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A three-stage optimization model for scheduling facility maintenance considering random failure rates

F. Zagia[a], O. Motamedi Sedeh[b], and B. Ostadi[b,*]

a. *Master of Civil Engineering, Center Tehran Branch, Islamic Azad University, Tehran, Iran.*
b. *Faculty of Industrial and Systems Engineering, Tarbiat Modares University, Tehran, Iran.*

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Abstract. The increasing value of facilities, on the one hand, and the complexity of the equipment used in them, on the other, have increased the importance of planning for the maintenance of facilities, especially for companies whose facilities are located in different locations. In this paper, a new hybrid model is presented to optimize facility maintenance scheduling by a combination of Genetic Algorithms (GA), Particle Swarm Optimization (PSO), and the Monte Carlo Simulation for organizing facilities located in different locations as well as determining the optimum number of crews with mechanical, electrical and simple skills. The main contributions of this paper include: (a) optimizing the number of crews by different skills in the first stage; (b) evaluation of fitness value for each solution through the Monte Carlo Simulation model; and (c) scheduling by considering different failure rates for different facilities in different locations. In order to evaluate the performance of the proposed model, the model has been compared with Golpira model, the results of which demonstrate that it is possible to reduce the cost by just over 39% and reduce Mean Time Between Failures (MTBF) by over half.

1. Introduction

Facility Management (FM) is the process of managing and maintaining facilities in an organization. Facilities include an office complex, physical resources at the company or site, and any other mechanical and electrical utilities that can cause health or create safety hazards for employees. FM is an integrated approach for an organization to operate, maintain, improve, and adapt its buildings and infrastructures in such a way that the primary objectives of the organization, occupants, owners, and facility managers can be supported [1].

FM deals with synchronizing activities, supporting main company activities by managing staff administration, auxiliary work activities and business environments-activities related to care of real estate, and building and selecting employee administration. According to the definition put forward by the IFMA Association, FM is "a method of an organization's alignment of work environment, workers, and work activities. It incorporates principles of business administration, architecture, humanities, sciences and engineering" [2].

Regarding these facts, the use of FM can affect the ability of an organization to carry out its activities more efficiently and meet all its requirements. The

*. *Corresponding author.*
E-mail address: bostadi@modares.ac.ir (B. Ostadi)

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FM objective is mainly to provide a better working environment and condition for an organization to help it meet its main goals. FM comprises various areas, but it is Facility Maintenance Management (FMM) that constitutes most (65%∼85%) of the total costs incurred by FM activities [3].

Facility maintenance is the process of increasing the utility of a building by regularly servicing capital assets, commercial appliances, and areas inside or around a building. Operations and maintenance of facilities encompass a broad spectrum of services, competencies, processes, and tools required to ensure the built environment will perform the functions for which a facility was designed and constructed [4]. However, due to the lack of comprehensive models and techniques for managing a facility and the absence of adequate building maintenance policies in most companies, all maintenance activities are usually done with high cost and delay [4]. Maintenance is a process that aims to prevent deterioration of buildings and to repair any damage to a building. Buildings are damaged when some of its components fail to function properly. There are many types of building damages, some of which can be seen in electrical system, water supply, floor, roof, drainage system, and the walls. This problem is solved through building maintenance utilized to repair or restore the equipment that cannot function well. The problem occurring in a building affects its tenants, which is the reason why the maintenance process is very important to implement. In other words, it is required to ensure that the tenants are convenient and safe to use the building. The longest span of time in the lifecycle of a building belongs to the Operation and Maintenance (O&M) or FM phase [5].

The maintenance optimization problem, which has been divided into three types, namely strategy selection, maintenance planning, and maintenance scheduling, consists of the development and analysis of mathematical models with the aim of improving or optimizing maintenance [6]. This paper focuses on optimization scheduling maintenance.

In terms of scheduling maintenance, several models and algorithms have been proposed for optimizing scheduling in the literature. These models can be divided into two groups, single-objective model [7] and multi-objective models [8] with different objective functions including optimization model based on cost minimization [9], reliability-based optimization function model [7], optimization model for safety maximization [10], risk of failure minimization model [11], maximization of profit [12], maintainability based model [13], and availability based model [9]. Different techniques such as Genetic Algorithm (GA) [14], Particle Swarm Optimization (PSO) [15], Non-dominated Sorting Genetic Algorithm-II (NSGA-II) [16], mixed integer linear programming [17], and Monte Carlo Simulation [12] have been applied for solving the aforementioned models.

In 2003, Cassady and Kutanoglu proposed a new model to optimize scheduling using a single-objective function that aimed to reduce tardiness. The model also took into account various constraints, including maintenance time, total weight of component, use of labor, and planning period [18].

In the same year, Dieulle et al. proposed a new model for scheduling optimization using a single-objective function that aimed to reduce tardiness. Their proposed model incorporated different constraints such as system availability requirements, inspection activity, use of labor, and planning period [19].

In 2004, Coolen-Schrijner and Coolen proposed a novel scheduling model that optimizes a single objective by incorporating tardiness as the objective function, along with various constraints such as component age, labor utilization, and planning period [1].

In 2008, Lugtigheid et al. proposed a new model for optimization planning using a single objective function by incorporating tardiness as the objective function, along with different constraints like maintenance time, component age, repair improvement factor, and planning period [20].

In 2012, Flage et al. introduced a novel approach to optimization scheduling using a multi-objective model. Their method focused on minimizing tardiness while taking into account various constraints, including component age, inspection activity, labor utilization, and planning period [21].

In 2013, Wang and Zhang presented a new multi-objective model for optimizing scheduling. Their approach aimed to minimize tardiness while taking into account various constraints such as system availability requirements, component age, inspection activity, failure rate, labor usage, and planning period [22].

In 2013, Zitrou, et al. proposed a new model for optimizing planning using a single-objective function aiming to reduce tardiness and while considering different constraints such as component age, failure rate, and planning period [2].

Finkelstein, in 2015, proposed a new model to optimize planning through a multi-objective function by considering tardiness reduction as the objective function, while taking into account different constraints such as system availability requirements, repair improvement factor, failure rate, and planning period [23].

In 2015, Lin et al. proposed a new model to optimize planning through a single-objective function by considering tardiness reduction as the objective function and different constraints such as repair improvement factor, failure rate, and planning period [24].

Zhou et al. in 2015, proposed a new model to optimize scheduling by a single-objective function by considering tardiness reduction as the objective function and different constraints such as component age, repair improvement factor, failure rate, component limit, labor utilization, and planning period [25].

In 2015, Liu et al. proposed a new model to optimize scheduling through a single-objective function aiming to reduce tardiness while taking into account different constraints such as component limit, maintenance priority, labor utilization, and planning period [3].

In 2018, De Jonge and Jakobsons proposed a new model for optimizing scheduling through a single-objective function by considering tardiness reduction as the objective function and different constraints, including component age, repair improvement factor, labor utilization, and planning period [26].

In 2018, Fouladirad et al. proposed a new model to optimize planning through a single-objective function by considering tardiness reduction as the objective function and different constraints, including component age, failure rate, and planning period [27].

From a review of the literature, different objective functions are considered for the scheduling problem, as indicated in Figure 1.

This study presents a new three-stage model for facility maintenance scheduling that functions based on GA, PSO, and the Monte Carlo Simulation model by considering different required work skills and the outsourcing possibility for each task in different locations. To answer the main question concerning the optimal number of maintenance teams and the best work flow and maintenance schedule for a whole year based on maintenance crew limitation, the current paper makes contributions in the following ways:

- A new three-stage model is proposed to optimize scheduling;
- The number of crews by different skills is optimized in the first stage;
- The fitness value for each solution is evaluated through the Monte Carlo Simulation model;
- Scheduling is optimized by taking into account different failure rates for different facilities in different locations.

According to the above, the remainder of this paper is organized as follows: In Section 2, the proposed model with its combination of GA, PSO, and the Monte Carlo Simulation is explained. In Section 3, the proposed model is applied to a real-world case study, the results of which are interpreted. Finally, a brief summary and some concluding notes are provided in Section 4.

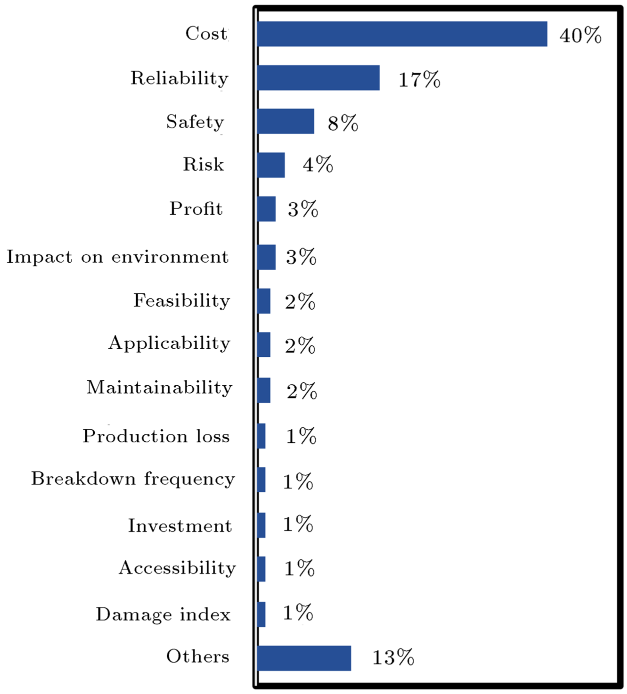

Figure 1. Frequency of different objective functions in maintenance scheduling [4].

2. Research methodology and proposed model

Different models have been considered in the literature to optimize the maintenance scheduling problem with different assumptions. The proposed model incorporates the following assumptions:

- Different failure rate functions correspond to different skills in different locations;
- Out-of-work-time transferring between all locations is assumed;
- Transferring time from one location to another takes less than one day;
- Maintenance tasks are independent;
- There is no possibility for outsourcing;
- There are workers with three mechanical, electrical, and simple skills for performing maintenance tasks;
- By assuming the consumption of parts and equipment in all models, the cost of buying parts is not considered;
- The location of all crews on day 0 are the same;
- All crews can stay in all locations.

The symbols related to sets, parameters, and decision variables used in the mathematical model are presented in Table 1.

Based on Table 1, the mathematical model to optimize the maintenance scheduling has been considered as the following equations where the objective function is based on cost minimization that consist of three parts of crew cost and transportation cost [5]:

Table 1. Notation of the mathematical model.

Sets	
$K = \{k_1, k_2, k_3\}$	Number of crews in each skill
$d = 1, 2, \cdots, T$	Number of days
$n_k = \{1, 2, ..., n_k\}$	Number of available workers with the kth type of specialty
$N = \{1, 2, ..., n\}$	Set of nods for services
$A = \{(i, j) \mid i, j \in N, i \neq j\}$	Set of arcs
Parameters	
T	Period of planning
S	Period of work time on each day
$t^d_{k,i}$	The demand time of the ith node for kth type of specialty on days d
$C_{i,j}$	Cost of travel from node i to node j
C'_k	Cost of using the kth specialty in all time periods
C''_i	Cost of failure in the ith location
$F_{k,i}$	Failure rate in the ith location where the kth skill is needed
Decision variables	
X^{d,n_k}_{ij}	1 if the nkth worker goes from node i to node j on days d; else, 0
X'^{d,n_k}_{ij}	1 if the node i is visited by the n_kth worker right before node j on days d; else, 0
Y_i	Number of failures in the ith location
Z_{ij}	Number of transfers from node i to node j

$$\min \quad z = \sum_{k=1}^{k} \sum_{i=1}^{n} C'_k n_k + \sum_{j=1}^{n} \sum_{i=1}^{n} C_{ij} z_{ij} + \sum_{j=1}^{n} C_i'' y_i, \tag{1}$$

$$\sum_{j}^{n} S y^{d,n_k}_{ij} \geq t^d_{k,i} \qquad \forall k \in K, d \in D, \tag{2}$$

$$Z_{ij} = \sum_{n_k=1}^{n} X^{d,n_k}_{ij} \qquad \forall i, j \in N, \tag{3}$$

$$\sum_{i=1}^{n} X^{d,n_k}_{ij} = \sum_{i=1}^{n} X^{d,n_k}_{ji} \qquad \forall i, j \in N, d \in D. \tag{4}$$

This model is applied to optimize the number of optimum crews by minimizing the maintenance cost for many facilities in different locations and each facility experiences certain failures due to explorational probability functions for different skills. Therefore, for solving the proposed model, a combination of GA, PSO, and Monte Carlo Simulation has been considered based on the following pseudocodes, as shown in Figure 2:

1. Generate crews randomly as an initial generation;
2. Put $g = 1$;
3. If $g = 1$, go to Step 7; else, go to Step 4;
4. Create a new generation for some crews by updating previous generation by selection, crossover, and mutation;
5. Check the feasibility of each solution and refine it, if necessary;
6. Put $g = g + 1$;
7. Generate maintenance schedules randomly as location of particles based on the number of crews;
8. Evaluate the fitness value of each solution based on Monte Carlo Simulation;
9. Check the stop condition for the PSO algorithm; if it is true, go to Step 10; else, go to Step 11;
10. Check the stop condition for the model; if true, stops the algorithm else go to Step 11;
11. Determine the best location for each particle;
12. Determine the best location for all particles;
13. Update the location of all particles; and
14. Go to Step 9.

Based on the proposed model, GA was applied in the first stage to optimize the number of crews in different skills. Then, based on the results of GA, scheduling was proposed for each crew by the PSO model. Finally, the simulation model was applied to evaluate the fitness value for each scheduling.

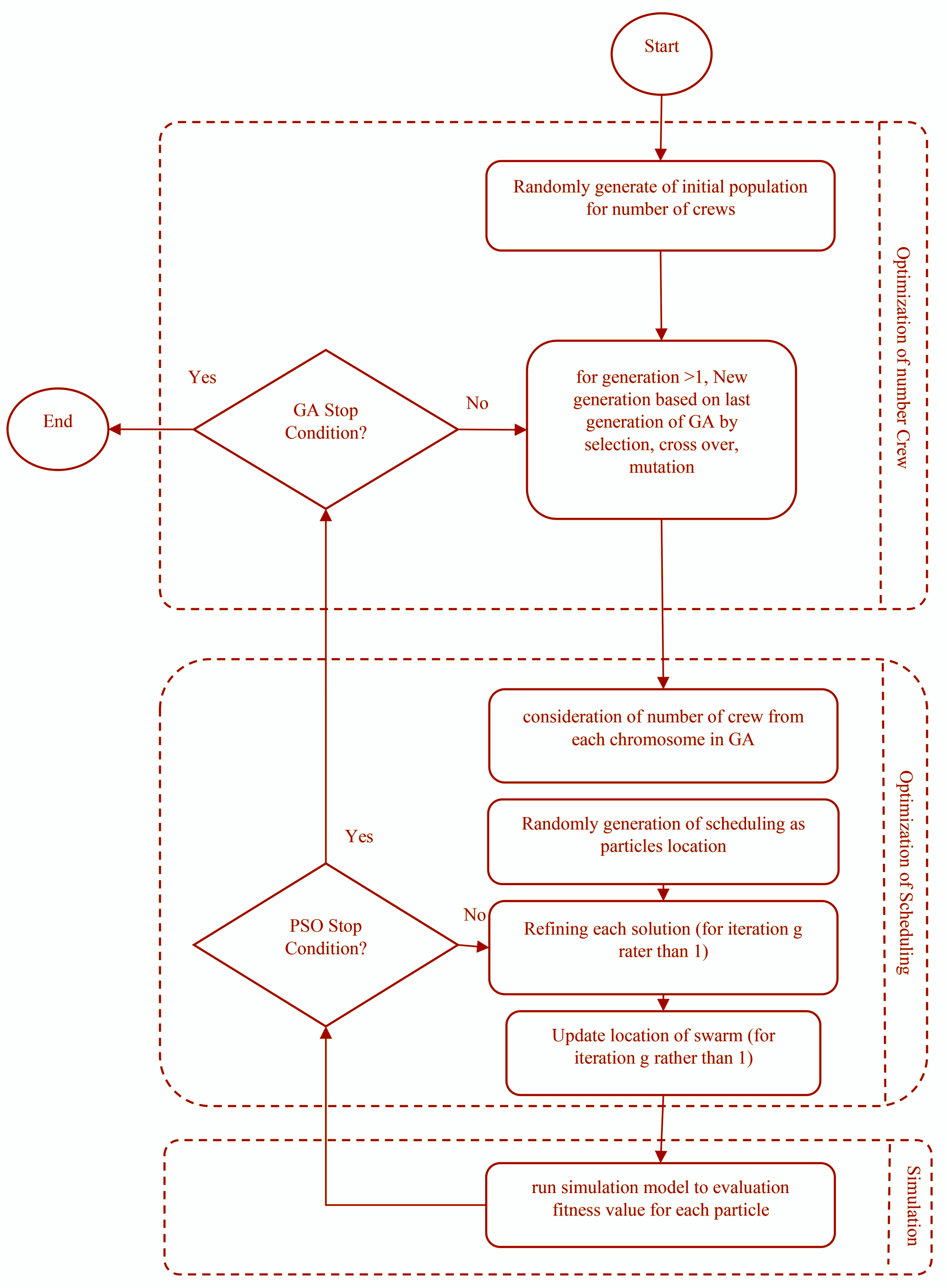

Figure 2. Proposed model.

2.1. Genetic Algorithm (GA)

GA is a heuristic algorithm for random search in the domain of biology evolution. The algorithm has been successful in solving hard optimization problems such as Traveling Salesman Problem (TSP), Vehicle Routing Problem (VRP), etc. GA includes operations of initial population generation, fitness evaluation, selection, crossover, and mutation [28].

In this paper, GA is employed to generate the number of crews with different skills due to its flexibility and ability to search for parts from populations of points in the entire problem space instead of one specific part of solution space. Therefore, GA is an efficient and effective technique to find an approximate solution to optimization and search problems. In the proposed model, GA is applied in the following manner:

Step 1. Randomly generate the initial population of chromosomes using the value encoding method. The ith chromosome in the initial population is shown by g_i^0 as $1\times k$ (k is the skill number), in which each value in this vector is an integer number indicating the number of crews with a certain skill.

$$g_i^0 = [\ a_{i1}^0 \quad a_{i2}^0 \quad a_{i3}^0 \qquad a_{ik}^0\ ]_{1k}. \tag{5}$$

All values on this vector are generated randomly.

Step 2. By considering each solution from Step 1, the PSO algorithm and Monte Carlo model were run and the fitness value of each chromosome was evaluated based on the result of Monte Carlo Simulation model.

Step 3. When the stop condition (when there has been no improvement in the population for 10 iterations) is satisfied, the GA algorithm process will be stopped; otherwise, it is resumed.

Step 4. Create a new population through selection, crossover, and mutation operations.

(a) Selection: Select two parent chromosomes from a population in terms of fitness based on Roulette wheel selection model;

(b) Crossover: In the proposed model, apply one point crossover, as the parameter of r (integer value between 1 to k) has been generated randomly and it changes the row from the rth to kth columns on parent I by parent j. The result is equal to the following value if $r = 3$:

$$g_i^{'0} = [\ a_{i1}^0 \quad a_{i2}^0 \quad a_{i3}^0 \qquad a_{jk}^0\ ]_{1k}, \tag{6}$$

$$P_i^{'0} = [\ a_{i1}^0 \quad a_{i2}^0 \quad a_{i3}^0 \qquad a_{ik}^0\ ]_{1k}. \tag{7}$$

(c) Mutation: in this survey, the uniform mutation model has been applied and it randomly changes one parent value by a random value.

$$g_i^0 = [\ a_{i1}^0 \quad a_{i2}^0 \quad a_{i3}^0 \qquad a_{ik}^0\ ]_{1k}. \tag{8}$$

Step 5. Go to Step 2.

Based on the above description, the GA pseudocodes are rewritten below:

1. Randomly generate a list of solutions as the initial generate;
2. Evaluate the fitness functions for each solution in the last generations;
3. Cheek the stop condition; if it is true, the algorithm stops; else, go to Step 4;
4. Create a new generation through crossover, mutation, and selection operations;
5. Check the feasibility of each solution and improve it, if required.
6. Go to Step 2.

2.2. PSO algorithm

PSO is a heuristic algorithm that aims to find a global optimum by iteratively attempting to increase the quality of candidate solutions. This algorithm randomly functions based on a group of birds to search for food in the solution space. Each bird is a single solution that moves in the solution space to look for better solutions [29].

PSO is characterized by certain advantages and disadvantages. The following advantages of the basic PSO algorithm are given as follows. It works based on intelligence and has scientifically research and engineering value. In addition, it is not subject to overlapping and mutation calculation. The search can be made depending on the speed of the particle. During the development of several generations, only the most optimist particles can transmit information to other particles and the speed of the researching is very fast. Next, calculability of PSO is quite simple. Compared to other developing calculations, the algorithm occupies a more efficient optimization ability and can be completed easily. The last advantage is that PSO adopts a real-number code that is directly determined by the solution. The number of dimensions is equal to the constant of the solution [29].

In this paper, PSO is applied to optimize scheduling through the following steps [30]:

(a) By considering the number of crews using GA, the initial particle location (scheduling) is randomly generated as follows:

$$P_i^0 = \begin{bmatrix} a_{11} & \dots & a_{1d} \\ \dots & \dots & \dots \\ a_{n_k 1} & \dots & a_{n_k d} \end{bmatrix} \qquad \text{where}$$

$$1 \le a_{ij} \le n \quad \text{for} \quad i = 1, \cdots, n_k,$$

$$j = 1, \cdots, d, \tag{9}$$

in this matrix, a_{ij} denotes the number of crews with the ith skill in the jth location for day number d.

(b) Each solution defined and allocated to all maintenance requests is implemented.

(c) Each solution has been evaluated by running the simulation model, and the fitness value of each solution has been assessed based on the simulation model.

(d) The location of the particles was updated by Eq. (10) for each particle:

$$P_i^{j+1} = P_i^j + V_i^{j+1}, \tag{10}$$

where V_i^{j+1} is the velocity for the ith particles in the $j+1$th iteration, and it is applied to the updated previous location of swarms. In Eq. (10), the new location of the ith particle in iteration number $j+1$ has changed due to the value of V_i^{j+1}. This change depends on the best location of the ith particle until the jth iteration, as well as the best location of all particles.

The value of V is computed according to the formula given in Eq. (11):

$$V_i^{j+1} = V_i^j + r\alpha[P_{best,i}^j - P_i^j] + s\beta[g_{best}^j - P_i^j]. \quad (11)$$

Based on Eq. (1), the direction of the ith particle toward its best location has been evaluated with $[P_{best,i}^j - P_i^j]$ by the weight of $r\alpha$ and its direction toward the best value of all particles has been evaluated with $[g_{best}^j - P_i^j]$ by the weight of $s\beta$. In this equation, $P_{best,i}^j$ is the best position for the ith particle at the jth iteration; P_{best}^j is the best position for all particles at the jth iteration; α and β are random parameters between 0 and 1; r and s are constants.

Based on the above description, the PSO pseudocode is rewritten below:

1. Generate random initial locations for particles;
2. Evaluate fitness functions for each solution in their respective last locations;
3. Check the stop condition; if it is true, the algorithm stops; otherwise, proceed to Step 4;
4. Determine the best location of each particle in all iterations based on fitness function;
5. Evaluate the best location among all particles;
6. Update the locations of the particles;
7. Repeat from Step 2.

2.3. Monte Carlo Simulation

The Monte Carlo Simulation is a method to model real-world uncertainty using normal or non-normal distributions and complex performance functions. The Monte Carlo Simulation uses repeated random sampling to simulate data for a given mathematical model and evaluate the outcome [30].

The process of the Monte Carlo Simulation involves the following steps:

1. Identify the transfer equation, known as the quantitative model, for the simulation;
2. Define the input parameters for the simulations;
3. Generate random data for each parameter using a specified probability function;
4. Run the simulation and analyze the results.

In this paper, the Monte Carlo Simulation was applied to calculate the fitness value of each proposed scheduling by PSO.

3. Numerical result

To evaluate the performance of the proposed model, it was implemented in a company with five distinct locations, each with different facilities. The failure function was considered an exploratory probability function with varying parameters for each skill in each location, as shown in Table 2. The function was redefined after each inspection.

The proposed model was coded on MATLAB and run for the proposed problem. The convergence trend of PSO in each loop is shown in Figure 3.

Based on Figure 3, it is clear that in the earlier iterations, there were significant improvements in con-

Table 2. Parameters of failure rate.

Location	Mechanical worker	Electrical worker	Simple worker
1	5.9	4.1	3
2	9.3	2.2	2.8
3	7.2	3.1	4.1
4	4.1	6.8	1.2

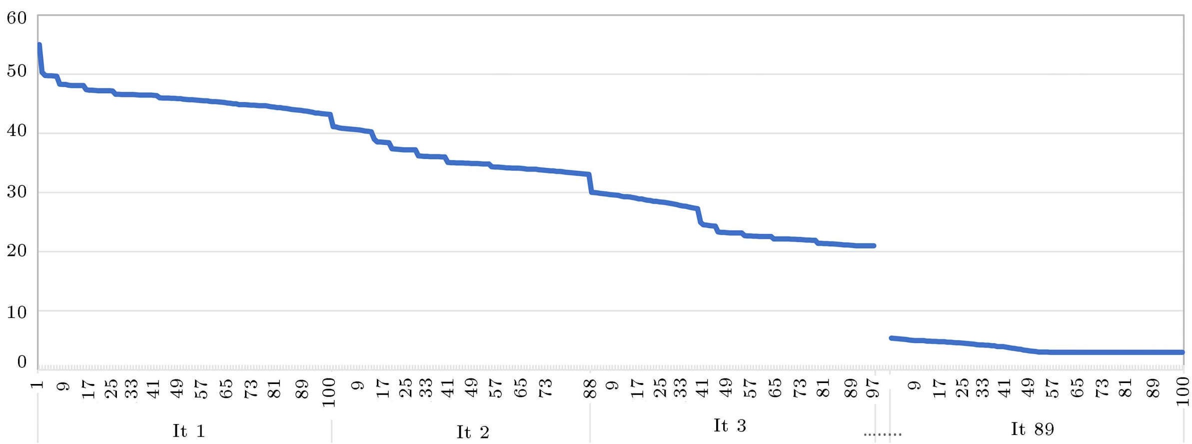

Figure 3. Convergence rate of PSO algorithm.

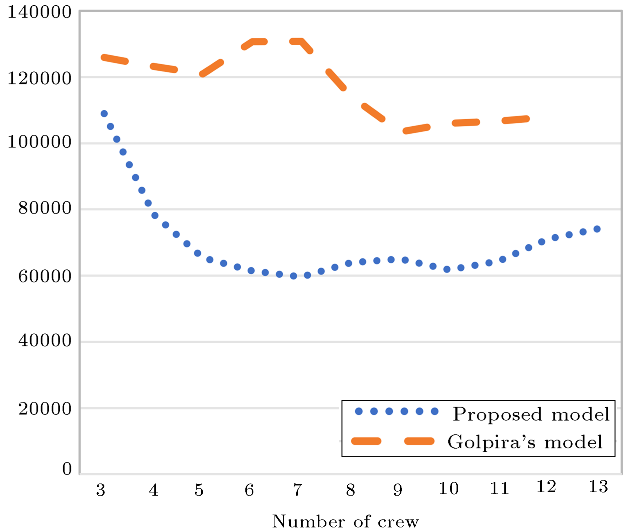

Figure 4. Comparison of the total cost in the proposed model and Golpira's model.

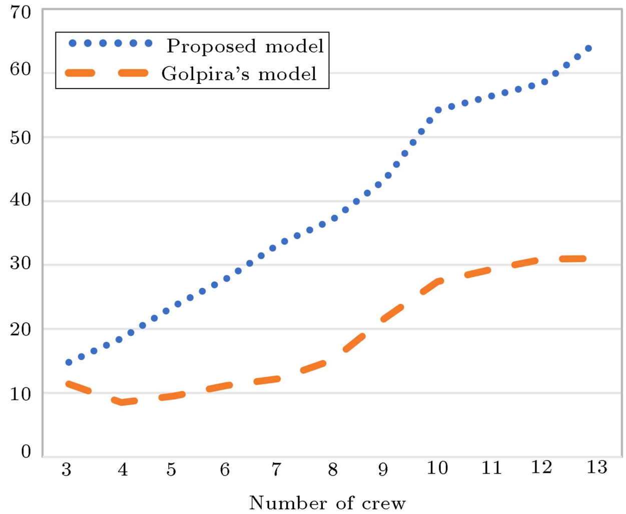

Figure 5. Comparison of total MTBF in proposed model and Golpira's model.

vergence with each step. However, these improvements became smaller in later iterations until convergence was achieved at the 89th iteration.

In order to evaluate the proposed model's performance, it was compared with the models proposed by Golpira. The results of this comparison are presented in Figure 4.

Based on Figures 4 and 5, it is clear that the proposed model outperforms Golpira's model in terms of cost and Mean Time Between Failures (MTBF). The proposed model boasts a significant cost advantage over Golpira's model, with a cost that is half of the latter in certain instances. Moreover, in general, the proposed model presents a cost-saving opportunity of up to 39% when compared to Golpira's model. The proposed model also showcases superior performance in terms of Mean Time Between Failures (MTBF), which can be

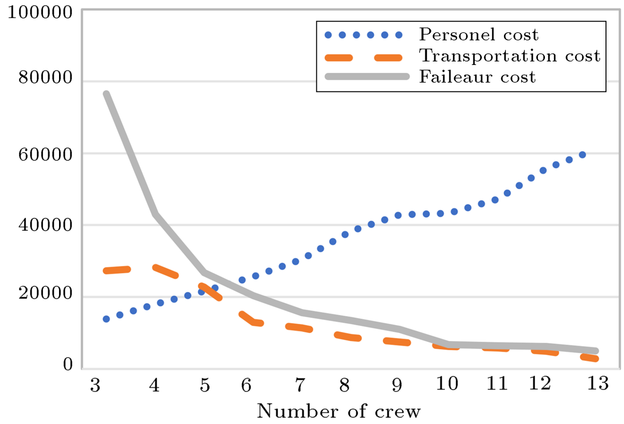

Figure 6. Total cost for different cost categories.

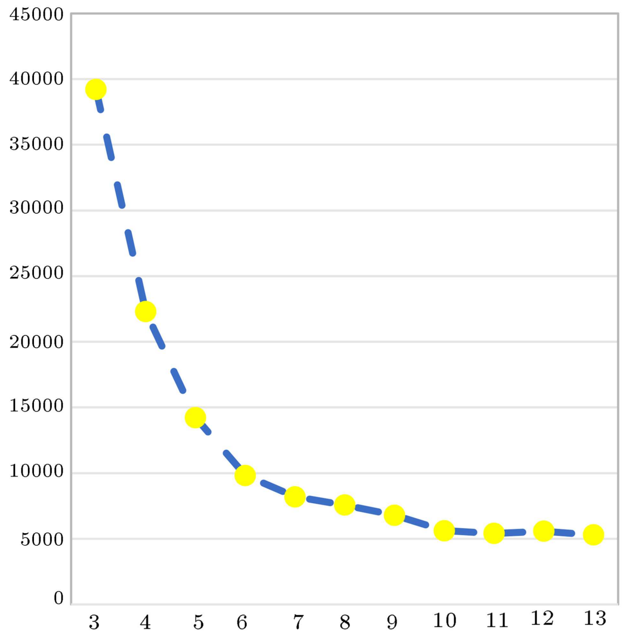

Figure 7. Total cost per person.

up to three times that of Golpira's model in certain scenarios. On average, the MTBF of the proposed model is twice that of Golpira's model.

In order to evaluate the performance of the proposed model, different types of costs in different scenarios are depicted in Figure 6, and the total cost per crews is shown on Figure 7.

In order to evaluate the performance of the proposed model, it is applied to a problem with different failure rate parameters, the results of which are shown in Figure 8.

Based on Figure 8, it is clear that as the Landa in the failure rate decreases, the total maintenance cost will increase. According to Figure 9, it is clear that MTBF increases as Landa expands.

On the other hand, to evaluate the performance of the proposed model in different situations, Figures 10 to 16 show the result of different costs of the proposed model in different situations.

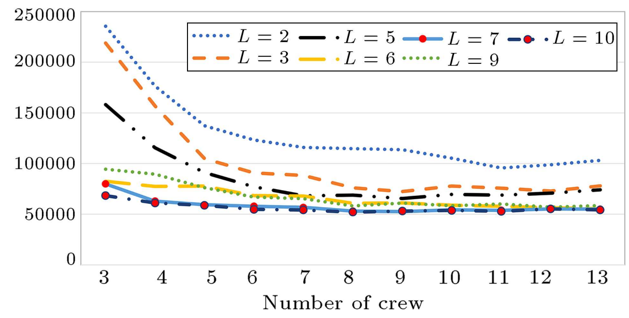

Figure 8. Total cost based on the failure rate.

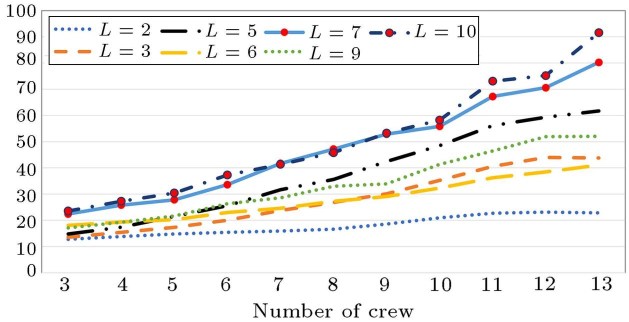

Figure 9. MTBF based on failure rate.

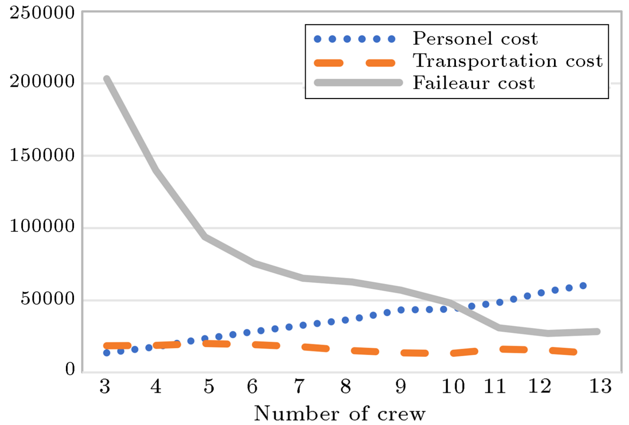

Figure 10. Total cost for different cost categories in *Landa* = 2.

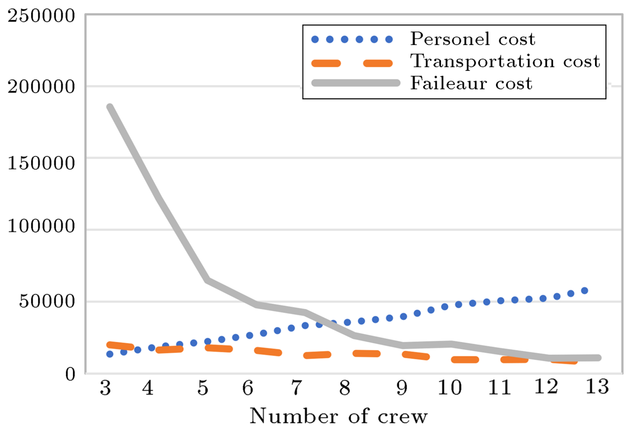

Figure 11. Total cost for different cost categories in *Landa* = 3.

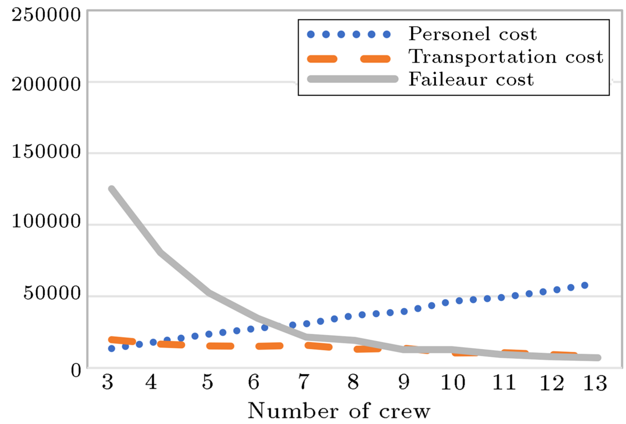

Figure 12. Total cost for different cost categories in *Landa* = 5.

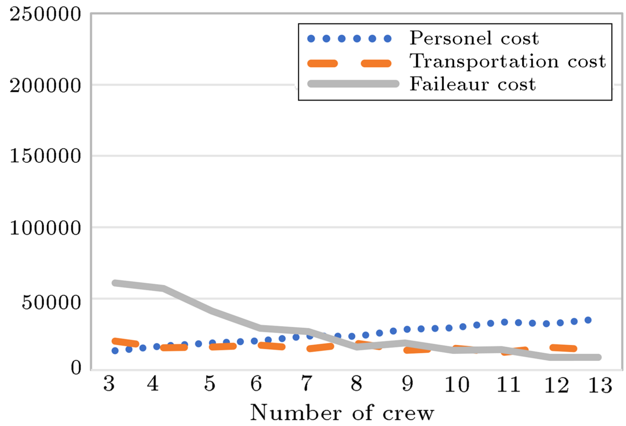

Figure 13. Total cost for different cost categories in *Landa* = 6.

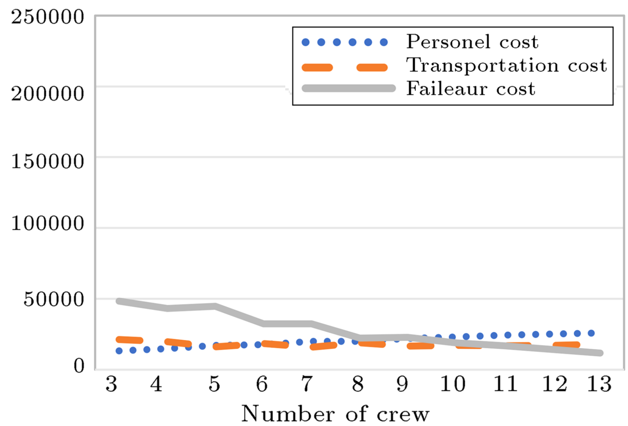

Figure 14. Total cost for different cost categories in *Landa* = 7.

After analyzing the charts above, it is evident that the number of crews employed has a significant influence on maintenance costs. Although there is a direct correlation between the number of crews and personnel costs, it also has a substantial impact on failure costs. For instance, a slight increase in personnel costs by hiring two or three additional staff members can result in a significant decrease in failure costs. On

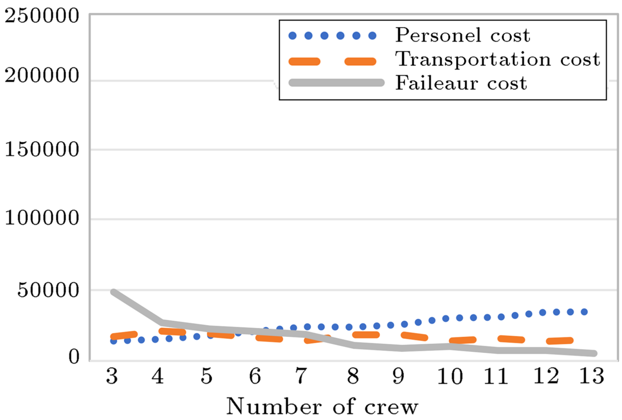

Figure 15. Total cost for different cost categories in $Landa = 9$.

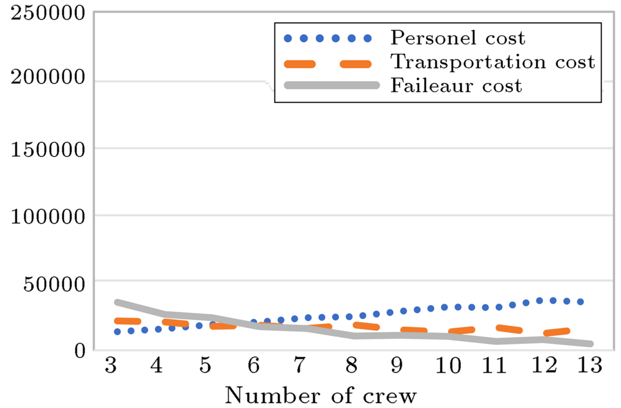

Figure 16. Total cost for different cost categories in $Landa = 10$.

the other hand, increasing the number of crews beyond 8 or 9 has a minimal impact on failure costs, and instead, it simply increases personnel costs. Therefore, determining the appropriate number of staff is crucial for effective maintenance planning. As the number of crews increases, there is a decrease in transportation costs due to fewer trips required. Consequently, there is a direct relationship between the number of staff and personnel costs, and an inverse relationship between the number of staff and failure and transportation costs.

Based on the results of the proposed model, it is evident that the model can be applied to a variety of scenarios involving facilities with different failure rates (related to number of facilities with different ages) and varying numbers of crews, even when all facilities are located in different locations. The model allows for the optimization of crew scheduling and the number of crews required simultaneously. The results indicate that increasing the number of crews can lead to a reduction in failure cost.

4. Conclusion

This study presented a new hybrid model to optimize facility maintenance scheduling for organizations by owning facility with different failure rates located in multiple locations. By using the proposed model, the maintenance tasks were categorized in three different independent groups and all maintenance actions should be done with the company staff. The total costs including salary of crews and transportation cost should be minimized.

The main contributions of this paper are given as follows: (a) optimizing the number of crews with different skills in the first stage; (b) evaluation of fitness value for each solution through the Monte Carlo Simulation model; and (c) scheduling by taking into account different failure rates for different facilities in different locations.

In order to evaluate the performance of the proposed model, it was compared with the performance Golpira's model. The results suggest that it is possible to reduce costs by more than 39% and Mean Time Between Failures (MTBF) by more than 50%.

5. Future suggestions

For future research, we propose exploring the following ideas:

1. Developing a maintenance scheduling model that takes into account material costs;
2. Categorizing failures based on their level of importance;
3. Exploring the potential benefits of outsourcing certain maintenance tasks.

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Biographies

Faranak Zagia holds a Master of Science in Civil Engineering from the Islamic Azad University, Central Tehran branch. She is also licensed by the Roads and Urban Ministry of Iran with a second-grade

Engineering System license in both supervision and implementation.

Omid Motamedi Sedeh holds a PhD degree in Industrial Engineering from Tarbiat Modares University and is a member of the National Elite Foundation of Iran. He is particularly interested in the fields of data mining, heuristic models, and artificial intelligence, and has authored several papers in refereed journals and conference proceedings. His research has focused extensively on the deregulation of power markets.

Bakhtiar Ostadi is an Associate Professor of Industrial Engineering at Tarbiat Modares University. He received his PhD in Industrial Engineering from the School of Engineering at Tarbiat Modares University. In addition, He received his MSc from the University of Tehran in the Industrial Engineering and his BSc in Applied Mathematics from K. N. Toosi University of Technology. His main areas of research interest include "Data-Driven Risk Assessment", "Pricing Strategies for Bidding", "Resilience Engineering", "Quality Engineering and Management", "Process Management, Modeling and Simulation", "Reliability Engineering", and "Customer Value, Customer Experience, and Marketing". He has published several articles in international academic journals and conferences including Int. J. Production Research, Computers and Industrial Engineering, Energy Policy, Energy, Journal of biomedical informatics, Applied Mathematical Modelling, Journal of Statistical Computation and Simulation, Journal of Risk and Reliability, Applied Mathematics and Computation, Scientia Iranica, Iranian Journal of Management Studies, Int. J. Productivity and Quality Management, International Journal of Business Innovation and Research, etc.