the search for regions of the space whose mean of the statistical function of the target is bigger, while genetic operators seek for new points of the search space in each computing iteration. Most of the time, a new population that replaces the old one is fitter than the old one. This implies that it will become better as time goes on. The best chromosome acquired from the most recent generation is picked as an estimated optimum solution or as the actual optimal solution for the issue after the search has reached the maximum generation feasible, convergence has been reached, or the stop requirements have been satisfied.

Mutation Operator: Due to the use of NSGA II to solve the problem, the mutation operator has been used to allocate new equipment and facilities to different parts of the hall. In this operator, in each iteration of the algorithm, a section of the hall is selected and a new number between 1 and $|E|$ is allocated as a new type of facility and equipment and replaces the previous gene on the chromosome. Figure 5 shows how a single-point mutation operator performs on genes in the third part of a modified chromosome.

Table 5. Function of a single-point mutation operator in the third section of chromosome

1	3	3	Child	1	2	3	Parent

According to Table 5, it can be seen that section 2 of the hall has been selected and the level of equipment and facilities of the second type of this section has changed during the mutation to the equipment and facilities of the third type.

Crossover Operator: The second type of operator used in the NSGA II is the crossover operator, which is used to prioritize the arrangement of departments in different parts of the hall. According to this operator, two genes are selected from the first part of the parent chromosome and the selected genes are inversely replaced in the child chromosomes. Figures 6 and 7 show how the combination operator performs on the genes of the first and second parts of the problem chromosome, as well as the modified chromosome, respectively.

According to Table 6, it can be seen that the priority of departments 2 and 3 in the first parent and also the priority of 1 and 3 in the second parent have inversely replaced the relevant genes in children 1 and 2. Also in the second part of the chromosome, the genes of the first / second parent have replaced the genes of the second / first child. Accordingly, the effect of the combination operator on the modified chromosome is shown in Table 7.

Table 6. Function of a two-point crossover operator in the first and second parts of a chromosome

Section 1	6		5		1		2		Parent 1
Section 1 (cont.)									
Section 2	0.23	0.15	0.37	0.11	0.09	0.76	0.67	0.53	
Section 1	2		4		1		3		Parent 2
Section 2	0.12	0.18	0.34	0.82	0.34	0.20	0.16	0.94	
Section 1	6		5		1		3		Child 1
Section 2	0.16	0.94	0.37	0.11	0.09	0.76	0.67	0.53	
Section 1	2		4		3		1		Child 2
Section 2	0.12	0.18	0.34	0.82	0.34	0.20	0.23	0.15	

Table 7. Modified chromosome to problem solving based on a combination operator

Parent 1	3	4	2	0	0	6	5	1
Parent 2	0	6	1	4	3	5	0	2
Child 1	4	6	2	0	0	5	1	3
Child 2	0	6	4	2	3	5	1	0

4.3. MOPSO

Kennedy and Eberhart suggested a technique known as particle motion based on their modeling of bird movement in the air, the finding of a logical link between the direction and speed of birds, and their understanding of physics. Later, the scientists discovered via their own study the reliance of these motions, and they discovered that a bird's movement was influenced by information from birds nearby. As a result, they finished the suggested procedure and named it a swarm motion. The PSO is often quite similar to other algorithms like ACO or GA, but there are also significant distinctions, which help to distinguish and simplify the method. This approach, for instance, does not use operators like intersection and mutation. As a result, this technique is simpler than others like GA since it does not involve the usage of numeric strings or the decoding stage. Using a pseudo-probabilistic function, this method separates the solution space into multi-path pathways, which are created by the motion of individual particles in space. Two key factors contribute to a particle group's mobility (definite and probable). The direction of the best current solution, x^*, or the best solution, g^*, as far acquired, is of importance to each particle.

There exist position and velocity vectors for each moving particle in space, whether or whether it obeys the swarm intelligence. The velocity vector for particle i (the bird) is shown as v_i if the current vector equals x_i. This is in accordance with Eq. (37):

$$v_i^{t+1} = v_i^t + \alpha\epsilon_1 \odot [g^* - x_i^t] + \beta\epsilon_2 \odot [x_i^* - x_i^t] \tag{37}$$

In this equation, the variables ϵ_2 and ϵ_1 are random vectors with element values that range from 0 to 1. Presents the inner multiplication of two matrices as well as learning and acceleration parameters, the variables and are used. The initial location of the particles should be evenly spread over the area, i.e., the position of the particles must be formed with uniform distribution. Additionally, the initial change in direction's velocity should be taken to be zero ($v_i^{t=0} = 0$). The new position vector of each particle will be based on the Eq. (37) in accordance with the velocity vector specified therein Eq. (38).

$$x_i^{t+1} = x_i^t + v_i^{t+1} \tag{38}$$

Any value between $[0, v_{max}]$ may be used for v_i in this equation.

4.4. Epsilon Constraint Method

Multi-objective optimization issues have more objective functions that need to be met than single-objective optimization problems do. When a collection of choice variables increases the value of one function, another function will deteriorate and vice versa. As a result, a collection of optimum candidate solutions is produced rather than a single optimal solution. The "Pareto front" is made up of this group of potential options. In this work, the epsilon-constraint approach was used to derive the Pareto front. While the remaining goal functions (Z2-Z5) are modeled as an inequality epsilon constraint, the first objective is thought of as the primary objective function (Z1):

$$\begin{gathered} Min\ Z1(x) \\ s.t.: \\ Z2(x); Z3(x); Z4(x); Z5(x) \leq \varepsilon \end{gathered} \tag{39}$$

4.5. Comparison Indicators of Efficient Solutions

The multiplicity of mathematical models leads to the creation of different efficient solutions by different solution methods, which makes it difficult to compare efficient solutions and make decisions about the performance of the solution method. Therefore, the following indicators are used to compare the efficient solutions generated by different solution methods (Epsilon constraint, NSGA II and MOPSO): MVOF, NPF, MSI, SM, CPU-Time

4.6. Parameter tuning of NSGA II and MOPSO

This section discusses the parameters used by NSGA II and MOPSO to solve the multi-objective RFLP. In the Taguchi approach, the suitable test design for these control factors should be created once the relevant variables have been discovered, their levels have been chosen, and the technique has been validated. Once the test design has been chosen, the tests are carried out and then evaluated to establish the ideal set of parameters. Three levels have been taken into consideration for each component in this study, and the experiment's design and execution have been chosen based on the number of variables and the number of their levels. The fact that each experiment was repeated an average of three times before the average data were eventually assessed is remarkable. Given that the planned model has several objectives, it is necessary to first compute the value of each experiment using Eq. (40). In this equation, the number of Pareto solutions, the maximum expansion, the spacing, and the processing time are utilized as indices in the comparison of meta-heuristic algorithms. After calculating the value of each experiment, Eq. (41) is used to determine the dimensionless value of each experiment in order to examine the Taguchi experiment's design.

$$S_i = \left|\frac{NPF + MSI + SM + CPU\_time}{4}\right| \tag{40}$$

$$RPD = \frac{S_i - S_i^*}{S_i^*} \tag{41}$$

S_i^* is the best index value across all Taguchi experiments, and S_i is the index value acquired from each Taguchi experiment in relation (41). The recommended and ideal parameter settings for the NSGA II and MOPSO in the small size sample problem are shown in Table 8.

Table 8. Proposed parameter levels for parameter adjustment of NSGA II by Taguchi method

Algorithm	symbol	Level 1	Level 2	Level 3	Optimal Level
NSGA II	max it	50	100	200	200
	Npop	50	100	200	100
	Pc	0.1	0.3	0.5	0.5
	Pm	0.1	0.3	0.5	0.3
MOPSO	max it	50	100	200	200
	Nparticle	50	100	200	100
	C1	1	1.5	2	2
	C2	1	1.5	2	2
	W	0.5	0.6	0.7	0.5

The mean S/N ratio diagram for the NSGA II is shown in Figure 8. As previously indicated, the criteria for choosing the values of the parameters is the greatest value of the SN criterion.

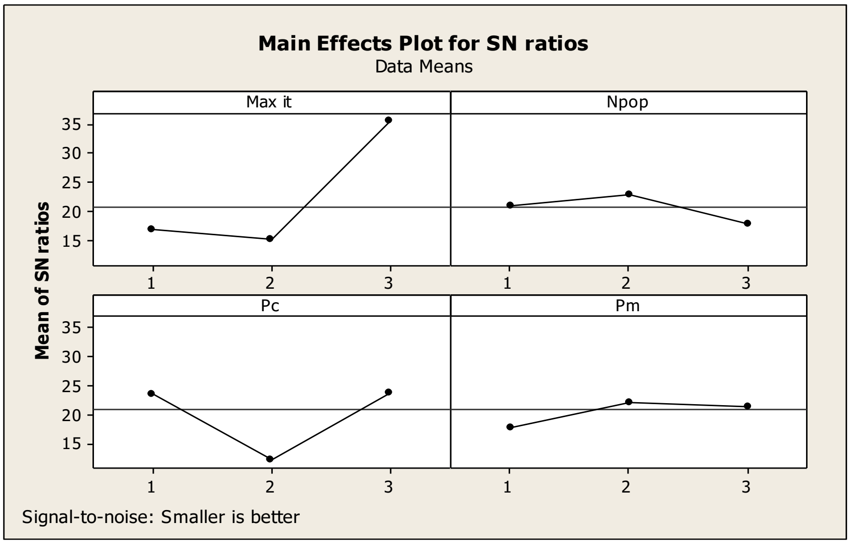

Figure 3. Average diagram of S/N ratio in NSGA II

According to the findings shown in Figure 3, the NSGA II will function most effectively if the maximum number of iterations is at level 3, the population is at level 2, the crossover rate is at level 3, and the mutation rate is at level 2.

The mean S/N ratio diagram for the MOPSO is shown in Figure 4. As previously indicated, the criteria for choosing the values of the parameters is the greatest value of the SN criterion.

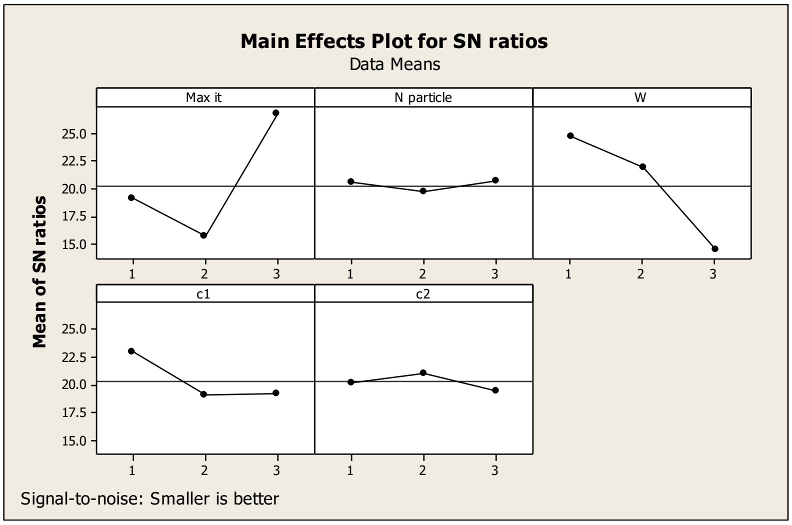

Figure 4. Average diagram of S/N ratio in MOPSO

According to the findings shown in Figure 9, the MOPSO will operate with the greatest efficiency when the maximum number of iterations is at level 3, the population is at level 2, the c1 parameter is at level 1, the c2 parameter is at level 2, and the w parameter is at level 1.

5. Analysis of Experiments

In this phase, the trials are examined and the Pareto front is generated in small and big sizes after creating the main chromosome and parameterizing the metaheuristic algorithms. Since there are 6 departments, 5 sections, 3 kinds of equipment and facilities, and 2 time periods assumed in this section, a small example problem is first evaluated. The problem parameters have been quantified using random data based on the uniform distribution function in line with Table 9 since real-world data is not readily available.

Table 9. Interval limits of certain and uncertain data of the problem

Certain Parameters	Interval Limits	Uncertain Parameter	Interval Limits
W	15	F_{re}	~U[900,1200]
H	10	MC_{re}	~U[1000,4000]
A_m	~U[6,10]	f_{mnt}	~U[10,20]
α_m	2	ToT	3500
P_m	~U[40,100]	V_{mn}	~U[1,6]
(a, b)	(0,0)	G_m	~U[10,60]
(c, d)	(W, H)		

Uncertain Parameter	Level 1	Level 2	Level 3	Level 4
$\widetilde{Tl}_{mn}$	~U[20,30]	~U[30,40]	~U[40,50]	~U[50,60]
$\widetilde{Tr}_{mn}$	~U[50,60]	~U[60,70]	~U[70,780]	~U[80,90]

For a better explanation of the problem data, Figure 5 shows the space of the hall before the FLP and the location of the firefighting equipment as well as the best position of the climatic conditions. On the other hand, Table 5 shows the distance and proximity relationships of departments in terms of noise pollution.

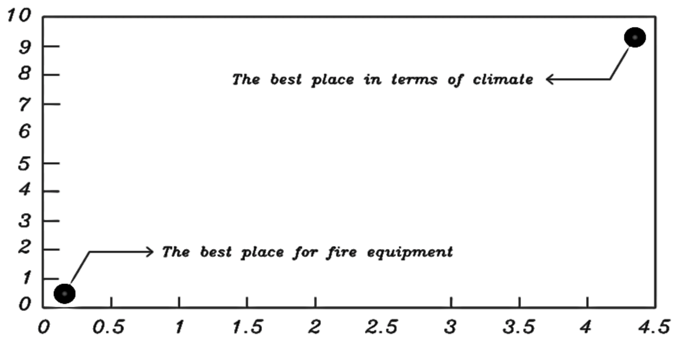

Figure 5. The location of firefighting equipment and suitable climatic conditions in the small size sample problem

Table 10. Department's relationships based on noise pollution criteria in small size sample problem

Department	1	2	3	4	5	6
1		E	I	E	E	I
2			A	U	O	A
3				A	I	I
4					I	O
5						E
6						

The Epsilon constraint approach has been utilized as the exact method and the NSGA II has been used as a meta-heuristic method to solve the issue in a compact size due to the 5 objective functions of the mathematical model. In small-size sample issues, the Epsilon constraint approach has been employed to find effective solutions. It is not feasible to solve example problems of greater sizes using the Epsilon constraint approach (using the CPLEX solver), since it has various restrictions. In order to tackle the issue and compare the outcomes with the Epsilon constraint technique, two algorithms, NSGA II and MOPSO, were utilized. Additionally, all issues have been resolved with the value of = 0.5 owing to the mathematical model's uncertainty. The needed level for departments 1 through 6 is equivalent to 6, 10, 8, 7, and 7 square units, respectively, based on the information in Tables 9 and 10. Table 11 displays the value of each objective function at its finest without taking into account any other objective functions and using a specific optimization technique. Figure 11, which also corresponds to the outcomes of Table 6, displays the ideal departmental organization for each goal function.

Table 11. The best value of each objective function by individual optimization method

Objective Function	The Best Value of VOF	Selected Sections	Optimal Level of Selected Equipment
1	144339.74	5-4	1
2	7505.00	2-1	3
3	1342.05	5-4	1
4	1202.53	5-3	1
5	6429.22	5-4	1

As shown in Table 11, in order to optimize the total cost of the layout, equipment level 1 has been used for sections 4 and 5. While equipment level 3 is intended to maximize the use of departmental equipment for sections 1 and 2 in the second objective function.

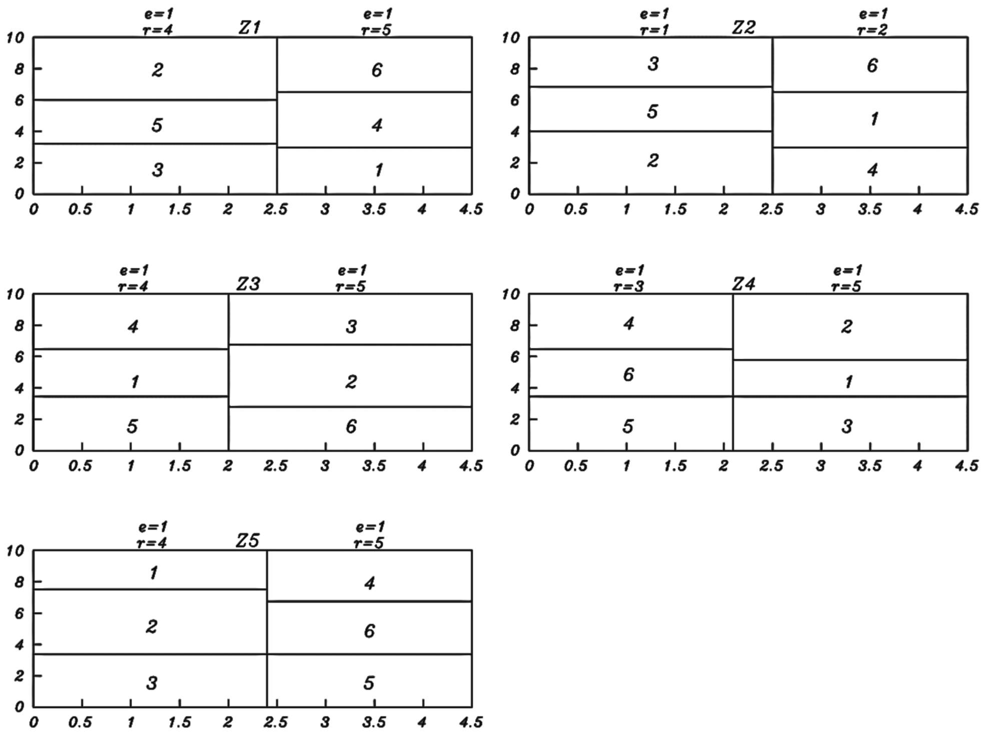

Figure 6. Optimal departments layout based on the best value of VOF

Figure 6 is a description of the model outputs for the accuracy of the results. The results show that the layout space in a hall is 10 x 4.5. The departments are positioned together to achieve the best value for their objective function. For example, in optimizing the first objective function, Department 2 is placed next to Department 6. However, due to the high noise pollution of these two departments, the model intends to place these two departments at two points away from each other. Also, based on the decision variables, each hall is assigned a type of equipment. The results of the previous section have been obtained by considering the width of 10 units for the hall. In the following, in Table 7, the values of the objective functions are shown in exchange for changes in different hall widths.

Table 12. The VOB under different widths of the hall

Width of Hall	6	7	8	9	10
Z1	133350.31	131426.67	133640.37	138974.34	144339.74
Z2	11060	11060	7505	7050	7505
Z3	1218.42	1171.28	1227.55	1295.33	1342.05
Z4	1134.78	1132.90	1142.80	1167.08	1202.53
Z5	5148.86	5541.05	5876.82	6166.90	6429.23

According to the Table 12, it is observed that with decreasing the width of the hall, the distances of the facility center are closer to each other, therefore, the transportation cost and as a result, the amount of the first objective function is reduced. Also, by reducing the width of the hall due to the reduction of access distances to climatic conditions, access to firefighting equipment has been made possible. Figure 7 shows the process of changing the VOB in different widths of the hall.

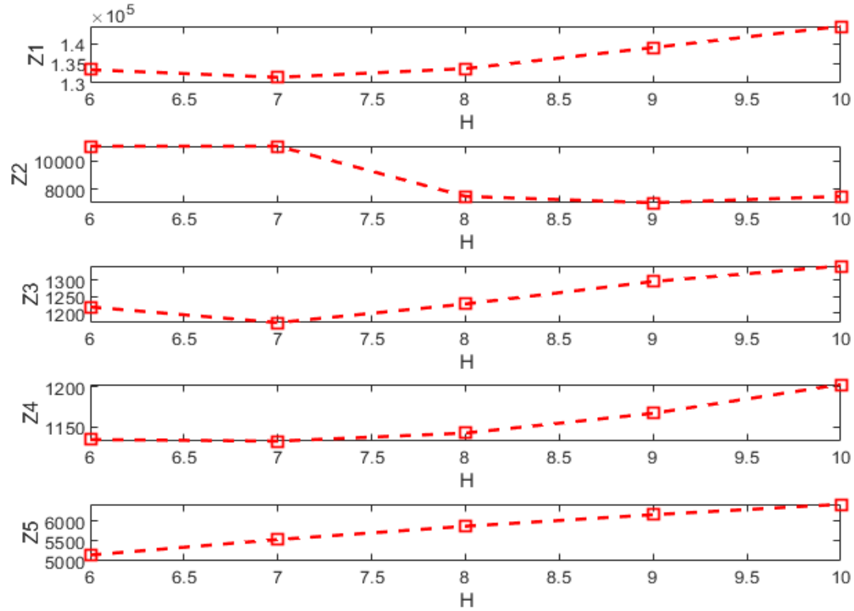

Figure 7. The changing the VOF for different widths of the hall

Due to the application of the Epsilon constraint method in solving the small size problem, 14 efficient solutions have been obtained according to Table 13.

According to Tables 13 and 14 efficient solutions have been obtained for the problem of stable arrangement of facilities in small size by Epsilon method. By analyzing efficient solutions, it can be concluded that the obtained efficient solutions are far from their optimal value and simultaneously optimize 5 objective functions. This conclusion can be reached by examining the output variables of the first efficient solution. Figure 13 shows the arrangement obtained from the first solution of the problem by the Epsilon constraint method.

Table 13. Efficient solutions obtained from problem solving with Epsilon constraint

Efficient Solution	Z1	Z2	Z3	Z4	Z5
1	144398.2	2583	1854.15	1363.89	6570.20
2	144426.6	2594	1584.15	1363.89	6570.19
3	144441.4	2764	1584.15	1363.89	6570.19
4	144395.2	2928	1584.15	1363.89	6570.19
5	146161.0	2583	1465.65	1326.19	6669.16
6	147788.3	2583	1426.62	1309.10	6623.14
7	149961.7	2583	1328.90	1310.89	6688.24
8	144762.5	2583	1652.42	1269.69	6578.91
9	144802.3	2583	1641.41	1260.41	6638.64
10	144787.0	3648	1641.41	1260.41	6638.84
11	144877.5	4075	1641.41	1260.41	6638.84
12	144854.5	4712	1641.41	1260.41	6638.84
13	144991.5	5025	1641.41	1260.41	6638.84
14	144541.0	5139	1584.15	1363.89	6570.19

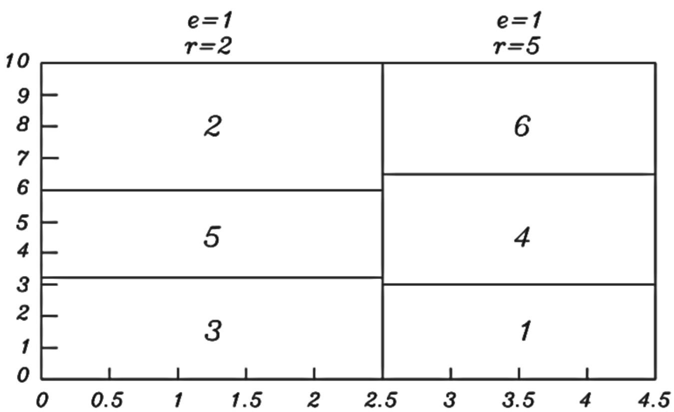

Figure 8. Optimal layout of the first efficient solution to the problem with the Epsilon constraint

As shown in Figure 8, sections 2 and 5 with equipment level 1 have been selected for the first efficient solution. In the following, the effect of the hall width on the layout and the amount of objective functions obtained from the small size problem is investigated.

After examining the output variables of the small sample size problem with the Epsilon method, due to the inability of the CPLEX solver in GAMS software, the NSGA II and MOPSO was used to solve the problem in other sizes. As a result, before designing sample problems in larger sizes, the small size sample problem designed in the previous section with the NSGA II and MOPSO is analyzed. Therefore, first using the GA and in 100 consecutive replications, the optimal value of each objective function of the problem and also the layout obtained in 100 consecutive replications of the GA are shown in Figures 9 to 13.

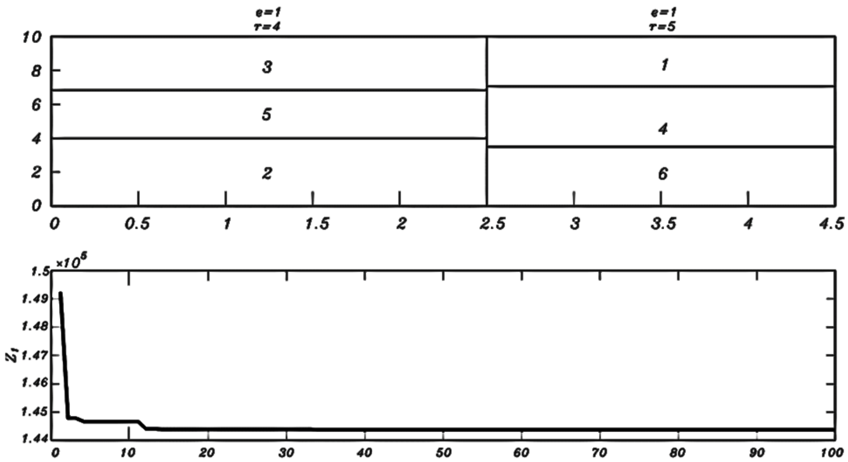

Figure 9. Optimal layout of departments considering the first objective function using GA

According to Figure 14, the GA in 100 consecutive replications has reached the optimal VOB1 with the value of 144339.74.

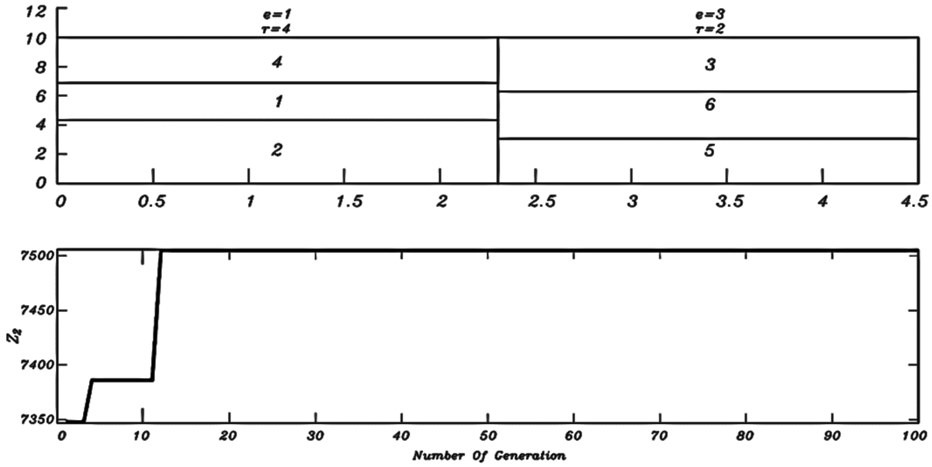

Figure 10. Optimal layout of departments considering the second objective function using GA

According to Figure 10, the GA in 100 consecutive replications has reached the optimal VOB2 with the value 7505.

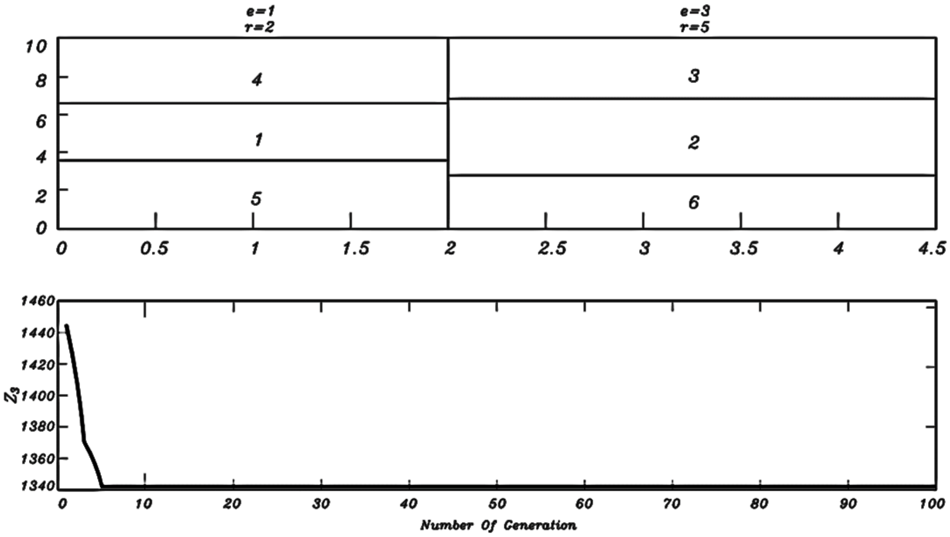

Figure 11. Optimal layout of departments considering the third objective function using GA

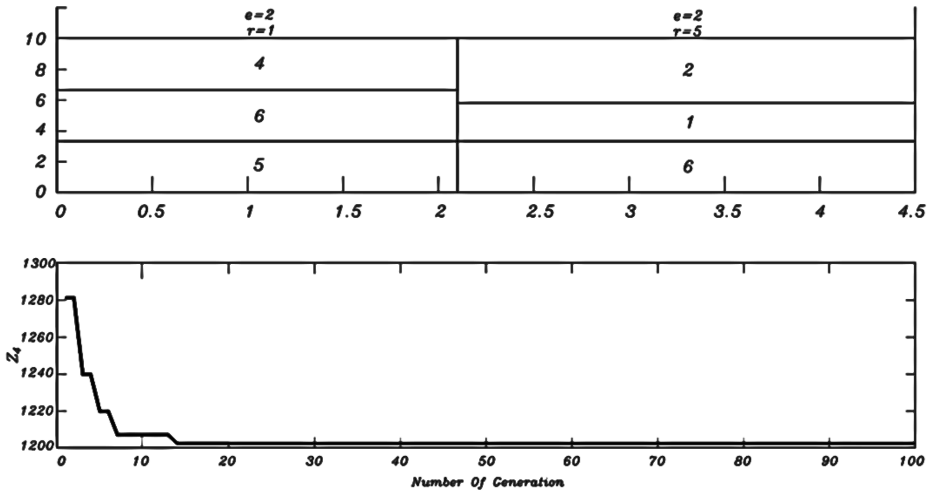

Figure 12. Optimal layout of departments considering the fourth objective function using GA

According to Figures 12 and 13, the GA in 100 consecutive replications has reached the optimal VOB3 with the value of 1342.05 and the optimal VOB4 with the value of 1202.53.

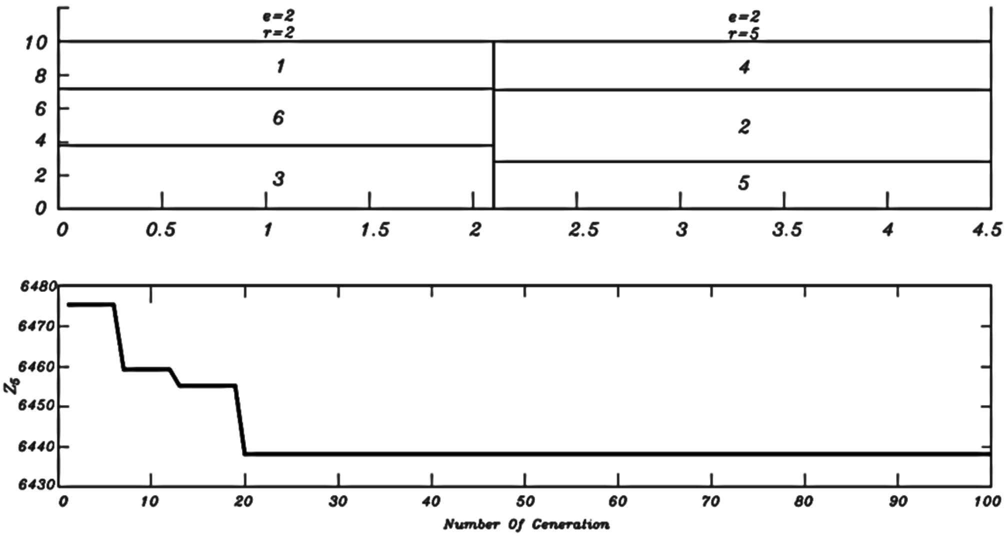

Figure 13. Optimal department layout considering the fifth objective function using GA

According to Figure 13, the GA has reached the optimal VOB5 with a value of 6429.22 in 100 consecutive replications. According to the analysis of 5 objective functions with GA, it can be said that the chromosome designed for the problem has the ability to search all the solution space and the algorithm has achieved the best value of the objective function in a shorter time than GAMS software. Therefore, in order to simultaneously achieve the VOB, the NSGA II and MOPSO has been used simultaneously, which in Figure 19 compares the Pareto front resulting from this method as well as the Epsilon constraint method.

According to the multi-objective functions of the mathematical model, the set of efficient solutions obtained from the three methods of Epsilon constraint, NSGA II, and MOPSO is based on the operators of each solution method. For this purpose, according to Figure 14, the set of efficient solutions is drawn based on the dominant and recessive methods, and it is not possible to compare each efficient solution between the three solution methods. The results show that the Epsilon method obtained a limit of 14 efficient solutions, the NSGA II 56 efficient solutions, and the MOPSO obtained 48 efficient solutions from solving the small size sample problem. Therefore, to compare the set of efficient solutions between the three methods, we used other indicators such as the means of efficient solution in each objective function, NPF, MSI, SM, and CPU-Time. Therefore, Table 9 compares the indices obtained from the two solution methods.

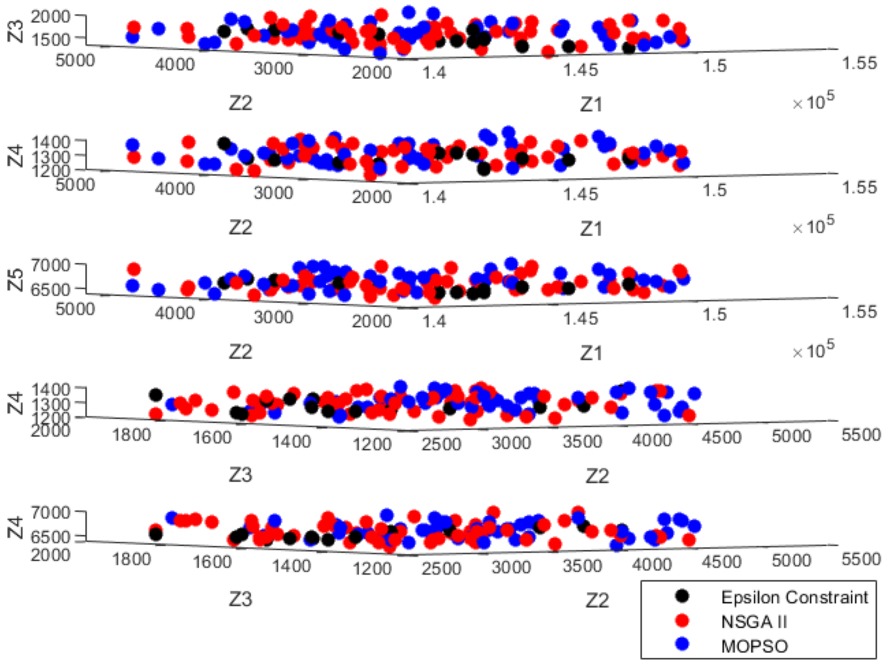

Figure 14. Comparison of Pareto front by different solution methods in small size problem

Table 14. Comparison of indices obtained by different solution methods in small size problem

Indicator	NSGA II	MOPSO	Epsilon Constraint Method
Z1	152559.11	151465.24	145370.61
Z2	3388.35	3320.34	3313.07
Z3	1543.83	1552.34	1592.95
Z4	1347.72	1349.27	1309.81
Z5	6634.23	6624.28	6614.60
NPF	56	48	14
MSI	18928.56	14552.53	6147.21
SM	0.37	0.48	0.83
Cpu-time	76.26	84.72	77912

The results of Table 14 show that the NSGA II and MOPSO has a very small relative difference with the Epsilon constraint method. Also, by comparing the indices, it can be stated that this solution method has performed better than the Epsilon method in obtaining the indices of the VOB2 and VOB3, NPF, MSI, SM and the CPU-time. Therefore, these algorithms can be used to solve large size sample problems with higher confidence. Table 15 shows 15 sample problems in different sizes (small to large) that have been solved by the NSGA II and MOPSO. Also, the data related to sample problems in different sizes are in accordance with the data of Table 4 presented in this section.

Table 15. Size of different sample problems in larger sizes

Sample Problem	I	J	T	E	H	W
Description	Departments	Sections	Period	equipment Level	Width of the Hall	Length of the Hall
1	8	5	4	3	10	10
2	10	5	4	3	10	10
3	12	6	5	3	10	12
4	15	6	5	4	12	12
5	20	8	6	4	15	12
6	30	8	6	4	18	15
7	40	10	8	5	20	15
8	50	10	8	5	22	15
9	60	12	10	5	25	20
10	70	12	10	6	28	20
11	80	15	12	6	30	20
12	100	15	12	8	35	22
13	120	20	15	8	38	25
14	140	30	15	10	40	25
15	150	40	18	12	50	25

It should be noted that each sample problem is solved 3 times by NSGA II and MOPSO and the average of three repetition results is shown in Table 15. Figure 15 also shows the trend of changes in efficient solution indices to solve larger sample size problems with the NSGA II and MOPSO.

Table 16, which presents the findings, reveals that the NSGA II handled the biggest sample issue significantly faster than the precise approach and MOPSO did for the small sample problem. To illustrate the layout, Figure 16 is an example of the layout of Problem No. 5.

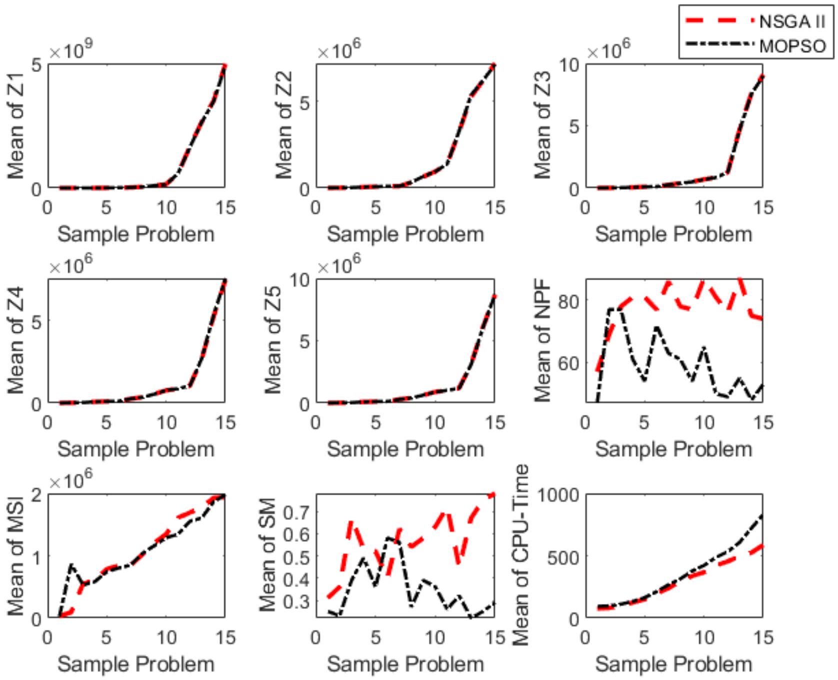

Figure 15. The trend of changes in the indicators obtained from larger size

Table 16. Average indicators obtained from solving larger sample size problems

Algorithm	Sample Problem	Z1	Z2	Z3	Z4	Z5	NPF	MSI	SM	CPU-time
NSGA II	1	604601.39	4560.25	1024.09	2367.98	4351.69	57	28335.03	0.31	76.93
	2	887478.48	11054.02	8946.34	15743.28	18367.16	69	95823.69	0.36	81.15
	3	971739.10	23466.25	19746.29	26846.97	31321.47	78	551380.23	0.67	99.16
	4	1243671.26	49636.28	51746.29	74519.48	86939.39	81	608919.66	0.53	124.69
	5	5892462.03	76198.24	96345.33	96541.68	112631.96	81	787045.30	0.52	149.69
	6	11171739.10	93515.89	112135.84	108664.73	126775.52	77	839400.43	0.40	196.15
	7	21564432.21	106989.11	258439.28	255883.29	298530.51	86	847148.69	0.62	238.49
	8	45759412.36	324578.98	377159.20	347423.36	405327.25	78	1019828.92	0.54	297.16
	9	97458813.56	653797.47	494251.89	542286.21	632667.25	77	1204811.42	0.58	337.25
	10	148267928.26	947883.12	684512.22	764895.68	892378.29	87	1346780.37	0.63	367.49
	11	578462816.18	1387368.48	849826.44	864482.35	1008562.74	81	1609488.85	0.72	421.68
	12	1654829737.67	3257281.28	1248354.90	1035299.53	1207849.45	76	1691987.99	0.45	454
	13	2651722898.00	5267883.26	4687817.00	2659794.11	3103093.13	87	1776773.49	0.67	496.49
	14	3493376750.45	6204124.76	7591312.62	5233833.79	6106139.42	75	1927387.88	0.75	525.10
	15	4981940516.60	7187365.65	9099814.96	7443840.07	8684480.08	74	1942519.37	0.78	585.58
MOPSO	1	607822.77	4495.82	1026.77	2358.80	4274.05	47	25701.36	0.25	93.62
	2	874556.25	11005.61	8931.15	15637.43	18629.69	77	865596.14	0.23	97.44
	3	975904.20	23181.95	19464.72	27134.10	31512.81	77	529008.61	0.39	111.72
	4	1235825.18	48755.95	51581.45	74402.82	87062.85	61	586489.17	0.49	132.98
	5	5969870.79	77717.24	95892.14	95344.87	114850.32	54	742514.01	0.36	163.57
	6	11252147.38	95142.68	112747.70	109311.09	126180.24	72	802727.85	0.58	211.59
	7	21157186.71	107387.39	260830.41	257450.57	293299.80	63	849537.64	0.56	266.24
	8	45124346.38	327898.17	377096.34	345816.44	401895.23	61	1036406.25	0.27	314.17
	9	96236159.47	665496.20	492236.46	534458.89	633714.26	54	1160577.81	0.39	377.16
	10	145483553.80	949720.12	681680.77	772879.53	880341.34	65	1288019.76	0.36	422.29
	11	577724700.42	1392565.27	835730.69	864383.48	1019733.53	50	1343745.97	0.26	486.50
	12	1630590978.02	3283364.93	1264869.69	1035844.01	1183925.04	49	1552220.48	0.32	532.56
	13	2636524486.62	5367556.19	4621185.80	2689026.92	3085837.36	55	1605701.61	0.22	607.21
	14	3462855558.07	6214897.48	7563145.39	5321825.81	6071187.71	48	1865596.15	0.25	720.91
	15	4904722278.57	7116953.59	8974483.98	7537069.96	8729513.91	53	1979008.97	0.29	831.01

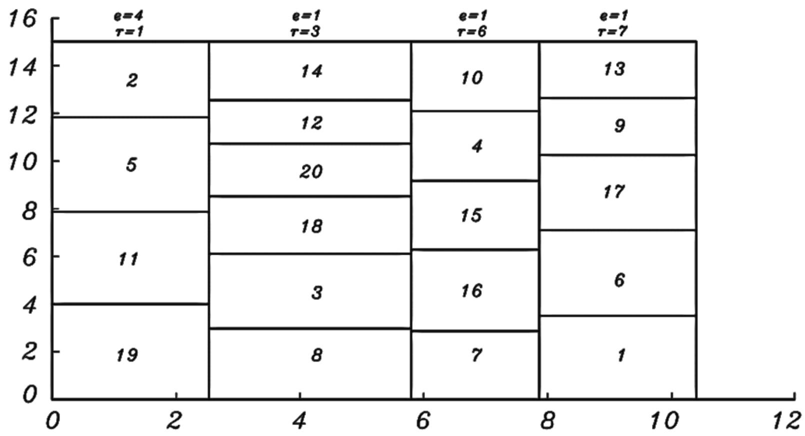

Figure 16. Optimal layout of the department from the first efficient solution to sample problem number 5

6. Conclusion

In this paper, a RFLP is modeled by considering health and environmental safety criteria under uncertainty. The main purpose of this issue was departments layout in different parts of a hall and to allocate the necessary space to the departments as well as to determine the type of equipment and facilities required for each selected section. To achieve the above goal, 5 criteria were the total cost of transfer and selection of the department, access to more equipment and facilities, access to firefighting equipment, access to favorable climatic conditions and the distance of noisy departments from each other. To solve the problem, the exact Epsilon constraint method as well as the NSGA II and MOPSO using a suitable chromosome were used. The results of computational results showed that the GA in all single-objective optimization problems has achieved the optimal value of the objective function, which indicates the high efficiency of the designed chromosome and the algorithm used to solve the sample problems. Also, the results of solving the problem of small size sample showed that the NSGA II has a relatively small relative difference with the Epsilon method. The SM index and computational time performed better than the constraint method. Therefore, 15 sample problems in different design sizes and efficient solution index averages were obtained for each sample problem. According to the results, the NSGA II solves the largest sample problem in a much shorter time than the exact method and MOPSO solving time in the small sample problem, so it has a high efficiency compared to accurate solving methods.

The results obtained from the article and its analysis show that not considering the location of cranes in production units in order to make maximum use of their capabilities can be considered as one of the limitations of the research. Also, if the considered physical space is an irregular polygon, it is not possible to model and solve it with exact methods. Therefore, the development of the model for its applicability in any situation is one of the researchers' suggestions.

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