FUZZY OPTIMIZATION AND MODELLING 2(3) (2021) 24-35

E-ISNN: 2676-7007

Contents lists available at FOMJ

Fuzzy Optimization and Modelling

Journal homepage: http://fomj.qaemiau.ac.ir/

Paper Type: Research Paper

Integrating Developed Evolutionary Algorithm and Taguchi Method for Solving Fuzzy Facility's Layout Problem

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ARTICLE INFO

Article history:

Received 15 May 2021r
Revised 8 September 2021
Accepted 16 September
Available online 16 September 2021

Keywords:
Fuzzy sets
Optimization
Facility's Layout
Quadratic Assignment Problem.

ABSTRACT

The quadratic assignment problem (QAP) is one of the combinatorial optimization problems belonging to the NP-hard problems' class and has a wide application in the placement of facilities. Thus far, many efforts have been made to solve this problem and countless algorithms have been developed to achieve optimal solutions, one of which is the Genetic Algorithm (GA). This paper aims at finding a suitable layout for the facilities of an industrial workshop by using a developed genetic algorithm and Taguchi Method (TM). The research method in the current study is mathematical modeling and data was analyzed using genetic algorithm in Minitab and MATLAB. The results show that the Developed Genetic Algorithm (DGA) is highly efficient, as it has the power to discover many optimal solutions. Therefore, according to the obtained results, it is recommended that when the genetic algorithm (GA) is used to solve problems, it is better to run this algorithm several times; because the proposed method increases the variety of answers in the genetic algorithm and power for discovering the optimal solution becomes more.

1. Introduction

The facility layout or the quadratic assignment problem is a spatial layout of goods production or service provision facilities. Koopmans and Beckmann were the first to define the issue of layout of facilities as a common industrial problem [1].

The design of the layout is an optimization problem that tries to make deployment more efficient, taking into account the various interactions between the facilities and materials transportation system [3].

The layout problem is used in many production systems. Typically, the problem of placing facilities (including offices and machinery) is in the factory space. Since the layout is affecting transportation costs, usually the main cost in manufacturing organizations, efficient layout will have a significant role in the

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DOI: 10.30495/fomj.2021.1930688.1027

performance of the organization. Transportation costs account for 20 to 50 percent of the total operating costs and also 15 to 70 percent of the cost of producing a commodity. This cost is calculated based on the flow of materials among the departments and the distance between them, and the best option is the arrangement that would have the lowest transportation cost [6].

For more than five decades, scientists have studied the quadratic assignment problem and have made remarkable discoveries in this regard. Most mathematical scientists, computer science experts, operative research analysts, and economists use the quadratic assignment problem to model a variety of optimization problems [1].

Hicks [12] developed Genetic algorithm to be used in facility layout in a set of productive cells. The results showed that the approach of redesigning facilities determines intracellular layout, then it localizes the cells among empty departments. Moradi and Shadrokh [13] investigated the site layout planning (SLP) with equal and unequal surface areas. The SA algorithm was used to find the optimal layout. Comparison of the SA results with those of other algorithms showed the superiority of the SA in finding optimal solutions with high speed in a shorter time. Jafari et al. [9] investigated the facility layout problem in an industrial workshop. Their problem-solving recommendation was to use a developed simulated annealing algorithm (DSAA). That algorithm is an iterative form of the basic simulated annealing algorithm (BSAA). The results indicate the ability of the proposed algorithm to find better solutions. Kane et al. [10] investigated the transportation problem (TP) and introduced a formulation of TP involving triangular fuzzy numbers for the transportation costs and values of supplies and demands. They proposed a two-step method for solving fuzzy TP where all of the parameters are represented by non-negative triangular fuzzy numbers i.e., an Interval Transportation Problems and a Classical Transport Problem. To illustrate the proposed approach two application examples are solved. The results show that the proposed method is simpler and computationally more efficient than existing methods in the literature.

This paper discusses the fuzzy quadratic assignment problem (QAP) as material handling is not often a crisp number. On the other hand, the QAP is a nonlinear assignment problem and there is, therefore, no exact solution (algorithm) for this problem. The FQAP problem is solved in this paper with the help of a developed genetic algorithm (DGA). The use of a largely diverse initial population is among the features of the proposed algorithm.

The paper proceeds as follows. The next section formulates the mathematical form of the classical quadratic assignment problem. Section 3 gives basic definitions of fuzzy set theory. Section 4 formulated the fuzzy model of QAP. In Section 5, the general steps of the genetic algorithm are introduced. Section 6 presents our proposed method for solving fuzzy QAP. Section 7 illustrates its applicability by use of a case study. Section 8 summarizes the main results obtained and suggests potential extensions.

2. Mathematical form of the classical problem

Assignment implies that each facility conforms to one location and vice versa. In quadratic assignment problem (QAP), the number of facilities and locations should be equal. The mathematical format of this problem is as follows [17]:

$$Min\ C = \frac{1}{2}\sum_{i=1}^{n}\sum_{j=1}^{n}\sum_{k=1}^{n}\sum_{s=1}^{n} d_{i,k} w_{j,s} x_{i,j}\, x_{k,s} \tag{1}$$

Subject to:

$$\sum_{j=1}^{n} x_{i,j} = 1\ ;\ i = 1,2,\dots,n \tag{2}$$

$$\sum_{i=1}^{n} x_{i,j} = 1\ ;\ j = 1,2,\dots,n \tag{3}$$

$$x_{i,j} = \begin{cases} 0 \\ 1 \end{cases} ;\ i,j = 1,2,\dots,n \tag{4}$$

In this mathematical model, $d_{i,k}$ represents the distance between the i^{th} and k^{th} locations, $w_{j,s}$ shows material handling between the j^{th} and s^{th} machines.

According to the constraint on the first group, each location is assigned to a machine and According to the constraint on the second group, each machine is assigned to a location. If $x_{i,j} = 1$, then the j^{th} machine is placed in the i^{th} location.

3. Fuzzy set theory

The need for paying attention to ambiguity (vagueness) was introduced in 1920, but it did not grow too much due to the lack of a strong rational until 1965 when the Iranian professor of the University of California (UC), Professor Lotfi Zadeh, proposed the fuzzy set or the so-called multi-valued set theory as a useful tool to deal with ambiguity and the lack of precision in human-made systems and fuzzy decision-making processes. Fuzzy thinking was raised following the objection to Aristotelian logic concerning the distance of logic and reality. Aristotelian logic forming the basis of classic mathematics assumes a two-valued universe. In fact, Aristotelian logic sacrifices precision for ease. Actual phenomena are always fuzzy, i.e., vague and inaccurate [5].

A triangular fuzzy number like $\tilde{A}$is represented as $\tilde{A} = (a^l, a^m, a^u)$ where a^l, a^m, and$a^u$are respectively called the left foot, middle foot, and right foot. The membership function of $\tilde{A}$ is defined as follows [5]:

$$\mu_{\tilde{A}}(x) = \begin{cases} \frac{x-a^l}{a^m-a^l} & a^l \le x < a^m \\ \frac{a^u-x}{a^u-a^m} & a^m \le x < a^u \\ 0 & \text{otherwise} \end{cases} \tag{5}$$

Addition, subtraction, multiplication, and division operations for the two triangular fuzzy numbers, $\tilde{A} = (a^l, a^m, a^u)$ and $\tilde{B} = (b^l, b^m, b^u)$, and the scalar number k, are as follows [2]:

$$\tilde{A} + \tilde{B} = (a^l + b^l, a^m + b^m, a^u + b^u) \tag{6}$$

$$\tilde{A} - \tilde{B} = (a^l - b^u, a^m - b^m, a^u - b^l) \tag{7}$$

$$\tilde{A} * \tilde{B} = (\min\{a^l b^l, a^l b^u, a^u b^l, a^u b^u\}, a^m b^m, \max\{a^l b^l, a^l b^u, a^u b^l, a^u b^u\}) \tag{8}$$

$$\frac{\tilde{A}}{\tilde{B}} = \left(\min\left\{\frac{a^l}{b^l}, \frac{a^l}{b^u}, \frac{a^u}{b^1}, \frac{a^u}{b^u}\right\}, \frac{a^m}{b^m}, \max\left\{\frac{a^l}{b^l}, \frac{a^l}{b^u}, \frac{a^u}{b^1}, \frac{a^u}{b^u}\right\}\right); 0 \notin \tilde{B} \tag{9}$$

$$k * \tilde{A} = (ka^l, ka^m, ka^u) \tag{10}$$

4. Mathematical formulation of the fuzzy QAP

The mathematical formulation of the fuzzy quadratic assignment problem (FQAP) is expressed as follows:

$$Min\ C = \frac{1}{2}\sum_{i=1}^{n}\sum_{j=1}^{n}\sum_{k=1}^{n}\sum_{s=1}^{n} d_{i,k}\widetilde{w}_{j,s} x_{i,j}\, x_{k,s} \tag{11}$$

$Subject\ to$:

$$\sum_{j=1}^{n} x_{i,j} = 1\ ;\ i = 1,2,\dots,n \tag{12}$$

$$\sum_{i=1}^{n} x_{i,j} = 1\ ;\ j = 1,2,\dots,n \tag{13}$$

$$x_{i,j} = \begin{cases} 0 \\ 1 \end{cases};\ \ i = 1,2,\dots,n\ \&\ j = 1,2,\dots,n \tag{14}$$

Here, $\widetilde{W}$ represents material handling under fuzzy conditions. Other variables are interpreted as those in the classical QAP.

The quadratic assignment problem is an exponential complex problem, as issues with dimensions larger than ten ($n \ge 15$) cannot be solved or a great amount of time is needed to solve them [12]. Hence, an evolutionary algorithm will be used to solve the layout problem in this research. The results of evolutionary algorithms, especially the genetic algorithm, are highly dependent on the primary population or the first generation [16]. In other words, if an appropriate original population is not available to the genetic algorithm, the likelihood of finding better solutions (in this research, better layouts) is reduced. On the other hand, according to the rules of the genetic algorithm, the primary population must be created completely randomly and no precise Operator has been introduced for creating the first generation so far. Therefore, in this research, which is dedicated to a case study, a simple method is suggested to solve this problem.

This research study aims to find a solution to a mathematical problem and formulate and solve the problem using mathematical literature. Hence, the mathematical modelling method (nonlinear allocation model) was used. In other words, the problem is modelled through mathematics and the final model is solved using a meta-heuristic algorithm (genetic algorithm).

Note that according to evolution theory of Darwin, generations with superiority over other generations will enjoy a greater chance of survival, and their superior characteristics will be passed on to their next generations. Also, the second part of Darwin's theory states that when a child's organ is propagated, some accidental events change the characteristics of the child organ; if these changes are beneficial to the child organ, it will increase the probability of the survival of that child organ. In computerized calculations, methods are suggested for optimization problems according to Darwin's theory; all these methods come from evolutionary processing in nature. Search methods are called evolutionary search algorithms [7].

5. Genetic Algorithm

Genetic algorithm (GA) is a search technique in computer science to find an approximate solution for optimization and search issues. Genetic algorithm is a particular type of evolution algorithm that uses evolutionary biology techniques such as inheritance and mutation. This algorithm was first introduced by John Henry Holland. In fact, genetic algorithms use Darwin's natural selection principles to find the optimal formula for predicting or matching patterns. Genetic algorithms are often a good option for regression-based prediction techniques. In artificial intelligence, genetic algorithm is a programming technique that uses genetic evolution as a problem solving model. The problem to be solved possesses inputs that are converted into solutions in a process modeled from genetic evolution; then, solutions are evaluated by the evaluation function as candidates, and the algorithm ends if the conditions required for exit are met. Genetic algorithm is generally a repetition-based algorithm, most of whose parts are selected as random processes [7]. The operators of this algorithm are described below.

5.1. Coding and evaluation operator

Genetic algorithms deal with their coded form rather than working on the parameters or variables of the problem. Binary coding is a method of encoding, in which the goal is to transform the problem's solution into a string of binary numbers. This Operator is also possible as a permutation [1].

The fitness function is acquired by implementing the proper transformation to the target function, that is, the function to be optimized. This function evaluates each string with a numerical value that specifies its quality. The higher the quality of the response's string, the more efficient the response will be, and the probability of participation for the next generation will also increase [1].

5.2. Crossover and mutation Operators

The most important operator in the genetic algorithm is the crossover operator. Crossover is a process in which the old generation of chromosomes is mixed and combined to create a new generation of chromosomes. The couples considered in the selection section as the parent exchange their genes together and creating new members in this section [1].

Mutation is also another operator that gives rise to other possible answers. In the genetic algorithm, after a member has been created in a new population, each gene mutate with the probability of mutation. In a mutation, a gene may be removed from a population of genes, or a gene that has not been present in the population may be added [11].

5.3. Different steps of GA

The main phases of the genetic algorithm from the beginning to the end include [12]:

1. Start
2. Creating a primary population.
3. Estimating the initial population and sort the members.
4. Determining the best member in the primary population.
5. Performing reproduction in the previous generation.
6. Making a jump in the previous generation.
7. Selecting the optimal members of the population from the previous generation, population from reproduction and mutated population.
8. Assessing the population in the new generation and sorting the members.
9. Determining the best member in all generations.
10. If the stop condition is not met, go to step 5 otherwise go to step 11.
11. End

These steps are also shown in the flowchart in Figure 1.

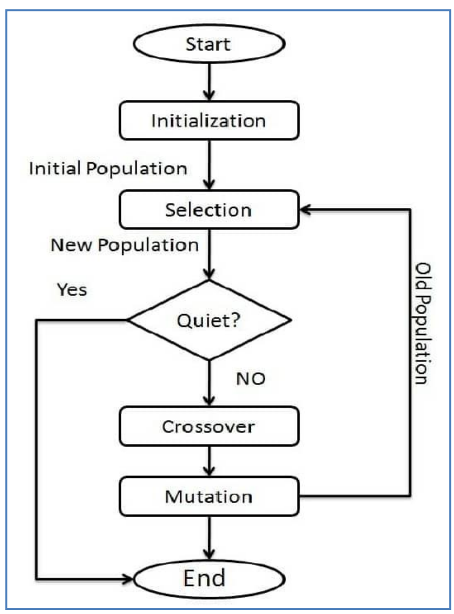

Figure 1. The Flowchart of genetic algorithm [12]

Figure 2 shows the structure of a chromosome, in fact, this chromosome is the coded shape of an answer to the layout problem. In Figure 3, an instance of crossover operator is shown, and Figure 4 illustrates an instance of mutation operator.

3	1	4	5	2
Gene1	Gene2	Gene3	Gene4	Gene5

Figure 2. The structure of a chromosome

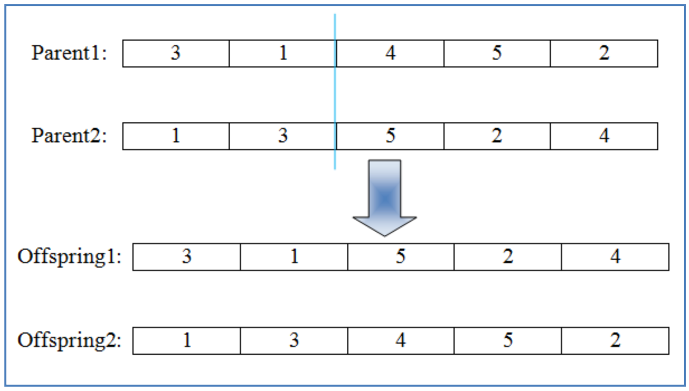

Figure 3. A sample of crossover operator

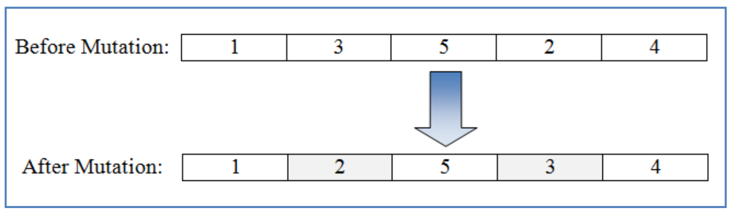

Figure 4. A sample of mutation operator

Note that the fitness function in the current genetic algorithm is the same objective function in the FQAP problem.

6. The proposed approach

After completing the computer codes associated with the genetic algorithm, the algorithm is placed in a repeating loop and it will be executed countless times (N). This causes the algorithm to be very diverse in the first generation. Finally, the best scenario is chosen from the recovery scenarios. Depending on the importance of the problem, researchers can select the N number large or small. Obviously, choosing larger Ns will yield more reliable results. The proposed algorithm is shown in Figure 5.

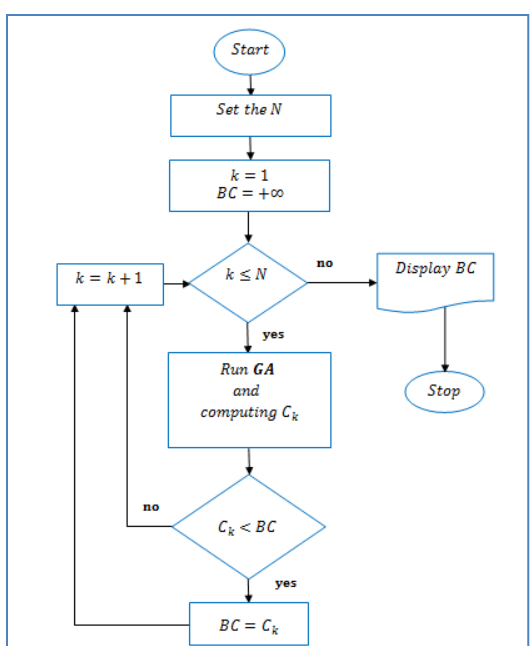

Figure 5. Flowchart of the Proposed Algorithm

7. Case study

A case study in this research involves an industrial workshop producing a variety of wood and metal products. The workshop consists of 15 facilities and 15 locations. The purpose of this paper is to establish optimal facilities at locations, based on the distance between locations and the machines transportation flow.

Facilities available in the industrial workshop include panel (F1), mitre saw (F2), MDF cutting machine (F3), profile saw (F4), sheet scissors (F5), metal profile and angle welding machine (F6), metal sheet welding machine (F7), paint gun and air pump (F8), various types of drills (F9), metal sheet bending jaw (F10), PVC thermal machine (F11), metal and wood surface grinding machine (F12), pattern printing machine on metal doors (F13), inbound warehouse (F14), and outbound warehouse (F15).
The distance between the locations is shown in Table 1.

Table 1. Location Distance Matrix

	L1	L2	L3	L4	L5	L6	L7	L8	L9	L10	L11	L12	L13	L14	L15
L1	0	8	17	25	33	41	42	34	26	18	12	8	11	18	26
L2	8	0	9	17	25	33	50	42	33	26	18	11	8	12	18
L3	17	9	0	8	16	24	59	50	42	34	26	18	12	8	11
L4	25	17	8	0	8	16	66	58	50	42	34	26	18	11	8
L5	33	25	16	8	0	8	74	66	58	50	42	33	26	18	11
L6	41	33	24	16	8	0	82	74	65	58	50	41	33	25	18
L7	42	50	59	66	74	82	0	9	17	25	33	42	50	58	66
L8	34	42	50	58	66	74	9	0	9	17	25	33	41	50	58
L9	26	33	42	50	58	65	17	9	0	8	16	25	33	41	49
L10	18	26	34	42	50	58	25	17	8	0	8	17	25	33	41
L11	12	18	26	34	42	50	33	25	16	8	0	9	17	25	33
L12	8	11	18	26	33	41	42	33	25	17	9	0	8	17	25
L13	11	8	12	18	26	33	50	41	33	25	17	8	0	9	17
L14	18	12	8	11	18	25	58	50	41	33	25	17	9	0	8
L15	26	18	11	8	11	18	66	58	49	41	33	25	17	8	0

Table 2 shows displacements between machines (facilities). Also, triangular fuzzy numbers in the verbal system (Figure 6) were used to convert verbal variables to numerical variables.

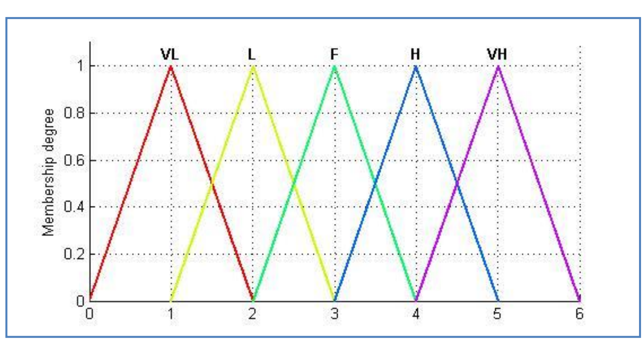

Figure 6. The verbal system [16].

Table 2. Material handling with verbal variables

	F1	F2	F3	F4	F5	F6	F7	F8	F9	F10	F11	F12	F13	F14	F15
F1	-	F	VL	-	F	-	VH	-	-	L	-	L	F	-	H
F2	F	-	-	L	-	F	-	F	-	-	VL	-	-	VL	-
F3	VL	-	-	F	VL	-	VL	-	VH	VL	-	-	-	-	F
F4	-	L	F	-	VH	VL	H	-	-	-	-	L	F	-	-
F5	F	-	VL	VH	-	F	VL	-	VL	-	L	-	-	-	H
F6	-	F	-	VL	F	-	-	H	-	F	-	VL	-	-	-
F7	VH	-	VL	H	VL	-	-	-	F	-	-	-	-	-	VL
F8	-	F	-	-	-	H	-	-	L	VL	VH	-	-	H	-
F9	-	-	VH	-	VL	-	F	L	-	VL	-	-	VL	-	-
F10	L	-	VL	-	-	F	-	VL	VL	-	-	L	-	-	F
F11	-	VL	-	-	L	-	-	VH	-	-	-	-	VL	-	-
F12	L	-	-	L	-	VL	-	-	-	L	-	-	-	-	-
F13	F	-	-	F	-	-	-	-	VL	-	VL	-	-	VH	-
F14	-	VL	-	-	-	-	-	H	-	-	-	-	VH	-	F
F15	H	-	F	-	H	-	VL	-	-	F	-	-	-	F	-

Table 3 explains this verbal system.

Table 3. Fuzzy membership functions [16]

Verbal variable	Membership function
Very Low(VL)	(0,1,2)
Low(L)	(1,2,3)
Fair(F)	(2,3,4)
Hight (H)	(3,4,5)
Very Height (VH)	(4,5,6)

Beginning reconstruction in the aftermath of the Second World War, Japan was facing such problems as lack of raw materials, quality equipment, and skilled engineers. The struggling country joined the competition for producing high quality products and maintaining quality improvement. The task of devising a novel method to deal with the problem of competition, quality improvement, and optimization of experiments was assigned to Genichi Taquchi, whose studies in the late 1940s helped expand the science of quality and specifically gave birth to the concept of a loss function. He combined loss, cost, and variation functions to obtain a measure of quality control. Using his method, Taguchi showed how engineers can design experiments to produce higher quality products at lower costs [4].

The Taguchi method is used by today's optimization experts to determine parameter values in Metaheuristic Algorithms (MA). The present study also utilized this approach to determine the optimum values for parameters of the Genetic Algorithm (GA) at 4 levels. These parameters and their default values are listed in Table 4.

Table 4. Parameters and their default values

Levels	Default Values			
	Number of Population	Number of Iteration	Percent of Crossover	Percent of Mutation
Level1	10	80	30	30
Level2	15	90	40	40
Level3	20	100	50	50
Level4	25	110	60	60

Implementing the Taguchi method in Minitab suggested the experiments shown in Table 5.

Table 5. Experiments suggested by the Taguchi method

Number of Experiment	Number of Population	Number of Iteration	Percent of Crossover	Percent of Mutation	Cost
1	1	1	1	1	2186.8
2	1	2	2	2	2164.2
3	1	3	3	3	2091.4
4	1	4	4	4	2129.5
5	2	1	2	3	2100.9
6	2	2	1	4	2109.6
7	2	3	4	1	2123.8
8	2	4	3	2	2148.1
9	3	1	3	4	2122.3
10	3	2	4	3	2125.9
11	3	3	1	2	2137.2
12	3	4	2	1	2087.4
13	4	1	4	2	2110.5
14	4	2	3	1	2134.9
15	4	3	2	4	2111.5
16	4	4	1	3	2117.6

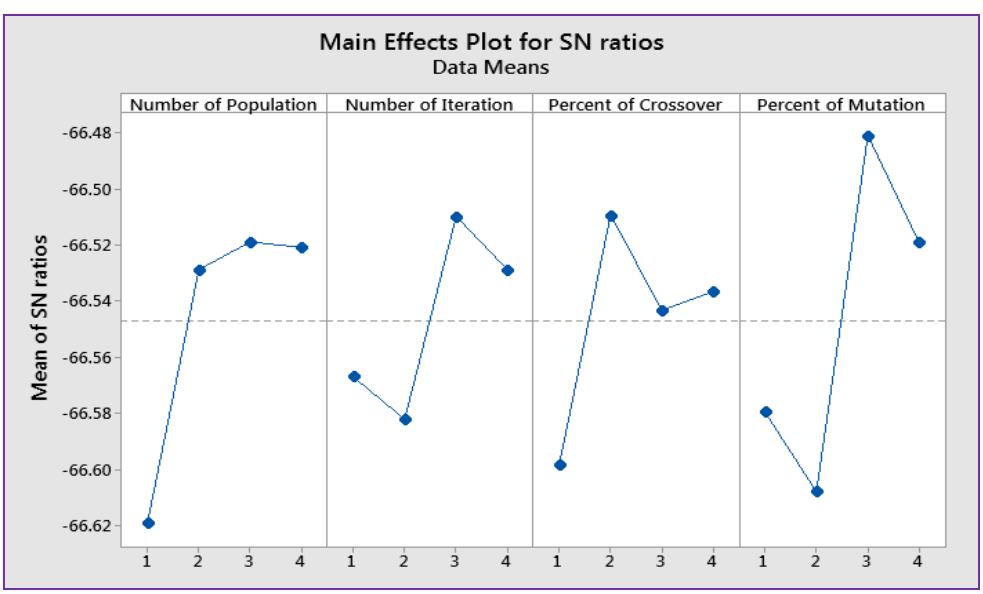

Figure 7. The results obtained by analyzing Table 5.

The Taguchi method suggested 16 experiments for the studied problem. The cost of each experiment is listed on the right column of Table 5. These values were obtained by running each experiment 10 times and calculating their average. An analysis of Table 5 by Minitab is resulted in Figure 8. It can now be concluded from Figure 7 that the best values for the GA parameters are according to Table 6.

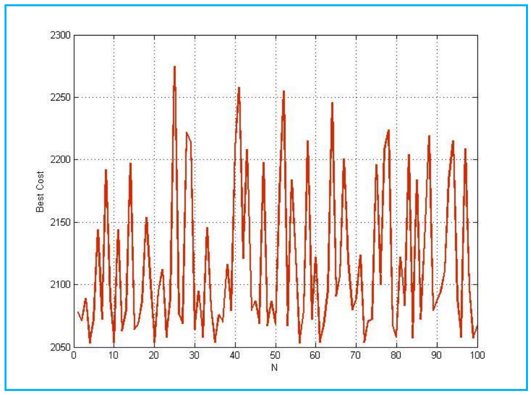

Figure 8. The amount of best costs in various algorithm performances

Table 6: The best values for the GA parameters

	Number of Population	Number of Iteration	Percent of Crossover	Percent of Mutation
Level	3	3	2	3
Value	20	100	40	60

To determine the best-case layout, the proposed algorithm has been used with $\mathrm{N} = 100$, population 20, iteration 100, 40% reproduction, and 60% mutation. In Figure 8, the amount of best costs is presented in various algorithm performances.

According to the results, the cost of the best layout obtained from the proposed method is 2053 equivalent to (1101, 2053, 3005) under fuzzy conditions. The average fuzzy cost is (1136.21, 2115.2, 3094.19) equivalent to 2115.2 under certain conditions. The cost of the present arrangement of the studied workshop equals 3186. Obviously, the cost of the layout obtained from the genetic algorithm (GA) is 64% of that of the present layout. In another words, the new layout causes 36% savings in the costs. Table 7 also shows the optimal layout.

For example, Facility 5 should be assigned to Location 1. Other cases are interpreted in the same way.

The following relation is used for defuzzification of layout costs as $\widetilde{Cost} = \left(C^l, C^m, C^u\right)$ [16]:

$$\frac{C^l+2C^m+C^u}{4}. \tag{15}$$

Most studies on facility placement assume that all machinery can be deployed in all locations. In real-world problems, however, this assumption may not be true. This study deals with a case in which certain machinery cannot be deployed in certain locations. This problem clearly requires more constraints than the basic problem. Therefore, a specific mathematical model was defined for the research problem. Since this model does not have an exact solution, genetic algorithm was employed to solve it. The results of the problem solution indicate an acceptable placement for the workshop under study. Moreover, the study is significant in another aspect. Here, different initial populations were used in the data analysis to arrive at different solutions, since the initial solutions played a crucial role in the genetic algorithm in the final solutions.

Table 7. The optimal layout

	F1	F2	F3	F4	F5	F6	F7	F8	F9	F10	F11	F12	F13	F14	F15
L1	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0
L2	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0
L3	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1
L4	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0
L5	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0
L6	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0
L7	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0
L8	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0
L9	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0
L10	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0
L11	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0
L12	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0
L13	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0
L14	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0
L15	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0

8. Conclusion

Proper layout of facilities has a direct relationship with the final cost of goods in large and small manufacturing units. If an incorrect location is found for facilities in industrial units, it is evident that the more the interactions between workstations or departments of production unit increase, the more the manufacturing costs will increase. Meanwhile, the mentioned problem is one of the exponential complex problems that generally need meta-analysis methods to be solved. In this study, by adding a simple step with genetic algorithm, attempts were made to create generations with greater diversity so that the algorithm could achieve better results and it does not stuck in local extrema. Future studies can address the problem of facility placement with unequal areas using meta-heuristic algorithms.

Conflict of interest: The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgment

Hereby, the Sajjad Cabinet Manufacturing Company is thanked for providing us with the required data.

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https://doi.org/10.30495/fomj.2021.1930688.1027

Received: 15 May 2021 Revised: 8 September 2021 Accepted: 16 September 2021