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RESEARCH PAPER

Computational Optimization of Preventive Maintenance Schedules in Repairable Mechanical Systems Using NSGA-II

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Abstract

In this study, a computational framework is proposed for optimizing preventive maintenance scheduling in complex mechanical systems, with a focus on minimizing total maintenance costs while preserving system availability and mechanical reliability. The model incorporates multi-level maintenance actions—including inspection, repair, and component replacement—over a defined planning horizon. A nonlinear integer programming formulation is developed to capture cost elements such as random failure, repair, replacement, and planned downtime. To address the combinatorial complexity of the problem, a Non-Dominated Sorting Genetic Algorithm II (NSGA-II) is employed to generate near-optimal solutions. The proposed method is applied to a real-world Cathodic Protection System used in steel gas distribution networks, which are critical mechanical infrastructures subject to electrochemical degradation. Results demonstrate a 36% reduction in total maintenance costs, highlighting the effectiveness of the model in improving asset performance and extending system life through optimized maintenance strategies.

Keywords: Preventive Maintenance Optimization; Computational Mechanics; Mechanical Asset Management; Multi-Objective Evolutionary Algorithm (NSGA-II); Nonlinear Integer Programming

1. Introduction

Corrosion is one of the main reasons for the destruction of Oil and Gas pipelines. The pipelines are widely used in the Oil and Gas industry, and corrosion causes heavy damage to the lines and increases maintenance costs, the consequences for safety, the environment, and lost product sales. Investigating the issue of corrosion management regarding inspection and maintenance of the equipment based on the risk is very important in the equipment's Life Cycle (LC). It makes the equipment ready to work and the transfer of Oil and Gas can be done with high reliability. In this regard, PAM will enable owners to maintain optimal performance while reducing cost and risk. Szczerbicki [1] showed that the optimum planning of operations at production and service organizations directly depends on the performance of equipment and components. Comprehensive corrosion studies have been carried out by Zhang et al. [2] that analyze failures to identify the critical maintenance interval and optimize tunnel maintenance strategies. Maintenance strategies are considered to monitor and improve system reliability and availability. Zhang et al.[3]

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presented a multi-objective maintenance strategy to enhance the effectiveness of cumulative reliability and availability. Maintenance activities are vital in the industry, especially continuous production industries. Duan et al. [4] investigated that these can be classified into preventive, corrective, and predictive maintenance categories, often called maintenance policy in some studies. Therefore, it protects the assets at a specific level of efficacy with an acceptable cost or risk that increases the useful life and prevents sudden breakdown. Zhang et al. [5] investigated Deep Learning (DL) methods in the field of Remaining Useful Life (RUL) prediction and Predictive Maintenance (PDM) of complex Gas systems. In the past, maintenance policies were focused on two approaches: time-based or use-based maintenance. The policies need to be provided by new approaches for planning maintenance activities, based on the reality and the state of the devices. Risk-based inspection is one of the most effective methods to increase maintenance productivity.

Song et al.[6] demonstrated that companies should focus more on equipment with higher risk than on equipment with lower risk. This concentration means allocating more resources and considering special maintenance activities compared to lower-risk equipment. Prassinos et al. [7] showed that the American Society of Mechanical Engineers (ASME) has developed several guidelines for implementing this approach. Also, based on the American Petroleum Institute (API) standard, Babaeian et al. [8] demonstrated that there are three risk-based inspection goals: Definition and measurement of risk, the possibility of reviewing the risk, and optimizing inspections based on the probability of failures. Sinha et al. [9] showed that Corrective Maintenance (CM) is a maintenance task performed to identify, isolate, and rectify a fault so that the failed equipment, machine, or system can be restored to an operational condition within the tolerances or limits established for in-service operations. Gentles [10] demonstrated that Preventive Maintenance (PM) is defined as maintenance carried out according to predetermined technical criteria, indicated in the instructions for use or manufacturers' technical documentation, intending to reduce the likelihood of equipment failure or degradation of a service rendered. It (includes cleaning, lubrication, oil changes, adjustments, repairs, and overhauls) improves system availability and reliability. PM policies are less costly than corrective maintenance. Increasing PM reduces CM, but It is necessary to consider the balance between these two policies. The last category is PDM, a variety of technologies are used as part of a comprehensive PDM program presented by Mobley [11]. Generally, vibration test monitoring is the critical component of most PDM programs. However, this activity cannot provide all the information required for an overall PDM policy. This technique is limited to monitoring the mechanical condition. Kamel et al. [12] presented three essential PM activities in the following. Inspection (I): In this action, there is no effect on the failure rate of the equipment. The component remains in a recent situation. Some inspection activities include lubricating the gears or bearings, cleaning the components, tightening the nuts, visual checking, etc. Repair (M): This activity is associated with precious parts. Opposite to the inspection action, the repair action affects the failure rate, but this effect is not enough to return the system to its initial state. Repair activities lead to replacing some simple and small parts such as springs and bearings or using base components such as seals, belts, etc. Replacement (R): In this action, the equipment arrives at the functional failure phase throughout the LC. Inevitably, replacement of the equipment must be done. In this case, the system returns to its initial or good state. The best level of reliability can be achieved based on the best maintenance policy selection.

1.1. Contribution of This Study

The main contribution of this study is diagnosing the current performance state of equipment based on online inspection data and assigning the most optimal maintenance activities and resources throughout the LC. The equipment life graph is drawn based on the inspection data and the estimation of the most optimal parameters of the related distribution function. Depending on the current state of the equipment, the proposed metaheuristic algorithm suggests three activities: repair, replacement, or re-inspection based on the risk, cost, and desired performance. We can assign the best maintenance schedule according to the current LC by continuously performing the mentioned process. Indicators such as reliability, availability, cost, risk, outsourcing, or a combination of these items have been mentioned to monitor the effectiveness of the measures. The results have been proven by using the NSGA-II and comparing with exact methods. In addition, based on the PAM requirements, the performance, risk, and cost of facilities are balanced as well as considering the effects of the maintenance scheduling model on the physical assets throughout the LC. So, the owners selected the best maintenance policies that maximize the productivity of asset portfolios. The complex topology, nonlinear functions, and initial nature states of the system urged the researcher to use meta-heuristic algorithms such as NSGA-II and MATLAB software to optimize the multi-objective problem. It is expected that researchers achieve the best values of metrics like higher availability and reliability of equipment, and the lowest operating costs and risk. According to the LC graph, the hazard rate be different, which is compliance with the Weibull distribution curve. Therefore, due to the dynamic nature of the mechanical systems in each stage of LC, researchers can recognize the current and future behavior of the system by using the proposed approach.

Finally, at the best level of resource allocation, the authors proposed a dynamic maintenance scheduling by considering the risk-based inspection at a certain or desired level of reliability, availability, and cost.

1.2. Organization of the study

The rest of this study is organized as follows:

Section 2 reviews the literature on the effects of PAM in constrained maintenance scheduling models and examines related studies. Sections 3 and 4 present the problem statement and the multi-objective model's formulation with a certain performance measure level respectively. Section 5 describes the solution representation and constraint handling by using evolutionary algorithms and extensions. Section 6, presents the constrained multi-objective maintenance model and introduces related work briefly. Section 7 provides computational experiments to clarify the applicability and efficiency of the model and the problem-solving approach. section 8 presents experimental results and discussion. Finally, section 9 includes concluding remarks and future research directions.

2. Literature review

Many studies have been done on maintenance policy selection, modeling, and optimization. Present research conducted in 7 fields that are presented in the following. Cost minimization, maximal demand coverage, maximizing availability and reliability, predicting functional failures, risk-based maintenance and inspection, etc. Also, a brief review of the algorithms in the research is presented. In this section, the findings of researchers in the field of maintenance scheduling optimization and their research gap with the requirements of asset management (AM) in industrial revolutions have been presented. In the following, the literature review will be conducted based on the priority of the aforementioned fields. Wang [13] presented the MILP model for maintenance schedules that minimize the overall crew work time. A study on selecting the optimal maintenance and reliability policy based on cost, condition monitoring, conditions, and probabilistic analysis of the length of shocks has been done by Zhao et al. [14]. By considering the maintenance policies based on LC, Badia et al. [15] investigated the effect of aging on the maintenance cost policies. In the Mourtzis et al. [16] study by using the Complex Neural Network technique and considering Augmented Reality, a material supply prediction model for the Maintenance and Repair Operations (MRO) was developed. Yousefi et al. [17] modeled the dynamic maintenance policy to determine the next period of inspection of parts and equipment. In Qiu et al. [18] research, network, and availability modeling of systems with multiple failure modes were performed. By considering the importance of failure modes and real conditions in reliability calculation, Yang et al. [19] based on two internal failure factors and external sudden shocks, implemented two types of performance reduction modeling with dual Poisson probabilistic and Wiener processes. Kamel et al. [12] presented a different study that optimized the inspection intervals and performed maintenance operations by meta-heuristic algorithms. Gao et al. [20] investigated reliability modeling in a system with a two-phase degradation mode with a change point based on the Wiener process and simulation. According to PAM fundamentals by Davis [21], to achieve optimum decision-making criteria, presented a novel approach based on constraints such as specified reliability and availability, financial and human resources, etc. Baptista et al. [22] used time series data to predict failure time in their study. They could estimate system reliability in the useful LC of maintenance and model-solving algorithms.

A reliability degradation analysis method regarding the coupling of multiple stochastic elements and multiple series damage components was proposed by Deyin et al. [23]. Brauman [24] introduced probabilistic differential equations with modeling applications. Concerning predictive maintenance, Zonta et al. [25] presented extensive research among different articles and showed its results in categories. C.zhang and Yang [26] presented an optimization model for maintenance planning and resource allocation in wind turbine farms using the NSGA-II. Also, Moradi et al. [27] used NSGA-II for multi-objective optimization of a pipe model, minimizing total weight and maximizing the natural frequency of the applied pipe. Detecting corrosion defects depth in the Oil and Gas industries was investigated by Ossai [28]. In another study, Sharifi et al. [29] focused on optimizing the inspection intervals of a complex system with the reliability of K out of N system[†] under the hybrid redundancy strategy. By considering the constraints of financial and human resources during the LC of assets, Sadeh et al. [30] provided a new model to optimize the maintenance schedule of facilities in multiple situations. The study to obtain preventive maintenance-based inspection intervals for mechanical equipment according to the above mode has been done by J.Zhang et al. [31]. Song et al. [6] used special techniques in the power plant and were able to arrive at a suitable

[†] In K out of N, the system works until at least K of N components are in service.

new risk-based quantitative inspection tool. Bhatia et al. [32] based on Dynamic Risk-Based Inspection showed that the actual results led to an increase in safety, the effectiveness of monitoring and intelligent systems, and a reduction in shutdown costs, etc. Determining the optimal schedule of risk-based inspection is one of the attractive topics for corrosion research in Oil and Gas industries, as presented by Escobedo [33].

The Institute of Asset Management (IAM) presented several ways to investigate the importance of PAM based on AM anatomy. Some benefits of AM can be directly evaluated and quantified, such as reducing investment and maintenance costs, increasing asset availability, reducing risk exposure, etc. Campbell et al. [34] demonstrated that the purpose of AM is to prevent or adjust the decreasing performance and efficiency of working assets. Petchrompo and Parlikad [35] investigated the grouping of multi-asset systems based on the diversity and interaction of their components to calculate reliability. Di Bona et al. [36] examined the framework of the maintenance strategies in the industry 4.0 and 5.0 revolutions in their studies. Ingemarsdotter et al. [37] investigated the selection criteria of the appropriate maintenance strategy in Industry 4.0.

Table 1 shows a general classification of research reviewed concerning the above literature review. In addition, in the last row, the characteristics of the present research are shown.

Table 1. General classification of research reviewed

Innovation	Solving method	Type of Study	Decision				Constraint					Type of model		Type of problem			Objective function				Author
Classification	Exact-Heuristic-Meta heuristic	Practical- Theoretically	Inventory of spare parts	Inspection planning	Schedule preventive maintenance	Schedule overhaul	Etc.	Minimum demand coverage	Minimum Availability	Minimum Reliability	Maximum budget	Probabilistic	Exact	Simulating	Analytical	Nonlinear programming	Maximum Availability	Maximum coverage of work order	Maximum Reliability	Minimum cost	Name. Organization. year
Dynamic risk-based inspection	Exact	Practical		*	*		*					*				*				*	Bhatia et al.[32]
Risk-based-inspection for oil and gas pipelines	Heuristic	Theoretically	*	*		*			*			*	*					*	*	*	Escobedo[33]
improved second-order fourth-moment approach for the reliability analysis	Exact	*		*			*						*	*					*		Lou et al.[٣٨]
semi-Markov model (SMM) to analyze system reliability	Exact	Theoretically			*		*		*	*			*		*		*		*		Vishnevsky et [٣٩] al.
k-out-of-n system is proposed to assess the reliability	Exact	Theoretically			*		*		*	*			*		*		*		*		Mittal et al.[٣٩]
Condition-based inspection	Heuristic	Theoretically		*	*	*		*			*	*				*			*	*	Yang et al.[19] & Larbi et al[40]
Maintenance and Availability modeling	Exact	Theoretically		*	*	*			*	*			*	*					*	*	Qiu et al.[18]
Dynamic modeling of maintenance	Exact	Practical		*	*	*	*	*					*			*			*		Yousefi et al.[17] & Chen et al. [41]
proposed effective method for time- and space-dependent reliability problems	Exact	Practical			*					*		*					*		*		Zhan and Xiao[٤٢]
Cost modeling	Exact	Theoretically			*						*		*		*	*				*	Badía et al[15]

Innovation	Solving method	Type of Study	Decision				Constraint					Type of model		Type of problem			Objective function				Author
Classification	Exact-Heuristic-Meta heuristic	Practical- Theoretically	Inventory of spare parts	Inspection planning	Schedule preventive maintenance	Schedule overhaul	Etc.	Minimum demand coverage	Minimum Availability	Minimum Reliability	Maximum budget	Probabilistic	Exact	Simulating	Analytical	Nonlinear programming	Maximum Availability	Maximum coverage of work order	Maximum Reliability	Minimum cost	Name. Organization. year
Failure's behavior Modeling by using the Wiener process and Markov chain	Exact	Theoretically			*		*					*		*					*		J. Zhang et al[31]
Modeling of degradation process by Wiener process	Exact	Theoretically			*		*					*		*						*	Braumann[24]
Markov chain to reduce cost and maximize reliability	Exact	Theoretically		*				*				*			*				*	*	Zhao et al[14]
Reliability modeling in the system with dual degradation mode by the Wiener process	Exact	Theoretically			*					*		*		*	*				*		Gao et al.[20]
An asset management modelling framework	Exact	Theoretically			*					*	*		*		*				*	*	Wu et al. [43]
Performance, risk, and cost evaluation modeling	Heuristic	Practical	*		*		*				*		*		*		*	*	*	*	Campbell et al.[34]
Grouping of multi-asset systems	Exact	Theoretically	*		*		*			*			*		*				*		Petchrompo and Parlikad[35]
propose an economic model for jointly optimizing the X-bar control chart	Exact	Theoretically			*		*			*			*			*			*	*	Chen et al.[44]
selecting the proper maintenance strategy	Exact	Theoretically			*		*						*		*			*	*	*	Di Bona et al.[36]
Propose an adaptive decomposition-synchronous-coordination approach to reliability analysis	Exact	Theoretically			*		*						*		*				*		Feng et al.[45]
selecting the proper maintenance strategy based on the condition-based maintenance	Exact	Practical			*		*						*		*			*	*	*	Ingemarsdotter et al.[37]
Time series data for failure time prediction and failure point estimation "system reliability" data-oriented models	Exact	Theoretically		*	*	*				*			*			*			*		Baptista et al.[22]
Predictive maintenance and time-based failures in the Fourth and Fifth Industrial Revolutions	Exact	Theoretically		*			*		*				*		*				*	*	Zonta et al.[25]
Data-oriented machine learning based on sub-cluster neural network	Metaheuristic	Practical			*		*						*			*		*		*	Ossai[28]
Preventive maintenance modeling to optimize inspection intervals at a level of reliability	Metaheuristic	Practical		*	*	*			*	*	*		*			*		*	*	*	Kamel et al.[12]

Innovation	Solving method	Type of Study	Decision				Constraint					Type of model		Type of problem			Objective function				Author
Classification	Exact-Heuristic-Meta heuristic	Practical- Theoretically	Inventory of spare parts	Inspection planning	Schedule preventive maintenance	Schedule overhaul	Etc.	Minimum demand coverage	Minimum Availability	Minimum Reliability	Maximum budget	Probabilistic	Exact	Simulating	Analytical	Nonlinear programming	Maximum Availability	Maximum coverage of work order	Maximum Reliability	Minimum cost	Name. Organization. year
and availability																					
Material forecasting model of the maintenance	Metaheuristic	Practical	*					*			*		*			*				*	Mourtzis et al.[16]
A model to optimize the facility maintenance schedule	Metaheuristic	Practical	*		*			*			*		*			*		*		*	Sedeh et al.[30]
Optimizing the inspection intervals of the complex system with reliability K of n	Metaheuristic	Theoretically	*		*		*	*				*				*		*		*	Sharifi et al.[29]
Strategic decision-making about outsourcing and insourcing	Exact	Practical	*			*	*				*		*		*			*			Charles and Ochieng[46]
Optimization model of maintenance planning and resource allocation	Metaheuristic	Practical		*	*	*		*			*		*			*		*		*	C. Zhang and Yang[26]
comprehensive framework to introduce efficient equipment inspection programs	Metaheuristic	Practical		*			*				*		*			*			*	*	Javid [۴۷]
Multi-objective optimization model to optimize Gas pipeline's cost rate and availability	Metaheuristic	Practical			*		*		*		*		*			*	*			*	Wang and su[۴۸]
Modeling of preventive and predictive maintenance schedule in terms of risk, cost, and performance balance	Meta heuristic	Practical	*	*	*	*	*		*	*			*		*	*	*		*	*	Present study

Table 1 shows brief research on optimizing maintenance planning in the scope of the PAM framework. As shown in the above table, based on the objective function, solution method, innovation, etc. various studies have been presented and comparable with different approaches. However, the lack of a comprehensive approach based on the industry's 4.0 and 5.0 revolutions requirements is visible.

3. Problem statement

The Fourth and Fifth Industrial Revolutions are transforming industries worldwide. While Industry 4.0 is primarily focused on efficiency, automation, and digitalization, Industry 5.0 envisions a more collaborative, sustainable, and personalized future where technology and humans work together to solve complex challenges. Merging these approaches will help organizations achieve their goals, such as profitability, stakeholder satisfaction, reputation, etc. The operational readiness of pipelines in the Oil and Gas industry plays a critical role in ensuring the stability of fluid transportation. Therefore, optimizing maintenance scheduling for equipment holds significant importance. One of the main causes of production downtime in steel pipelines is corrosion. Comprehensive studies by Zhang et al. [49], involving the analysis of corrosion-induced failures, have been conducted to identify critical time intervals for maintenance schedules. So, all corrosion management actions are implemented to reduce corrosion rates and mitigate its consequences, such as unplanned production downtime, safety, and environmental effects. To ensure timely and proper maintenance, it is necessary to do a risk assessment and develop an inspection schedule based on prioritization and frequency. Resource allocation is then carried out, considering cost and performance constraints. Anyway, inspections are optimally planned, and maintenance scheduling ensures the best operational readiness of equipment by incorporating activities such as repair, replacement, or re-inspection. The main focus of the present research is on PM, which encompasses activities aimed at preventing equipment failures and, on a broader level, managing and reducing corrosion rates. Moreover, due to the different hazard rate throughout the lifecycle, different scenarios arise within the Weibull distribution function, which is widely used in reliability analysis. Therefore, by using the proposed approach at each stage of the lifecycle, the system adapted to dynamic conditions and was enabled to maintain the operational functionality. Also, the suggested maintenance scheduling method determines how to allocate resources or utilize outsourcing services. To overcome the under-investigation research challenges, the following issues are discussed: repair, replacement, and inspection intervals, reliability and availability analysis, risk assessment, TMC, the system behavior throughout the LC, and decision-making criteria for outsourcing and insourcing.

4. Modeling

Notations of variables and parameters and their brief description are given in Table 2.

Table 2. Notation and brief description of parameters

EA_{ij}	effective age of $trans_i$ at the end of period j	β_i	Improvement factor	Re_0	Minimum reliability	tp	PM interval
SA_{ij}	effective age of $trans_i$ at the start of period j	D_i	Shutdown cost	Re_j	Total reliability	λ_i	scale parameter
Mc_i	Repair cost	Ic_i	inspection cos	Wr_i	replacement Resource	tm_i	Repair time
C_i	Unplanned failure cost	tc_i	Corrective time	m	Number of Trans.	Wm_i	Repair Resource
k_i	Shape parameter	tr_i	Replacement time	j	Number of periods	Wi_i	Inspection Resource
Rc_i	Replacement cost	AV_0	Minimum availability	T	planning horizon	ti_i	inspection time
COM	Outsourcing Cost of Repair	COR	Outsourcing Cost of Replacement	COI	Outsourcing Cost of Inspection	CIM	Insourcing Cost of Repair
CIR	Insourcing Cost of Replacement	CIM	Insourcing Cost of Inspection	TCO	Total Outsourcing Cost	TCI	Total Insourcing Cost
O	Risk Opportunity	S	Risk Severity	D	Risk Detection	RPN	Risk Priority Number

The decision variable for repair, replacement, and inspection is an integer and is shown by $M_{i,j}$, $R_{i,j}$, $I_{i,j}$ notation, respectively. Also, only one of these activities could be executed. When the model runs by repaired, replaced, or inspected action allocated to $trans_i$ at period j, relative integer variables are 1, otherwise zero respectively.

It is assumed that the occurrence failures follow the Nonhomogeneous Poisson process and the rate of failure at time t is followed by:

$$f_i(t) = \lambda_i . k_i . t^{k_i - 1} \qquad \lambda, k>0;\ t > 0;\ \text{for } i=1, \dots, m \tag{1}$$

Crow[50] showed that regarding the feature of statistical distribution functions, it can be claimed that the Nonhomogeneous Poisson process is capable of presenting a change point or showing the trend mode in the intensity of the system failure rate. Discrete-time intervals, along with horizon plan [0, T] are one of the main assumptions in the present study. Three mentioned PM activities occurred at the end of each cycle. M and R activity reduce the hazard rate and the effective age of each trans (See Eq.2- 5), while the I activity was done in period j, there is no change in hazard rate and the effective age of the trans (See Eq.6). Also, when the $trans_i$ is repaired in period j, the repair activity reduces the age of it on the next period and reduces the rate of failure.

$$EA_{i,j} = SA_{i,j} + tp \qquad \text{for } i=1, \dots, m, \text{ for } j=1, \dots, T \tag{2}$$

$$SA_{i,j+1} = EA_{i,j} \qquad \text{for } i=1, \dots, m, \text{ for } j=1, \dots, T \tag{3}$$

$$SA_{i,j+1} = \beta_i . EA_{i,j} \qquad \text{for } i=1, \dots, m, \text{ for } j=1, \dots, T \tag{4}$$

$$\beta_i = (Rc_i - Mc_i)/Rc_i \qquad \text{for } i=1, \dots, m \tag{5}$$

$SA_{i,\,j+1}=0$ for i=1, …, m, for j=1, …, T (6)

Effect of M action on the valuable age of the CPS showed by β parameter that is an improvement factor. The improvement function is studied by Usher et al. [51] that is calculated in terms of the difference between R and M costs. R activity is to be considered when the components of CPS in $trans_i$ are replaced at the end of period j. For this reason, the subsystem is referred to as an early LC situation. Also, the hazard rate trended to 0.

4.1 Total Maintenance Cost (TMC)

Maintenance costs are a significant element of TMC in all manufacturing or service plants. Every piece of equipment inevitably confronts malfunction in its LC. A good practice is to manage direct and indirect maintenance costs regularly. This budget should cover the TMC imposed for materials, software, spare parts, labor, services, etc. Therefore, if proper maintenance is scheduled and carried out, fewer failures will have occurred, a better MTBF can be achieved and overtime or reworking on service costs can be reduced. In the following, the cost components such as unplanned failure cost, repair and replacement cost, and planned downtime cost are explained. Assume that the cost of each failure is C_i (Rial. Failure event), which includes the average cost of corrective maintenance time. The cost of failures attributed to a $trans_i$ in period j is $C_{i,\,j}$. Also, regarding the nonhomogeneous Poisson process, the Expected Number (EN) of failures for $trans_i$ in period j can be obtained by the following:

$$EN_{i,j} = \int_{SA(i,j)}^{EA(i,j)} f_i(t)dt = \lambda_i (EA_{i,j})^{k_i} - \lambda_i (SA_{i,j})^{k_i} \quad \text{for i=1, …, m, for j=1, …, T} \tag{7}$$

$$C_{i,\,j} = C_i.\lambda_i.[(EA_{i,\,j})\ k_i - (SA_{i,\,j})\ k_i] \quad \text{for i=1, …, m, for j=1, …, T} \tag{8}$$

Decision-making about repair and replacement conditions of equipment is one of the most critical issues on LC cost by researchers. Here, when $trans_i$ is repaired or its component/subsystem replaced in period j, Mc_i and Rc_i are the repair and replacement costs for $trans_i$, respectively. When $machine_i$ is repaired or replaced in period j, it is related to a downtime situation, which, in turn, affects the service rate and the total cost and maintenance metrics. There are two types of downtime: planned and unplanned. The purpose of planned downtime is to prevent unplanned downtime. Planned downtime cost for $trans_i$ (D_i: Rial. hr.) can be obtained as follows:

$$Sc_{i,j} = \sum_{i=1}^{m} \sum_{j=1}^{T} D_i (M_{i,j}.tm_i + R_{i,j}.tr_i) \quad \text{for i=1, …, m, for j=1, …, T} \tag{9}$$

5. Solution representation and constraint handling

The reversible, Non-Linear, complexity condition of the suggested NLIBP model, and an abundance of maintenance failure data, forced the researchers to implement a metaheuristic method like a GA and NSGA-II. In the present study, GA and NSGA-II will optimize the PM scheduling and a novel decision-making model for multi-objective problems respectively. In Various Sciences by John [52], GA and its development is the most widely applicable and popular evolutionary optimization method. For example, Bavarsad Salehpour and Shahrokhi [53] used GA on the multilevel maintenance scheduling model. Elsewhere, Salehpour and Molla-Alizadeh-Zavardehi [54] used the developed GA and other metaheuristics for portfolio selection in the Iranian stock exchange. This metaheuristic algorithm used consecutive steps such as Reproduction (P_r), Selection, Crossover (P_c), and Mutation (P_m) to obtain a near-optimal solution.

At first, a random generation is produced according to the type of problem. Once the initial population is produced, two solutions as the parents are selected and recombined to generate the Childs by Selection and Crossover operators, respectively. The last operator of the algorithm used in producing the new generation is the Mutation operator. In the final step, an objective function evaluation of the new generation must be done. Here, we will follow the Chromosome encoding. In the present study, the random number method was used to code the chromosomes.

The chromosome is described as a matrix with m × T dimension. M and T are defined as some trans and time intervals, respectively. The cell in this matrix indicates the PM actions and I, M, and R represent inspection, repair, and replacement actions, respectively. The I action depends on the M and R action. If the M and R actions are not taken, then I action is done. The chromosome is divided into three arrays: (I) M action array, (II) R action array, (III) I action array in each of lengths is m × T. First, the M action array that each cell contains 1 or 0. This means that the M action is allocated or not respectively. Second, the R action array that each cell includes is 1 or 0. This means that the R action is allocated or not respectively. Eventually, the I action array that each cell contains is 1 or 0. This means that the I action is allocated or not respectively. By considering the constraint $M_{i,\,j} + R_{i,\,j} + I_{i,\,j} \leqslant 1$, GA produced the first population with size n. In the present study, the One-Point crossover type is selected. In this crossover, n random combination points on both parents are chosen and each pair of them is swapped with each other along both chromosomes. Also, the Uniform mutation type is selected. So, the mutation operator changes randomly in the new offspring. Now, it's time to decode the chromosomes. The structure of the decoded solution explores three matrixes: (I) $M_{i,j}$ representing genes that show $trans_i$ when repaired or not in period j. (II) $R_{i,j}$ represents genes that indicate $trans_i$ when replaced or not in period j. (III) $I_{i,j}$ representing genes that indicate $trans_i$ when inspected or not in period j. The three matrixes are decoded to the Optimal Preventive Maintenance (OPM) scheduling solution shown in the following. By using the proposed GA, as shown in Table 3, the structure of the chromosome with a length of 720 was considered and divided into three sub-chromosomes, 1:240 gene for repair activity, 241:480 gene for replacement activity, and 481:720 gene for Inspection activity.

Table 3. Chromosome structure

$[M_{1,1}, M_{1,2}, \ldots, M_{1,T}, M_{2,1}, M_{2,2}, \ldots, M_{2,T}, M_{m,1}, M_{m,2}, \ldots, M_{m,T}, R_{1,1}, R_{1,2}, \ldots, R_{1,T}, R_{2,1}, R_{2,2}, \ldots, R_{2,T}, R_{m,1}, R_{m,2}, \ldots, R_{m,T}, I_{1,1}, I_{1,2}, \ldots, I_{1,T}, I_{2,1}, I_{2,2}, \ldots, I_{2,T}, I_{m,1}, I_{m,2}, \ldots, I_{m,T}]_{1*720}$

0	0	1	0	1	1	0	0	0	0	1	0
M Activity-Dependent Variable											
1	0	0	0	0	0	1	0	0	1	0	1
R Activity-Dependent Variable											
0	1	0	1	0	0	0	1	1	0	0	0
I Activity -Independent Variable											

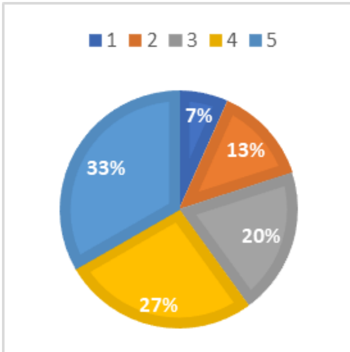
The instance of the selection mechanism using the roulette wheel method is given in Table 4.

Table 4. Instance of selection mechanism

solution	f_ best	fitness=(1/f_best)	chance	cumulative
1	38,889,160	2/57141E-08	0/200578053	0/200578053
2	38,938,006	2/56818E-08	0/200326437	0/400904491
3	38,959,304	2/56678E-08	0/200216924	0/601121415
4	39,034,542	2/56183E-08	0/199831012	0/800952426
5	39,062,045	2/56003E-08	0/199690314	1

R=rand (0,1) → R_1=0.63, R_2= 0.19

$Parent_1$= 4, $Parent_2$= 1



Single-point Crossover operator is applied to the proposed GA. Also, the structure of the single-point Crossover is given in the upper part of Table 5. In this crossover, n random combination points are chosen on both parents and each pair of them is exchanged with each other along both chromosomes. As shown in Table 5, the recombination operator for repair activity has been done in 12 months for the single-point crossover operator at the marked points.

Table 5. An instance of one point-crossover operator

Repair Activity	Parent.1	**1**	**1**	**0**	**1**	**0**	1	1	1	0	0	0	0
	Parent.2	0	0	1	0	1	**0**	**0**	**0**	**1**	**1**	**1**	**1**
	Child.1	**1**	**1**	**0**	**1**	**0**	**0**	**0**	**0**	**1**	**1**	**1**	**1**
	Child.2	0	0	1	0	1	1	1	1	0	0	0	0
	An Instance of Uniform Mutation												
	Parent	0	0	1	0	0	0	0	0	1	1	1	0
	Rand	0/17	0/32	0/12	0/91	0/31	0/78	0/13	0/24	0/89	0/40	0/42	0/28
	Child	1	1	0	0	1	0	1	1	1	1	1	1

In the current research, a uniform mutation operator is considered to repair activity extracted from the permutation operator. The lower part of Table 5 shows an instance of the current problem on the small domain in 12 months for the proposed decoded uniform mutation operator at a mutation probability of 0.4.

By using the design of experiment methods like Taguchi, various solutions can be estimated in terms of specific control factors. By performing the tests at the optimal level of the factors and comparing the actual results with the estimated value, the accuracy of the design is determined. This method reduces the number of tests required for optimization and increases the accuracy of the results. Also, to do the Taguchi method, the Signal-To-Noise ratio method (S/N) at Minitab.22 software was used to analyze and determine the appropriate values of the effective parameters of mutation, crossover, and population size of GA. Therefore, the estimated optimal parameters of the GA are given in Fig.1.

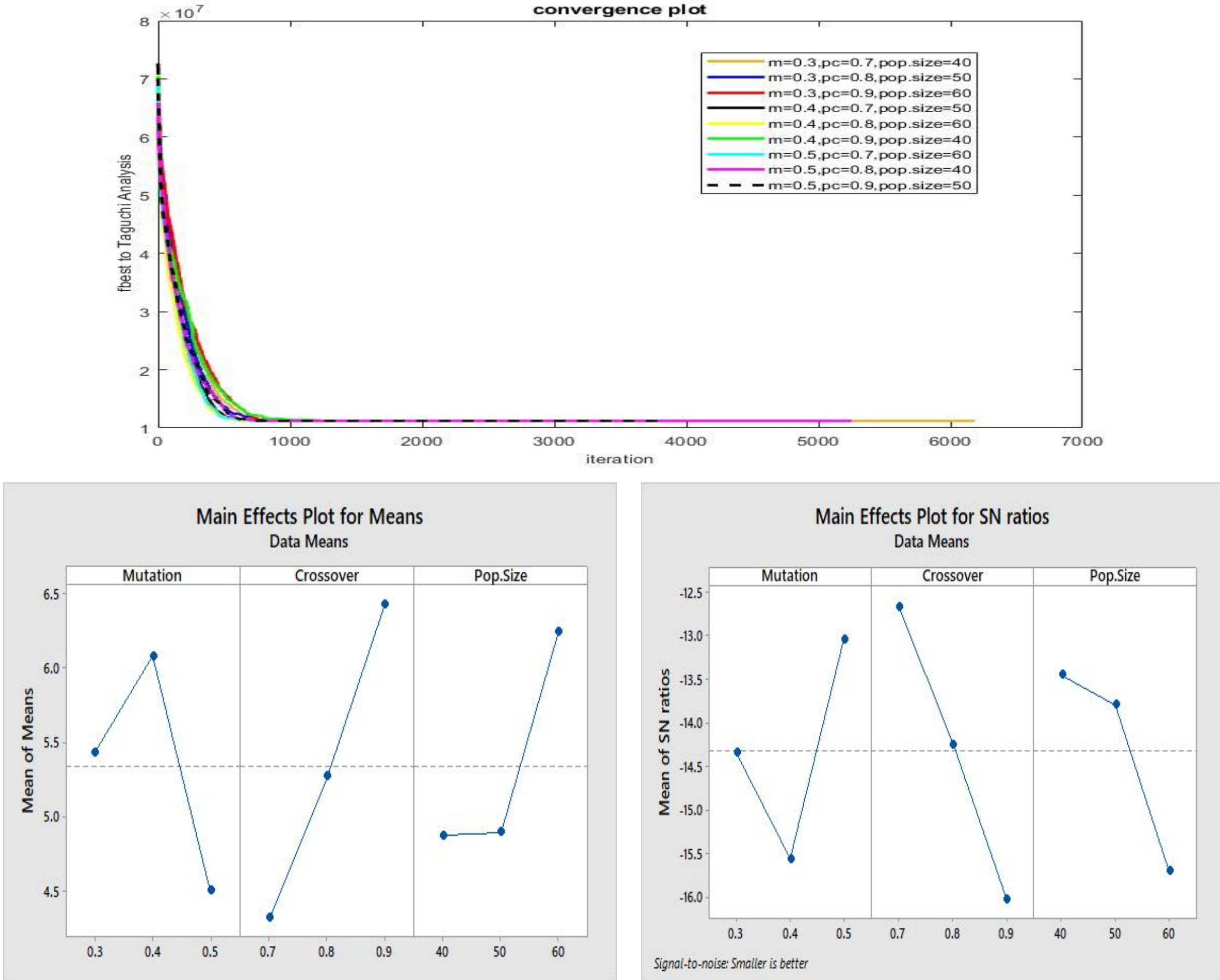


Fig.1. Taguchi's signal-to-noise analysis & convergence plot of GA

The convergence plot of this issue is given in the upper part of Fig.1. In this plot, 9 arrays of Taguchi analysis with parameters of population size, crossover, and mutation rate of each generation are given. The convergence of the diagrams indicated the validation of the algorithm to reach the optimal solution. Combining some parameters with a significant difference in less time has made the algorithm reach the optimal solution. Finally, as shown in the mean and signal-to-noise analysis diagram in the lower section of Fig.1, the best values for the Mutation, Crossover, and population size of the GA are 0.4, 0.9, and 60.

6. Multi-objective maintenance model

So far, a lot of studies have been done about single-objective PM. There has been a lack of studies on multi-objective PM policies, which should be urgently investigated. In particular, PM strategies in continuous production industries like Oil and Gas companies focus on the single-objective problem by considering reliability, costs, etc. Therefore, it is argued that the scope of related studies will be limited and there are a lot of development capabilities. Investigating multi-objective optimization of the vibration analysis of composite natural Gas pipelines using NSGA-II done by Moradi et al. [27].

The proposed formulation of the present study is based on the total annual costs due to unplanned failure, PM and inspection, replacement, and planned shutdown (e.g., overhaul). Therefore, based on the PAM requirements, authors have introduced the multi-objective NLIBP model and formulated as below:

$$Min(TMC) = \sum_{i=1}^{m}\sum_{j=1}^{T}[c_i \lambda_i [(EA_{i,j})^{K_i} - (SA_{i,j})^{K_i}] + Mc_i .M_{i,j} + Rc_i .R_{i,j} + Ic_i .I_{i,j} + D_i (M_{i,j} .tm_i + R_{i,j} .tr_i + I_{i,j} .ti_i)]$$

for i=1, …, m, for j=1, …, T (10)

$$Max\,(M_1) = \sum_{j=1}^{T} Av_j \quad \text{See Eq.20}$$ for j=1, …, T (11)

$$Max\,(M_2) = \sum_{j=1}^{T} \mathrm{Re}_j \quad \text{See Eq.21}$$ for j=1, …, T (12)

S.t

$SA_{i,1}=0$ for i= 1, …, m (13)

$SA_{i,j}= (1-M_{i,j-1}).(1-R_{i,j-1})\, EA_{i,j-1} + M_{i,j-1}(\beta_i.\, EA_{i,j-1})$ for i=1, …, m, for j=1, …, T (14)

$EA_{i,j}= SA_{i,j}+ tp$ for i=1, …, m, for j=1, …, T (15)

$M_{i,j}+ R_{i,j} + I_{i,j} =1$ for i=1, …, m, for j=1, …, T (16)

$EA_{i,j}, SA_{i,j} \geq 0$ for i=1, …, m, for j=1, …, T (17)

$M_{i,j}+ R_{i,j} \leq 1$ for i=1, …, m, for j=1, …, T (18)

$\sum_{i=1}^{m} R_{i,j}Wr_i + \sum_{i=1}^{m} M_{i,j}Wm_i + \sum_{i=1}^{m} I_{i,j}Wi_i \leq W_j$ for i=1, …, m, ∀j 1≤j≤T (19)

The objective function is shown in Eq.10 as TMC and consists of five cost terms: unplanned, repair, replacement, inspection, and planned costs. Eq.11 and Eq.12 show the minimum availability and reliability of the system as two other objectives of the proposed model, which is supposed to achieve the most optimal alternatives for these purposes according to the existing constraints. Eq.13 shows that the useful life of all equipment at the beginning period is zero (equipment is new). Eq.14 shows the useful life of the equipment for the rest of the period by considering whether to select the repair or replacement activities. For example, if a repair action is selected, the life of the equipment will change based on the life improvement factor (β). Eq.15 shows the useful life of the equipment at the end of each period. Eq.16 presented the binary condition that shows planners are only allowed to choose one option from the repair, replacement, and inspection activities in each period. Eq.17 shows the positive condition of useful life at the beginning and end of each period. Eq.18 shows the selecting or not condition rules of the repair or replacement activities. Eq.19 presented the resource limitation for replacement, repair, and inspection actions, which should be equal to the total allocation in each period.

7. Computational experiments

The case study in this research is the CPS of the Iranian natural Gas distribution steel network in Ahvaz City in Khuzestan Gas Company (KHGC). A schematic of the CPS and topology obtained from Geographic Information System (GIS) is displayed in Fig.2. On the left side of Fig.2, the components of CPS are shown, and on the right side, the topology of CPS is displayed.

Fig.2. Schematic plan of the CPS

The proposed PM scheduling model was applied to the KHGC, and the CPS consists of 20 transformers. The failure data was gathered from the Tolal Maintenance Management System (TMMS). Other data related to the cost, risk, and time obtained from the actual information available in financial, safety, and maintenance software respectively. Some of the collected data was used to calculate scale and shape parameters (λ,k) of non-homogeneous Poisson process distribution as presented in Crow [55] and Gannon and Kang [56] studies. The scope of replacement activity consists of the main parts that the failure of each causes the functional failure of the system. The scope of repair includes the repairable parts that must be done to enhance the efficiency of the CPS.

7.1 metrics

The present study will introduce 10 metrics (M_1-M_{10}) in the Risk, Cost, and Performance fields. The results of the proposed multi-objective NLIBP model will be presented in the discussion section with these metrics and the Pareto set.

7.1.1 Performance

Based on the availability metric, it is so important to calculate the allocated maintenance time for each PM activity in detail. This time includes repair (t_m), replacement (t_r), corrective (t_c), and inspection maintenance time for repair, replacement, corrective and inspection activities respectively. Availability metric(M_1) depends on the Mean Uptime and the Mean Downtime that is shown by MUT and MDT, respectively, in Eq.20. The reliability metric(M_2) of $trans_i$ in the period j can be expressed by Eq.21-22. Resources (teamwork) implemented throughout the period j are limited and should not be more than the current resources (W_j), as shown in Eq.23 (M_3). MTBF is based on the estimated Weibull distribution defined by metric M_4 (See Eq.24).

$$M_1 = \quad Av_j = \frac{tp - \sum_{i=1}^{m} tc_i . \lambda_i [(EA_{i,j})^{k_i} - (SA_{i,j})^{k_i}]}{tp + \sum_{i=1}^{m} [M_{i,j} .tm_i + R_{i,j} .tr_i + + I_{i,j} .ti_i]} \quad \text{for i=1, …, m; for j=1, …, T} \tag{20}$$

$$M_2 = \quad \mathrm{Re}_{i,j} = e^{-[\lambda_i (EA_{i,j})^{k_i} - \lambda_i (SA_{i,j})^{k_i}]} \quad \text{for i=1, …, m; for j=1, …, T} \tag{21}$$

$$\prod_{i=1}^{X} \mathrm{Re}_{i,j} \;:Series, 1 - \prod_{i=1}^{Y} (1 - \mathrm{Re}_{i,j}) : Parallel \quad \text{for i=1, …, m; for j=1, …, T} \tag{22}$$

$$M_3 = \quad \sum_{i=1}^{m} R_{i,j} Wr_i + \sum_{i=1}^{m} M_{i,j} Wm_i + \sum_{i=1}^{m} I_{i,j} Wi_i \le W_j \quad \text{for i=1, …, m; for j=1, …, T} \tag{23}$$

$$M_4 = \quad MTBF_i = \lambda_i \Gamma(1 + 1/k_i) \tag{24}$$

7.1.2 Risk

Based on the API-580 [57], Risk prioritization is a numerical evaluation used in risk management and reliability engineering to prioritize potential risks based on their severity, probability of occurrence, and detectability. This quantitative method allows organizations to identify and address the most critical risks and ensure efficient resource allocation to mitigate risk. However, inspection techniques should be considered for the consequences of failure.

According to Eq.25-26, the prioritization of assets is calculated based on the identified risk and shown by M_5.

$$M_5 = \text{RPN}^{\ddagger} = \text{Occurrence (O)} * \text{Severity (S)} * \text{Detection (D)} \qquad O\sim U(0,1);\ S, D = 1 \text{ to } 10 \tag{25}$$

$$\text{Occurrence (O)} = F(t) = 1-R(t), \text{ (See Eq.21)} \qquad t = 0 \text{ to } tp \tag{26}$$

The risk probability was calculated based on Eq.26. The Severity and Detection were obtained by the experts' comments in the range of 1 to 10.

7.1.3 Cost

To calculate TMC, all cost elements must be minimized. The NLIBP model that minimizes the TMC based on resource constraint is presented as an M_6 metric and shown in Eq.27. Based on PM scheduling, decision-making about outsourcing and insourcing is shown by related metrics (M_7, M_8) in Eq.28-29. By considering a shortage of resources as one of the main aspects of risk management that can lead to a decrease in M_1, a Balance of Teamwork (BOT) is defined by the M_9 metric. (See Eq.30).

$$M_6 = \text{TMC} = \sum_{i=1}^{m}\sum_{j=1}^{T}[c_i\lambda_i[(EA_{i,j})^{k_i} - (SA_{i,j})^{k_i}] + Mc_i.M_{i,j} + Rc_i.R_{i,j} + Ic_i.I_{i,j} + D_i(M_{i,j}.tm_i + R_{i,j}.tr_i + I_{i,j}.ti_i)] \tag{27}$$

$$M_7 = \text{TCO} = (COM)_{i,j} + (COR)_{i,j} + (COI)_{i,j} \qquad \text{for } i=1,2,3: (i_1=M, i_2=R, i_3=I); \text{ for } j=1, \ldots, T \tag{28}$$

$$M_8 = \text{TCI} = (CIM)_{i,j} + (CIR)_{i,j} + (CII)_{i,j} \qquad \text{for } i=1,2,3: (i_1=M, i_2=R, i_3=I); \text{ for } j=1, \ldots, T \tag{29}$$

$$M_9 = (BOT)_{i,j} = (W)_{i,j} - (NE)_{i,j} \qquad \text{for } i=1,2,3: (i_1=M, i_2=R, i_3=I); \text{ for } j=1, \ldots, T \tag{30}$$

The $BOT_{i,j}$ is the ninth metric that shows the present resource allocation situation at each period by this metric. we are supposed to optimize the resource allocation. Based on the failure on $trans_i$, the number of required teamwork in each period j is displayed by $NE_{i,j}$.

7.2 Parameter setting

In the present study, authors assumed that the transformers have a Weibull distribution. To estimate relative parameters, we now determine the parameters λ and K that are most likely to be the actual parameter value given the dataset. For given parameters λ and K, the likelihood of an event duration with length t equals f (t, λ, K). For given parameters λ and K, the Likelihood (LLH) of censored duration with length t is equal to:

$$R(t; \lambda, k) = 1 - F(t; \lambda, k) \tag{31}$$

The length of duration (T), shape and scale parameter, probability density (f), and cumulative distribution function (F) can be calculated using the Excel solver module. Table 6 shows the likelihood of each duration for 2 years with 15-day intervals. The result of this likelihood per duration is the likelihood of the complete dataset and is denoted by L (λ, k). The values of λ, k that maximize this function are the Maximum Likelihood Estimation (MLE) of λ, k. Given our dataset, for example, the MLE estimations of the λ_1, λ_{20}, λ_{pilot}, k_1, k_{20}, and k_{pilot} parameters are calculated in the above way as shown in Table 6. We refrained from mentioning the rest of the steps for calculating the λ_i and k_i of other transformers, but this data set based on actual data for CPS is shown in Table 7. All of the costs in this study are in terms of 1000 Rials. Gas delivery is continuing for all of the week and 24 hours a day. The planning horizon is one year with monthly PM intervals. The minimum Reliability (Re_0) and availability (Av_0) should be 90% and 95% considered for all periods, respectively. The hazard rate variable (h(t)) was obtained according to the ratio of probability density function to reliability.

Failure and working condition specified by "YES" and "NO" respectively that reports from TMMS data. Then, f(t), R(t), LLH, and h(t) based on the MLE method should be calculated. Eventually, by using the solver module on Excel software, optimum λ and K parameters were obtained for each trans, as showed the end of the above table. Also, the MLE estimation of the cumulative distribution function, hazard rate, and reliability is presented in Eq.32-34.

‡Risk Priority Number

Table 6. MLE estimations of the λ, k for transes 1, 20

Trans.1								Trans.20						
Duration (month)	Failure	f(t)	R(t)	LLH	Log (LLH)	h(t)		Duration (month)	Failure	f(t)	R(t)	LLH	Log (LLH)	h(t)
0	-	-	1	-	-	-		0	-	-	1	-	-	-
0.50	YES	0.296926	0.508902	0.296926	-0.52735	0.583465		0.50	NO	0.179949	0.508902	0.508902	-0.29337	0.353602
1.00	NO	0.158214	0.402025	0.158214	-0.80075	0.393543		1.00	NO	0.090634	0.402025	0.158214	-0.80075	0.225444
1.50	NO	0.105552	0.337688	0.105552	-0.97653	0.312572		1.50	NO	0.05985	0.337688	0.105552	-0.97653	0.177235
2.00	YES	0.077645	0.292512	0.077645	-1.10989	0.265442		2.00	YES	0.044278	0.292512	0.077645	-1.10989	0.151373
2.50	NO	0.060401	0.258306	0.060401	-1.21895	0.233837		2.50	NO	0.0349	0.258306	0.060401	-1.21895	0.135112
3.00	NO	0.048742	0.231193	0.048742	-1.3121	0.210828		3.00	NO	0.028649	0.231193	0.048742	-1.3121	0.123916
3.50	NO	0.040372	0.209021	0.040372	-1.39392	0.19315		3.50	NO	0.024193	0.209021	0.040372	-1.39392	0.115744
4.00	NO	0.034102	0.190473	0.034102	-1.46722	0.179039		4.00	NO	0.020863	0.190473	0.034102	-1.46722	0.109533
4.50	NO	0.029251	0.174684	0.029251	-1.53386	0.167451		4.50	NO	0.018284	0.174684	0.029251	-1.53386	0.104671
5.00	NO	0.025402	0.161056	0.025402	-1.59513	0.157722		5.00	NO	0.016231	0.161056	0.025402	-1.59513	0.100782
5.50	NO	0.022286	0.14916	0.022286	-1.65197	0.149408		5.50	NO	0.014561	0.14916	0.022286	-1.65197	0.097617
6.00	NO	0.01972	0.138679	0.01972	-1.70508	0.142202		6.00	NO	0.013176	0.138679	0.01972	-1.70508	0.095009
6.50	NO	0.017579	0.129369	0.017579	-1.75501	0.13588		6.50	NO	0.01201	0.129369	0.017579	-1.75501	0.092839
7.00	NO	0.01577	0.121045	0.01577	-1.80218	0.130278		7.00	NO	0.011017	0.121045	0.01577	-1.80218	0.091019
7.50	NO	0.014225	0.113556	0.113556	-0.94479	0.125271		7.50	YES	0.010162	0.113556	0.014225	-1.84694	0.089486
8.00	NO	0.012895	0.106784	0.012895	-1.88957	0.120761		8.00	NO	0.009417	0.106784	0.012895	-1.88957	0.08819
8.50	YES	0.011741	0.100631	0.011741	-1.9303	0.116672		8.50	NO	0.008764	0.100631	0.011741	-1.9303	0.087093
9.00	NO	0.010732	0.095019	0.010732	-1.96933	0.112944		9.00	NO	0.008187	0.083	0.010732	-1.96933	0.09864
9.50	YES	0.009844	0.089879	0.009844	-2.00682	0.109528		9.50	NO	0.007674	0.065	0.009844	-2.00682	0.118057
10.00	NO	0.009059	0.085157	0.009059	-2.04291	0.106382		10.00	NO	0.007214	0.05	0.009059	-2.04291	0.144286
10.50	NO	0.008361	0.080806	0.008361	-2.07773	0.103474		10.50	NO	0.006801	0.03	0.008361	-2.07773	0.226699
11.00	NO	0.007738	0.076784	0.007738	-2.11138	0.100775		11.00	NO	0.006427	0.02	0.007738	-2.11138	0.321368
11.50	YES	0.007179	0.073057	0.007179	-2.14395	0.098262		11.50	NO	0.006088	0.01	0.007179	-2.14395	0.608814
12.00	NO	0.006675	0.069596	0.006675	-2.17553	0.095914		12.00	NO	0.005779	0	0.006675	-2.17553	#DIV.0!
lambda=1.2, k=0.43								lambda=0.87, k=0.25						

$$F(x) = 1 - e^{(t/\lambda)^k}, t \geq 0 \tag{32}$$

$$R(t) = e^{-(t/\lambda)^k}, t \geq 0 \tag{33}$$

$$h(t) = (\lambda / k).(t / k)^{\lambda-1}, t \geq 0 \quad (34)$$

MTBF is defined as the inverse of the failure rate. The new metric (M_{10}) for the MTBF based on the estimated Weibull distribution can be calculated as below. Fig.3 shows the MTBF of 20 transformers based on the MLE estimation.

$$M_{10} = MTBF = \lambda\Gamma(1+1/k) \quad (35)$$

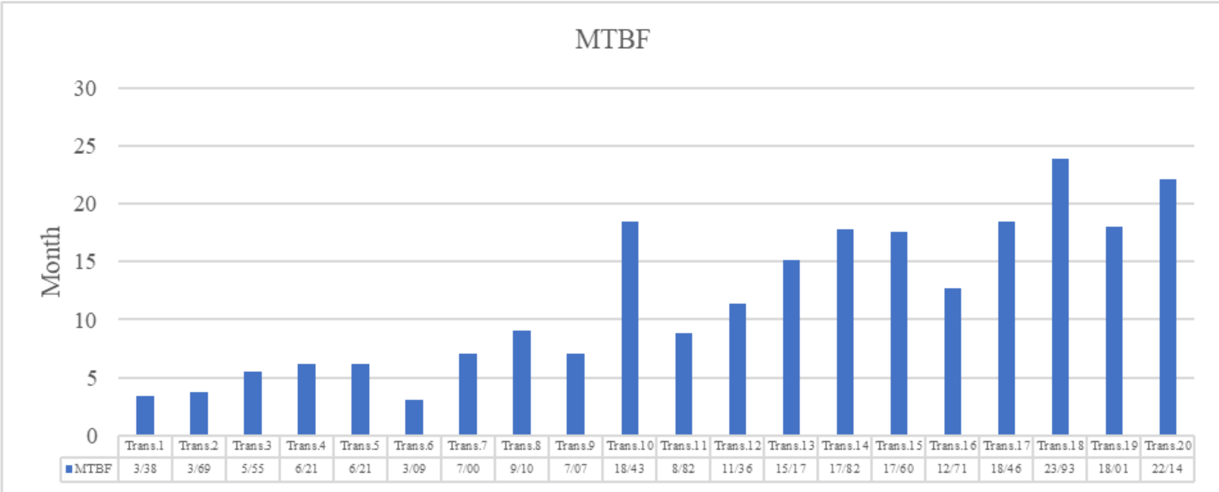


Fig.3. MTBF of 20 transformers

The authors have used the Kaplan-Meier method to validate the estimated parameters by MLE. Kleinbaum [58] demonstrated that Kaplan-Meier curves can be used for survival probability (R). Fig.4 shows the actual reliability of trans 1, 20, and the deviation from the Kaplan-Meier curve. In this study, researchers will prove the effect of the proposed scheduling on increasing reliability and other metrics. Based on Weibull distribution features, the schematic of the well-known bathtub curve for the reliability analysis of components is shown in Fig.5. It consists of three parts. The portion with the constant failure rate is taken as the component's lifespan. Components that undergo high early failure rates can be screened out by the manufacturer before distribution. The high failure rate due to wear-out is dependent on the materials and processes used to make the device.

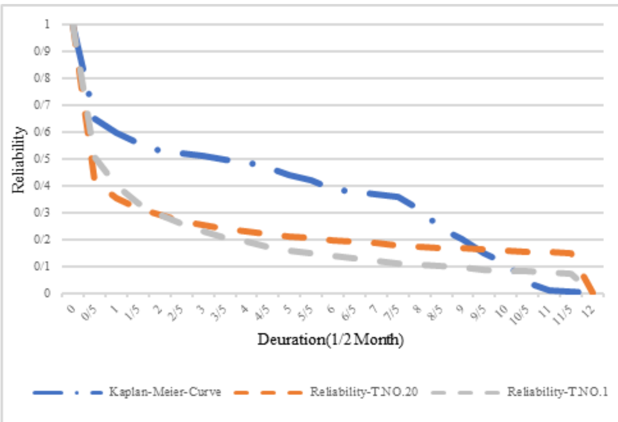


Fig.4. Reliability of trans 1, 20 compared with Kaplan-Meier curve

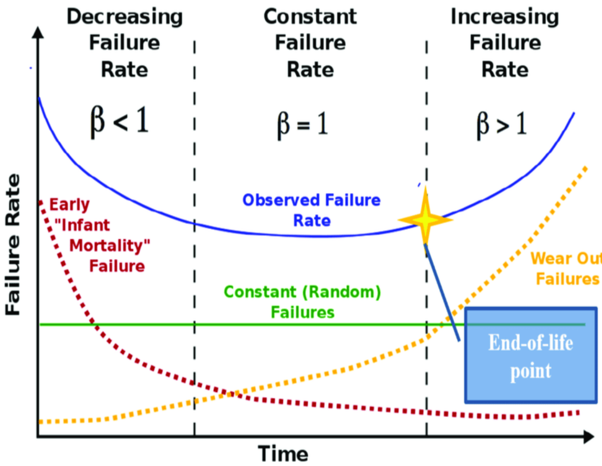


Fig.5. bathtub curve based on Weibull distribution

Weibull distribution has many applications, especially in survival and reliability analysis. Suppose that the random variable X has non-negative numbers and continuous values so that its density function is written in the following form, then we say that this random variable has a Weibull distribution with shape and scale parameters with K and λ parameters respectively according to Eq.36.

$$f(x,\lambda,K)=\frac{K}{\lambda}\left(\frac{x}{\lambda}\right)^{K-1}e^{-\left(\frac{x}{\lambda}\right)^{K}} \qquad X\geq 0 \tag{36}$$

Based on a dataset from Table 6, the probability density function and failure (hazard) rate diagram with half-month duration intervals until 2 years are drawn at the left and right side of Fig.6 respectively. By considering Weibull distribution features, we can now analyze these curves briefly. Also, the authors compared the results with a pilot trans by lambda and Beta parameters with 5 and 3 values respectively. From the commissioning to the third period, the hazard rate in Trans.1 and Trans.20 is decreasing, but it is increased in the pilot Trans. This means that the first two trans are in their early course and the pilot trans is in its wear-out course of the LC. At first, Trans.1 and Trans.20 had a high failure rate at the beginning of their cycle, which was mainly due to weak or non-standard parts, inappropriate operation processes, etc. Early failures can be avoided by using a burn-in strategy, improving operating and maintenance processes, etc. After the initial failure period, finally, the failure rate reaches a constant value and we will mainly see the normal working conditions of the equipment. But pilot trans had an increasing failure rate. The beginning of this area occurred when the failure rate suddenly started to increase, and these failures are no longer due to random factors, but due to the long life of the system. In this area, the device has reached its economic life (useful or design life). To minimize failures in the wear area, changes in the PM strategies and replacement of devices or parts are proposed.

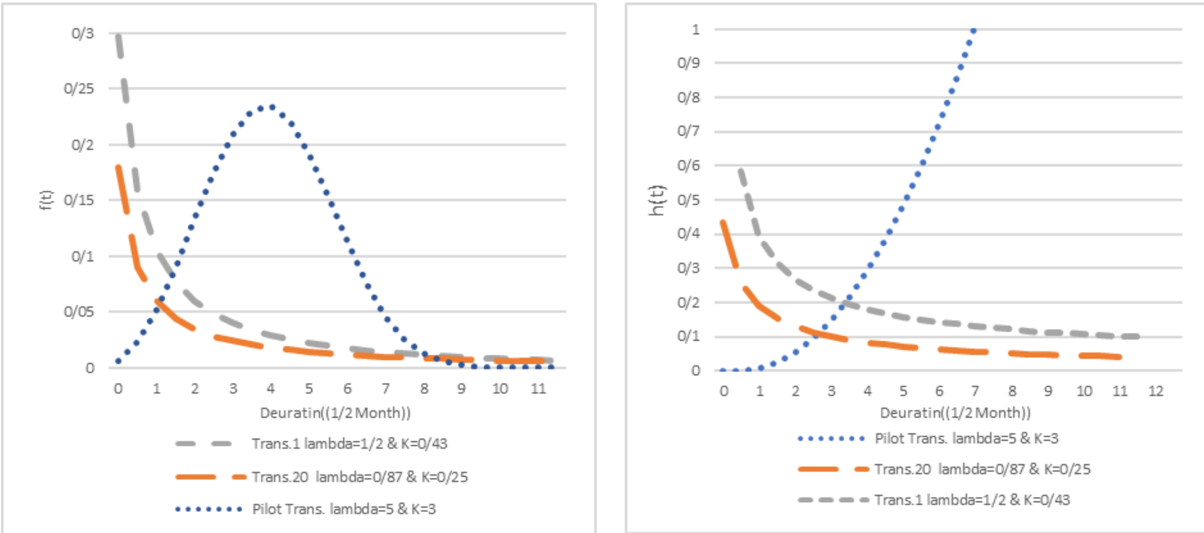


Fig.6. f(t): Probability density function - h(t): Failure rate diagram

Based on the optimal parameters obtained from the MLE, the authors used Table 7 as the input data to verify the reliability of the Kaplan-Meier method. Also, these data were implemented as the initial input of the multi-objective NLIBP in this research.

Table 7. The input parameters for PM scheduling.

Trans. NO	λ	K	β	C	Mc	Rc	Ic	tr (min)	tm (min)	ti (min)
1	1.240136122	0.431876401	0.63	20000	90	30000	79000	1200	1000	2500
2	1.145098955	0.404363953	0.67	10000	300	25000	85500	3000	3600	3000
3	1.256165318	0.363768664	0.4	10000	800	64000	81000	1500	2500	3000
4	0.986659903	0.332181984	0.6	1200	200	65000	76000	2000	2000	3500
5	0.986659903	0.493181984	0.6	40000	400	230000	55000	1000	1600	6000
6	1.263409992	0.452736864	0.7	22000	300	30000	52000	2000	3000	3200
7	1.248241885	0.33945184	0.4	4000	95	20000	11000	3000	3500	3500
8	1.101921814	0.307936884	0.5	33000	350	40000	50000	1500	4000	5000
9	1.073610989	0.325345494	0.5	10000	500	60000	10000	1000	4000	2500
10	1.309974386	0.275071676	0.31	10500	900	38000	72000	2500	1800	4000

11	1.189695376	0.31592961	0.31	1000	300	38000	58000	2000	3000	3000
12	1.273760058	0.30257168	0.33	1100	300	60000	50000	2000	1800	3000
13	1.351063049	0.287817632	0.67	12200	40	40000	81000	2500	3000	4200
14	1.286663769	0.281669293	0.47	4500	500	65000	50500	3500	1500	6000
15	1.427629494	0.276591698	0.6	16000	600	5500	50000	1000	4000	4800
16	1.273052595	0.295097144	0.5	36000	400	40000	13000	1200	3000	4000
17	1.255443805	0.272747548	0.5	9500	800	60000	13000	6000	3000	3600
18	1.103744965	0.254308606	0.6	15000	600	25000	33500	2000	2000	6000
19	1.128487239	0.268587155	0.64	20000	600	30000	52200	4000	4000	4000
20	0.848345175	0.24657486	0.64	5000	80	50000	16000	3000	4000	3000

8. Experimental results and discussion

The suggested mathematical model was applied to the Iranian natural Gas distribution steel network in KHGC. This model solved to gain an optimal PM schedule. The algorithm's code is written in MATLAB (R2019 b) software and then run on a Personal Computer (PC). The chromosome structure with length 720 was considered and divided into three sub chromosomes, the 1:240 genes are the repair action, the 241:480 genes are the replacement action and the 481:720 genes are the inspection action. By using a random search algorithm like GA, it is clear that the quality of the solutions is affected by different values. The authors explored the features of the proposed GA and NSGA-II in levels of parameters and found the optimum level by using the Taguchi method which is shown in Table 8.

Table 8. The best level of operators for the algorithm and PC.

GA & NSGA-II	Pop. size	Crossover rate	Mutation rate	No. of generations	NO change	Length of chromosome
	60	0.9	0.4	2120 & 2980	3	720
PC	Intel (R) Core i7-2630QM, CPU 2.00GHz, Ram 4.00 GHz					

The pseudo-code and Convergence plot for the proposed algorithm is presented in Fig.7.

Procedure
Initialization
Fitness evaluation
X_{best} = Update
While the stopping criterion is not met **do**
Reproduction (p_r%)
Crossover (p_c%=1- p_r%)
Mutation (All offspring produced by crossover, p_m)
Fitness evaluation
X_{best} = Update
End while

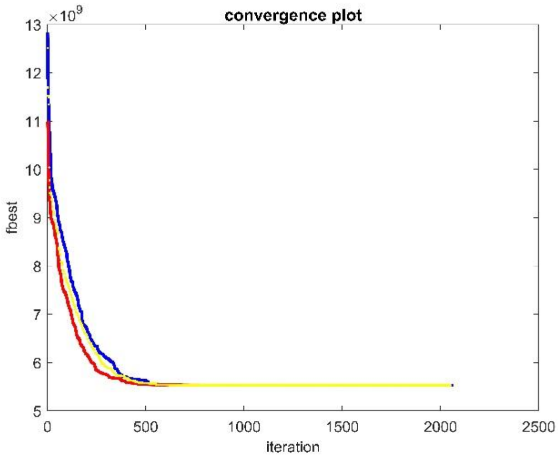


Fig. 7. The pseudo code and Convergence plot for the proposed GA.

The search time for GA is considered to be 20 minutes. Even though the algorithm ran three times, As shown in the convergence plot in Fig.7, no solution improvement was obtained by increasing the search time. On the other hand, the proposed algorithm provides the best solution. The following, approaches to solving single and multi-objective NLIBP are described.

8.1 Proposed PM Scheduling regarding the single-objective problem

Considering that cost is one of the important components in corporate-level decision-making, the researchers tried to obtain the optimal schedule based on a single-objective problem like TMC. So, GA was used to get the best solution which is mentioned in this section. Because owners tend to be able to have decision options based on other metrics like performance in addition to minimizing costs, therefore, NSGA-II was used to solve the multi-objective problem. The results of this approach are given in section 7.2. The corresponding OPM schedule using the proposed model, with relative Reliability and availability results, is shown in Table 9 in which N, M, and R stand for inspection, repair, and replacement actions, respectively. The TMC of the solving model resulted in 11,214,556 (1000. Rial) as the value of the best objective function. The budget spent in the year 2023 for the Gas distribution steel network was 13,245,728 (1000. Rial). Based on the OPM, the RPN of a non-protecting underground steel network has been shown in Fig.8. The proposed OPM results in a reduction of TMC by about 19%. Fig.9 indicates a comparison between the current and proposed maintenance plan cost. To reduce the failure rate, by using the proposed OPM, until actions (N, M, R) were done at each period, reliability and Availability will be increased. Given that, the owners had considered at least Reliability and Availability as 90 and 95 percent, respectively. In addition, these metrics of the proposed OPM schedule are higher than the actual plan in most periods (see Fig.10). Comparing the risk, cost, and performance values of the current situation with the proposed model demonstrated the effectiveness of the proposed scheduling.

Table 9. Optimal PM (OPM) schedule and performance metrics

T Trans	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**
1	M	M	I	M	I	I	M	R	I	R	I	M
2	I	R	I	R	R	M	R	I	I	M	M	I
3	I	I	I	I	I	R	R	R	M	I	M	I
4	I	**R**	I	I	M	I	I	M	I	I	I	I
5	**R**	I	M	M	I	I	I	M	**R**	M	M	M
6	M	I	R	I	I	I	R	M	I	I	I	I
7	I	I	I	M	R	I	I	I	R	I	I	I
8	I	M	I	M	I	R	I	R	I	I	I	I
9	R	R	I	I	I	I	I	I	I	R	R	I
10	I	R	M	M	M	I	M	I	I	I	I	I
11	I	I	I	I	I	R	I	R	I	I	I	M
12	R	M	I	I	I	R	M	I	M	I	R	I
13	I	M	I	I	I	R	I	I	I	I	R	R
14	**R**	M	M	M	**R**	**R**	M	M	M	M	M	M
15	**R**	**R**	M	**R**	M	**R**	I	**R**	**R**	M	**R**	M
16	I	I	R	R	I	I	I	R	R	M	I	I
17	I	I	I	I	I	I	I	I	I	I	I	I
18	M	I	I	I	I	I	I	I	I	I	I	I
19	I	I	I	I	I	I	R	I	I	I	I	R
20	I	I	M	M	I	I	I	I	R	I	I	I
RE	0.831	0.895	0.89	0.936	0.923	0.924	0.92	0.934	0.917	0.934	0.904	0.904
AV	0.941	0.942	0.955	0.958	0.957	0.957	0.958	0.96	0.965	0.962	0.952	0.949

As shown in Table 9, GA presented its OPM for transformers in each period including repair, replacement, or inspection action. For example, Trans.1, has 5, 2, and 5 types of actions like M, R, and I during the 12-month horizon. Also, the reliability and availability of the entire system are shown in each period. The best level of the system metrics in each period could be obtained using the data in this table. Table 10 presents the monthly cost of the system in real mode.

Here, an investigation of the risk metric in terms of the proposed model is done. The RPN chart of CPS is drawn in Fig.8 based on OPM by Eq.25-26.

Each box in the bar charts of Fig.8 represents the RPN of the related Trans. For example, the RPN of Trans.9 is shown in gray. Also, period 1 has a high-risk level of about 116, which can be related to the system commissioning period.

Table 10. Current PM Plan Costs

T	1	2	3	4	5	6
Cost	1,226,503	963,277	1,120,922	907,265	1,318,315	1,180,077
T	7	8	9	10	11	12
Cost	1,151,658	870,041	1,244,116	1,149,579	1,046,582	1,067,393

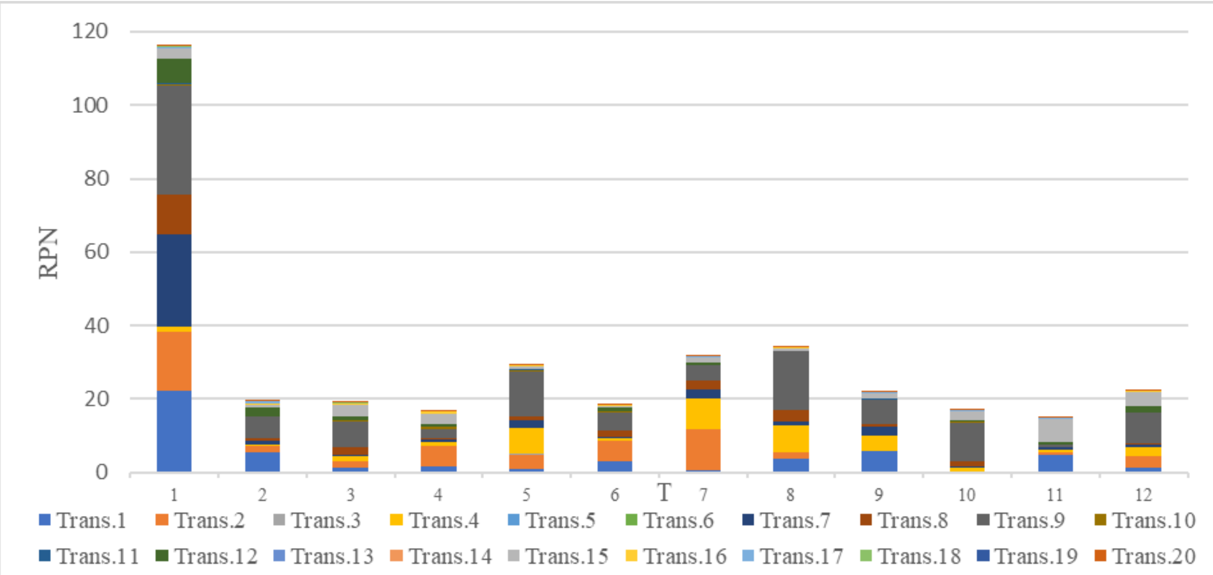


Figure 8. RPN chart for the CPS

Here, an investigation of the cost metric in terms of the proposed model is done. A comparison between the proposed and current maintenance schedule costs is shown in Fig.9.

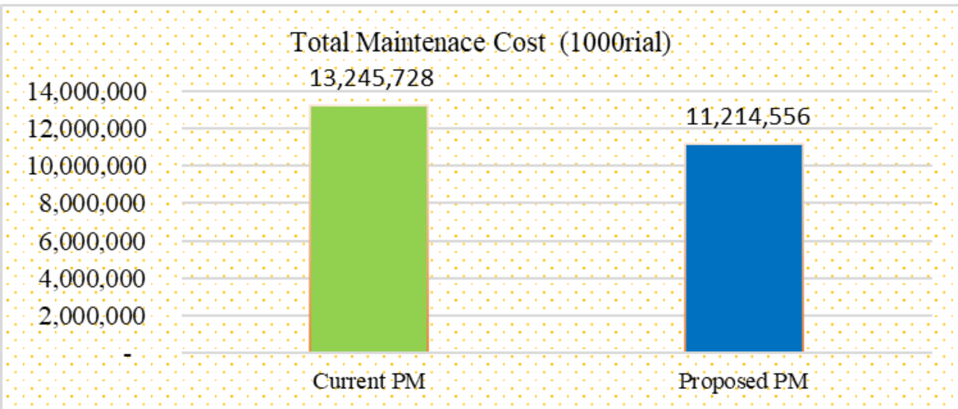
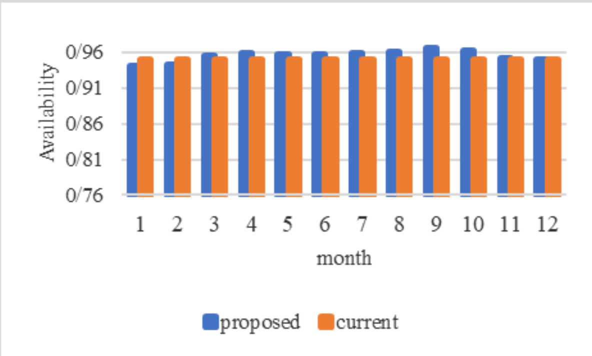


Figure 9. Comparison between the proposed and current maintenance schedule cost

By considering Fig.9, the capability of the proposed model in the cost metric of the PAM approach was proved. The Availability and Reliability of a current and proposed plan are shown in Fig.10.



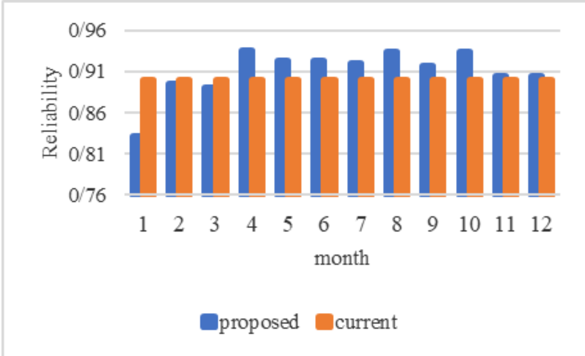


Fig.10. Availability & Reliability for a current and proposed plan.

One of the essential factors affecting Availability is the unscheduled shutdown or emergency maintenance that decreased as a consequence of OPM. Another factor that affects the proposed performance is the scale and shape parameters, which were determined according to the MLE method. As shown in Fig.10, in most periods, reliability and availability are higher than what is considered by owner default. As proved in Sedeh et al.[30] research, decision-making about outsourcing, and insourcing play a key role in the PAM. Also, Charles and Ochieng [46] presented extensive research on the strategic role of outsourcing in the performance of employees. In the present study, an investigation of outsourcing as another performance metric in the proposed model is done. Based on risk-based maintenance and using the proposed model, a balance between cost and performance has been made. The priority is to carry out PM activities using internal resources, but when there is a shortage of manpower, outsourcing of activities is allowed. In this study, 6, 3, and 10 teamwork are allocated for M, R, and I activities in each month, respectively. For example, in the random iteration of the algorithm, the following resources were required based on the OPM shown in Table 11. These data presented the balance between maintenance activities vs human resources allocation and costs. Maintenance planners can estimate the allocated resources and shortages in each period using the proposed model.

Table 11. The balance between maintenance activities vs resources & costs

T		1	2	3	4	5	6	7	8	9	10	11	12
NE	**M**	4	2	7	7	5	7	6	1	3	2	5	6
	R	6	6	7	3	8	2	3	7	4	6	5	3
	I	10	12	6	10	7	11	11	12	13	12	10	11
BOT	**M**	2	4	-1	-1	1	-1	0	5	3	4	1	0
	R	-3	-3	-4	0	-5	1	0	-4	-1	-3	-2	0
	I	0	-2	4	0	3	-1	-1	-2	-3	-2	0	-1
COM		0	0	30 0	90 0	0	350	0	0	0	0	0	0
COR		135000	130000	220000	0	223000	0	0	148000	30000	99500	90000	0
COI		0	135500	0	0	0	16000	79000	74 000	18 1000	114500	0	52200
TCO		135000	265500	220300	**900**	223000	16350	79000	**222000**	211000	214000	90000	52200
CIM		1230	990	1875	3550	2240	3245	2250	60 0	1150	700	1995	2495
CIR		250000	248000	330000	83500	331000	94000	128000	473000	155000	22 9500	380000	310000
CII		180600 0	155060 0	974000	142090 0	163280 0	15678 0	158360 0	162630 0	150440 0	171450 0	115940 0	139990 0
TCI		205723 0	179959 0	130587 5	**150795 0**	196604 0	16650	171385 0	**209990 0**	166055 0	194470 0	154139 5	171239 5

In the first period, we need 6 teams to carry out the replacement action. By considering 3 available replacement teamwork, the planner is facing a lack of 3 teamwork. One of the most important applications of this model will be resource-leveling. In addition, the planner can get the allocated budget in each of the action categories in outsourcing or insourcing. For example, in periods 4 and 8, the lowest and highest total budgets of 1,508,850 and 2,321,900 have been allocated, respectively. Unlike linear problems, relative to Non-Linear Programming (NLP), the number of solutions and solving time will be incremental according to the input, the size of the problem, etc. as shown by Murty & Kabadi[59]. The researchers proved nonlinear and complex optimization problems are unsolvable in polynomial time. In the present research, authors faced an NLBIP problem that cannot be solved by exact methods in a reasonable time. However, the researchers proved their claim by solving the model on a different scale and compared the results with the proposed algorithm in the following. The NLBIP was solved by the exact method in General Algebraic Modeling System (GAMS) software version 24.8.2 on a personal computer with the previous specifications, and the relevant results are given in Table 12.

Table 12. Comparing GAMS vs GA Results on a different scale

m	Metrics	GA	GAMS	Gap (%)
20	Fitness	11,214,556	11,112,305	**1**
	Time (s)	3/8	13	**-71**
40	Fitness	22,429,113	21,024,605	**7**
	Time (s)	8/2	16	**-49**
60	Fitness	33,643,669	32,536,905	**3**
	Time (s)	10	23	**-57**
80	Fitness	44,858,226	44,049,195	**2**
	Time (s)	13	37	**-65**
100	Fitness	56,097,113	55,079,559	**2**
	Time (s)	18	89	**-80**

As shown in Table 12, the problem was investigated on a different scale with 20, 40, 60, 80, and 100 Trans. considering the fitness function (total cost in 1000 Rials) and the solution time. The Gap analysis between these factors is done in Eq.37 and shown in the last column of the above table.

$$Gap_m = \left(\frac{metric_{GA} - metric_{GAMS}}{metric_{GAMS}}\right)*100 \qquad \text{for m= 20, 40, 60, 80, 100} \tag{37}$$

For example, when 20 transformers were selected, considering the Gap analysis, the fitness and solution time Gap of the exact and meta-heuristic methods were about 1 and -71 percent respectively. The results indicate that both methods were capable of reaching the optimal solution but the meta-heuristic method has reached in a very short time.

8.2 Proposed PM Scheduling regarding the multi-objective problem

Based on the Industry 4.0 and 5.0 revolution requirements in the PAM, managers are interested in paying attention to risk and performance in addition to the cost. As mentioned in the literature review, comprehensive studies on these topics have not been conducted. Therefore, in the current research, the development, and solving of the multi-objective optimization model are prioritized by researchers in addition to solving the single-objective optimization model. Based on the single-objective function, the proposed GA omits some alternatives despite the high reliability, availability, risk, etc. Therefore, based on the proposed NLIBP model, NSGA-II was used in the present research to solve this problem and create a decision-making rule for managers. The proposed alternatives are based on the objective function for three important performance indicators: risk, reliability, and availability as shown in Fig.11-15.

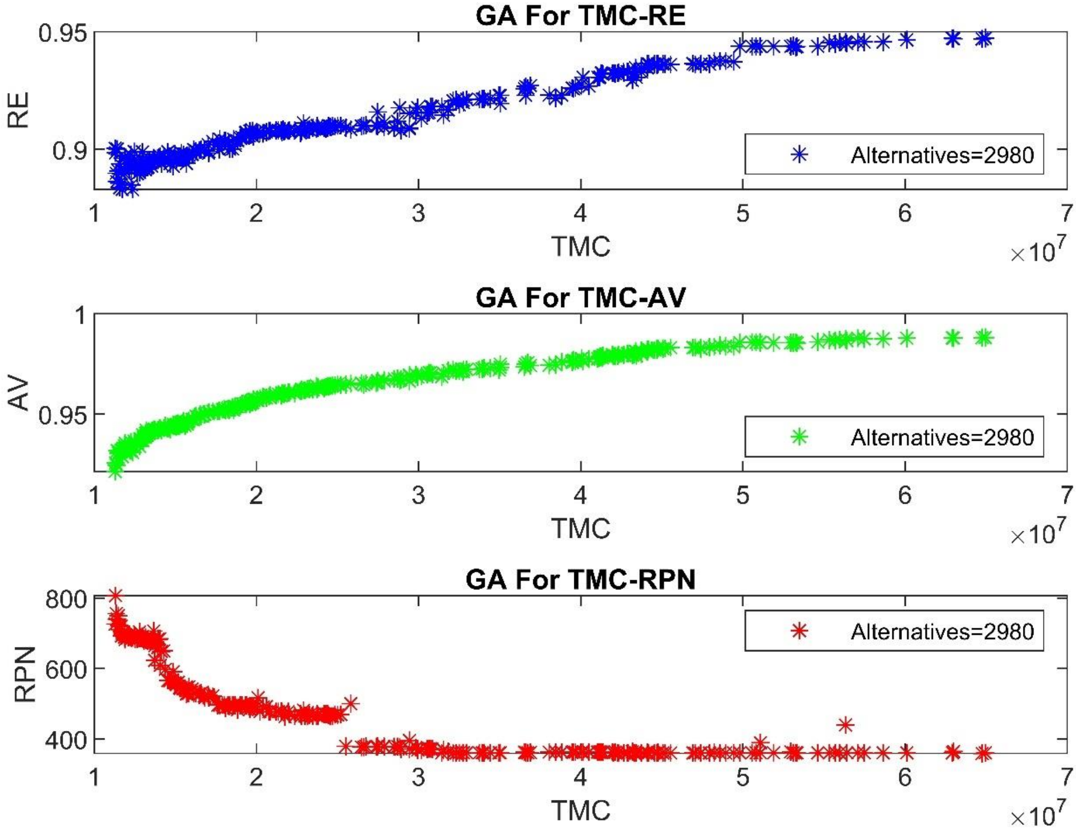


Fig.11. The results of the GA in obtaining the optimal solution

As shown in Fig.11, the GA based on the TMC as a single objective in 2980 iterations has only proposed a schedule to carry out repair, replacement, and inspection activities. However, it is conceivable that managers based on proportional budgets sometimes tend to choose their schedules based on reliability, availability, or acceptable risk. Therefore, the GA does not have the necessary efficiency and the NSGA-II should be used. As shown in Fig.12, NSGA-II based on TMC and considering the minimum reliability as 0.8 and availability as 0.85, proposed 77 and 141 alternatives respectively.

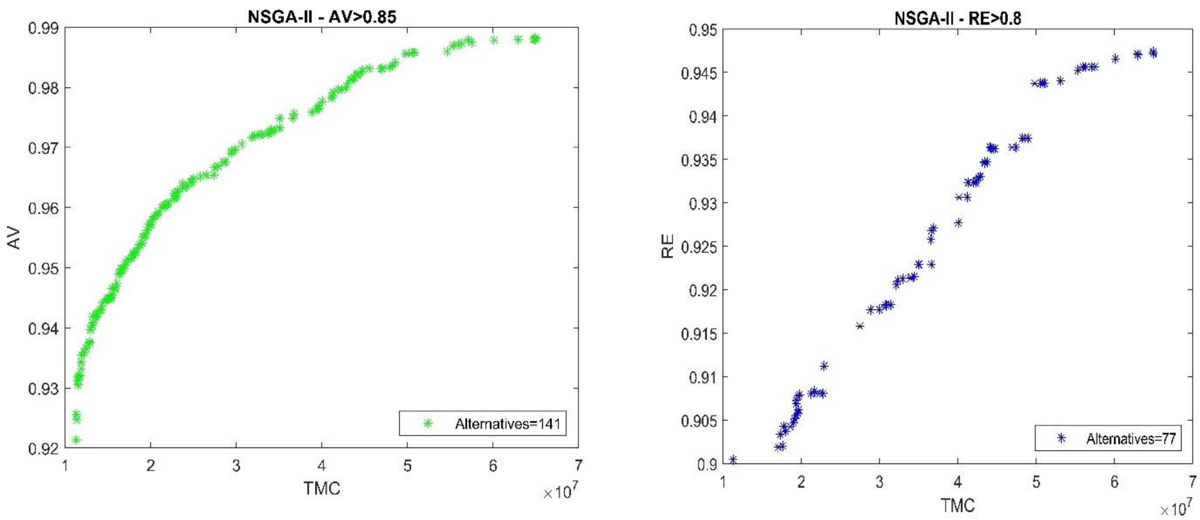


Fig.12. The proposed alternatives of the NSGA-II in RE: 0.8 & AV: 0.85.

As shown in Fig.13, NSGA-II based on TMC and considering the minimum reliability as 0.92 and availability as 0.95, proposed 50 and 101 alternatives respectively.

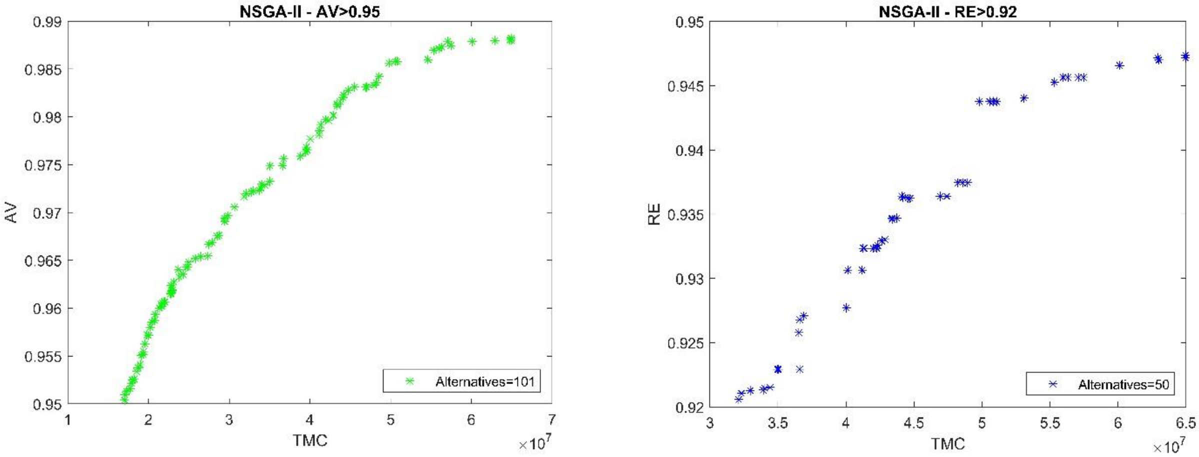


Fig.13. The proposed alternatives of the NSGA-II in RE: 0.92 & AV: 0.95.

As shown in Fig.14, NSGA-II based on TMC and considering the minimum reliability as 0.94 and availability as 0.97, proposed 15 and 52 alternatives respectively.

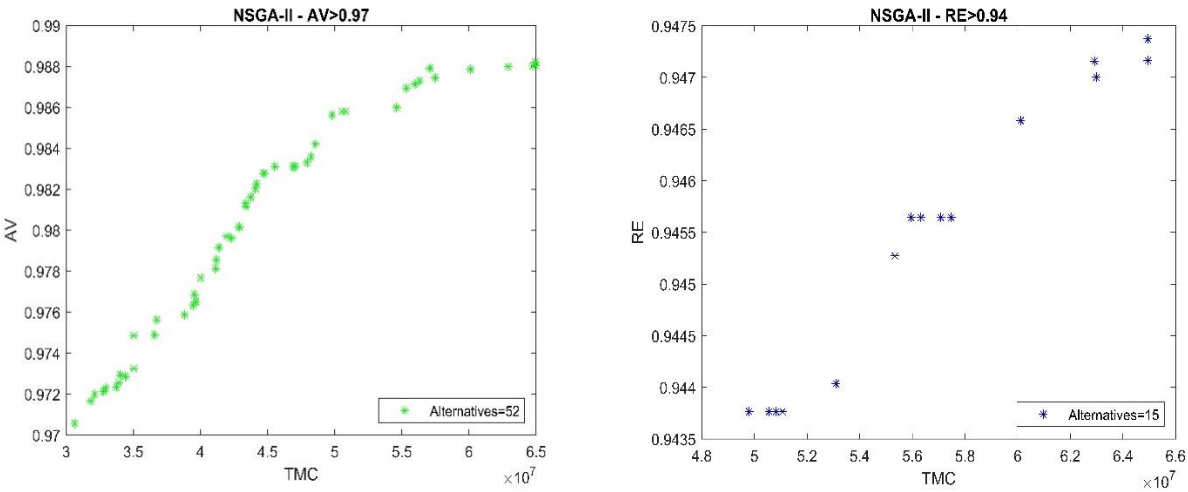
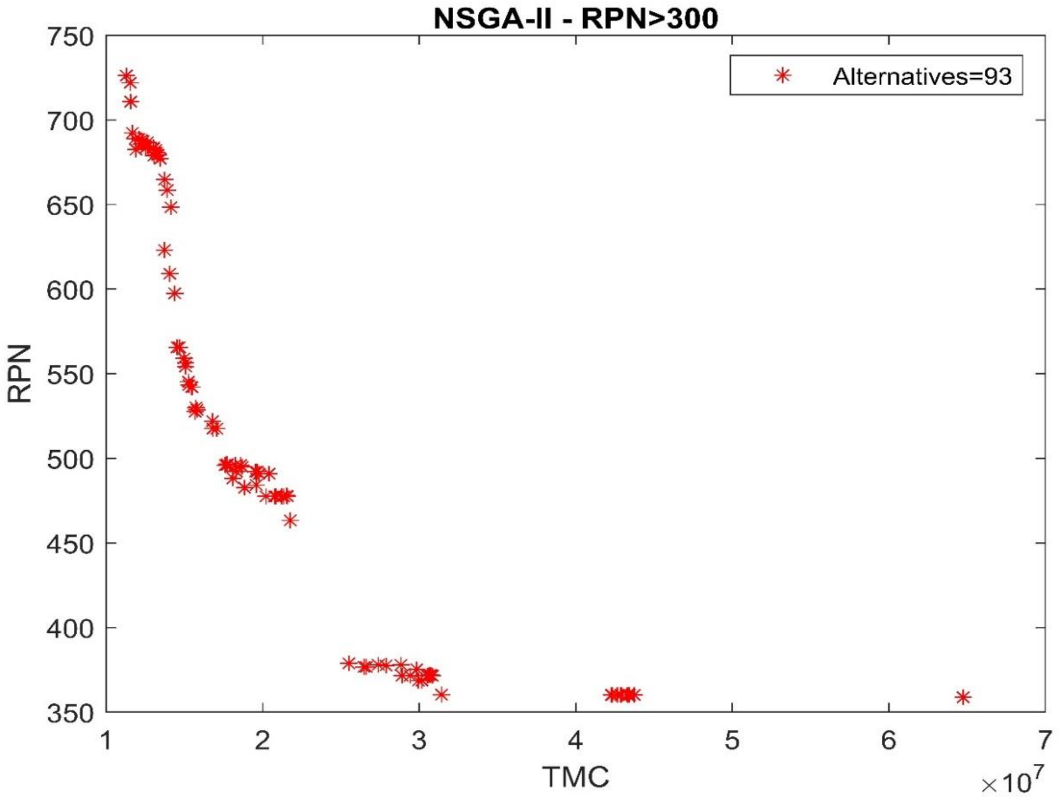


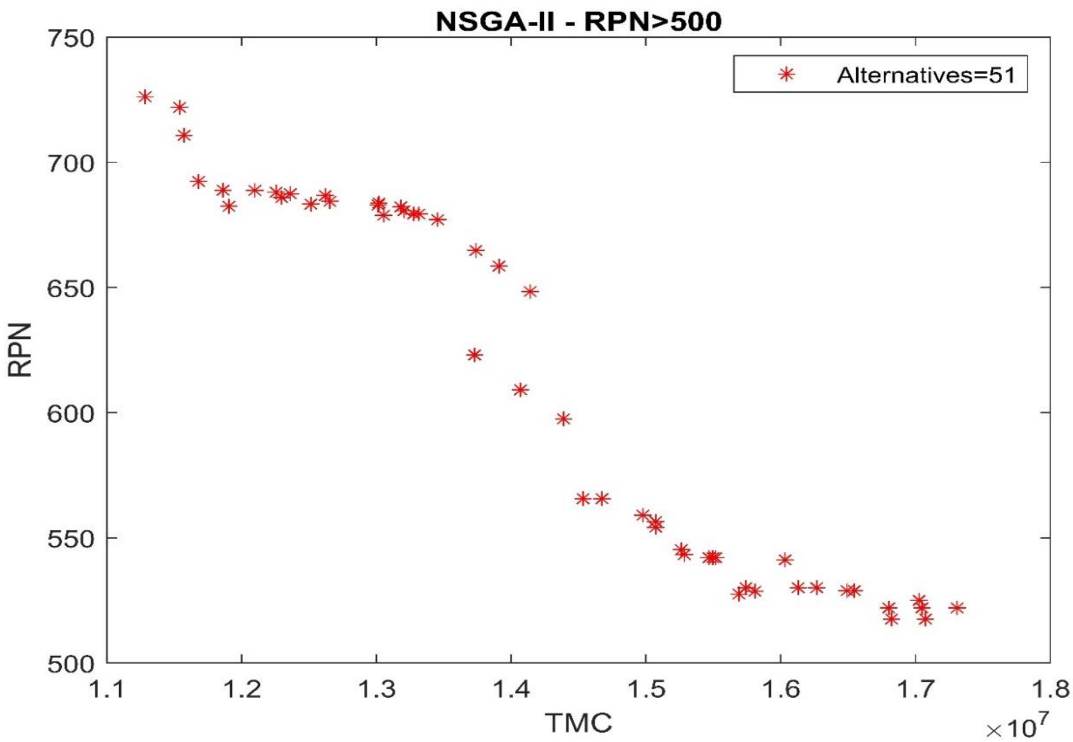
Fig.14. The proposed alternatives of the NSGA-II in RE: 0.94 & AV: 0.97.

As shown in Fig.15, from up to down, considering the minimum risk as 300, 500, and 600 out of 1000, the NSGA-II has proposed 93, 51, and 30 fixed-cost schedules, respectively. This shows that if the cost of the OPM is reduced, then the relative risk of the OPM will increase.

8.3 Sensitivity Analysis

Based on the proposed OPM in Table 9, it is possible to trace the Trans. aging. For example, the trend of the useful life of two transformers, 1 and 2 is shown in Fig.16.


NSGA-II - RPN>300
Alternatives=93
RPN
TMC
750
700
650
600
550
500
450
400
350
1
2
3
4
5
6
7
$\times 10^7$


NSGA-II - RPN>500
Alternatives=51
RPN
TMC
750
700
650
600
550
500
1.1
1.2
1.3
1.4
1.5
1.6
1.7
1.8
$\times 10^7$

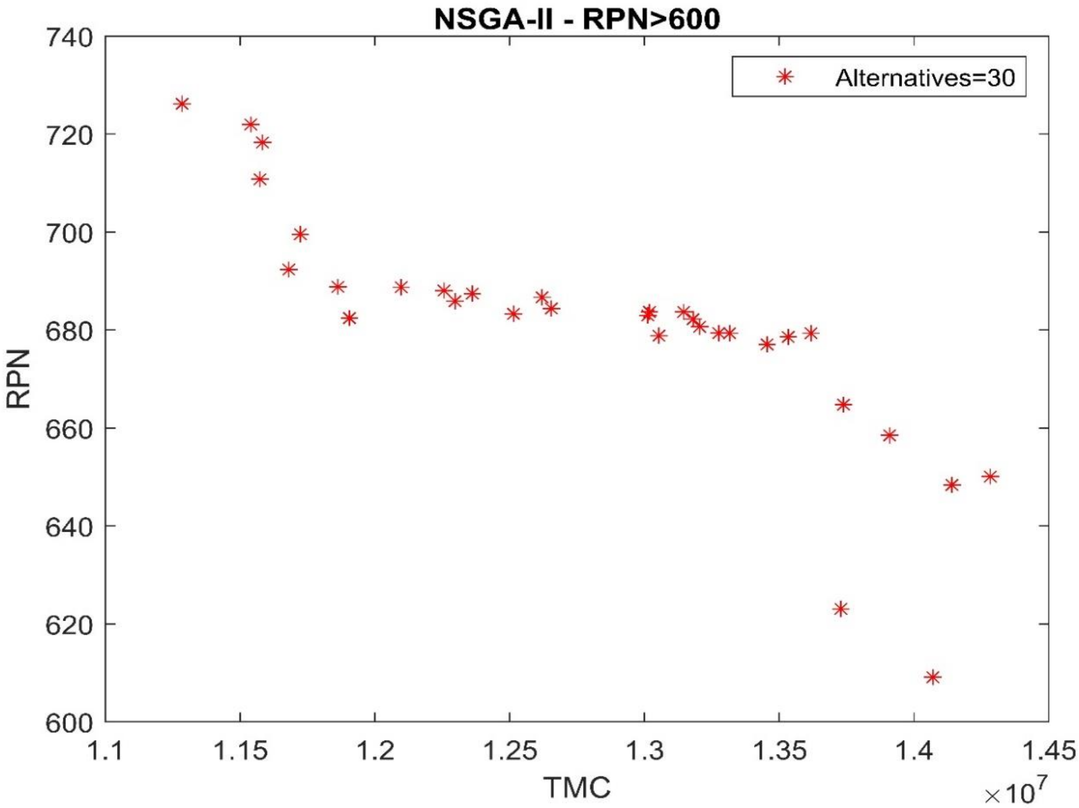


Fig.15. The proposed alternatives of the NSGA-II in risk sizes 300, 500, and 600.

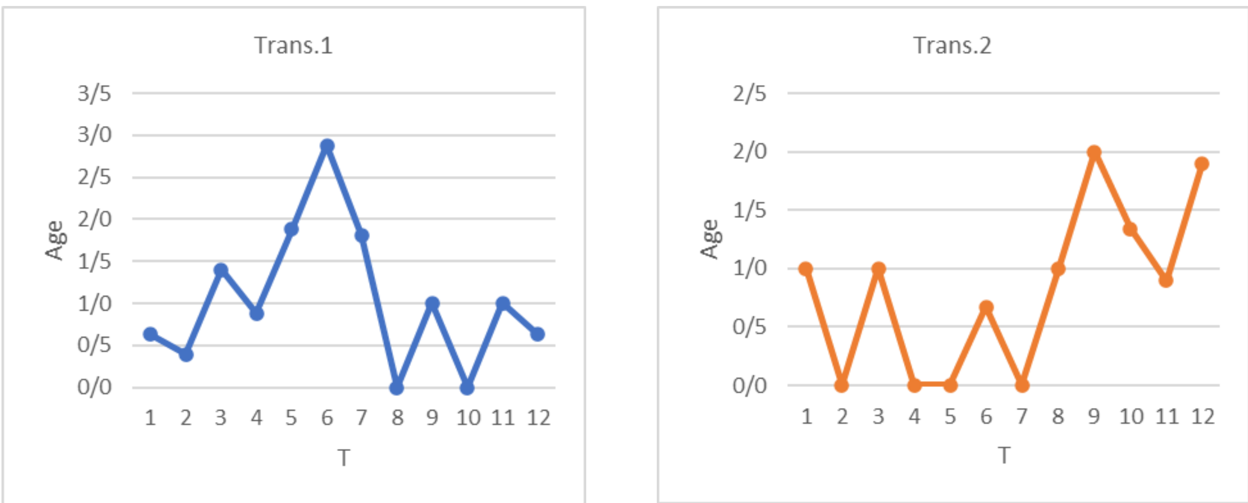


Fig.16. The life cycle diagram of transformers 1 and 2

For example, Trans.1 was replaced 2 times in periods 8 and 10. These changes will be visible when the life curve graph reaches zero (so-called new equipment), 5 times repaired at periods 1, 2, 4, 7, and 12. These changes will be visible when a decreasing slope (so-called equipment is repaired and ready to work). Also, inspected at other periods. The LC curve can be analyzed similarly for Trans.2. By considering the critical role of λ and K in the structure of the OPM, there will be particular parameters that should be investigated. To prove its ability and essential effect in preparing the schedule, the sensitivity analysis of these parameters on the replacement operations, which play an essential role in the TMC, has been done. For example, according to Fig.17, transformers 14 and 15 have the same shape parameter, but Trans.14 has a smaller scale parameter than Trans.15. This leads to fewer replacement activities for Trans.14 (R = 3) compared to Trans.15 (R = 7), as shown in Table 9.

Table 13. Sensitivity analysis after a change in λ_i and k_i parameters.

Trans \ T	1	2	3	4	5	6	7	8	9	10	11	12
4	**R**	I	I	M	M	**R**	**R**	M	I	I	I	**R**
5	I	**R**	M	**R**	I	I	M	I	I	M	**R**	I

Therefore, the scale parameter has a more significant effect on the optimal preventive maintenance schedule. Another example, is the scale parameter of transformers 4 and 5 are fixed (0.98). When the shape parameter increased from 0.33 to 0.7 in Trans.4, then the number of replacement activities increased from 1 to 4, which led to more replacement activities for Trans.4 (see Table 13). To better understand the effect of shape and scale parameters, the sensitivity analysis diagram is shown in Fig.17.

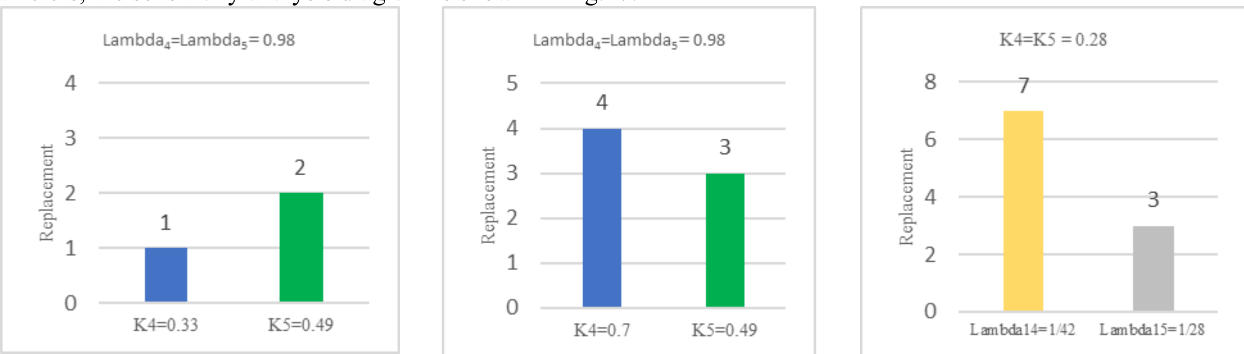


Fig.17. sensitivity analysis of shape and scale parameters on the replacement operation

This shows that transformers with lower reliability and higher hazard rates will have more replacement operations in their records than transformers with high reliability and lower hazard rates. Increasing the scale and shape parameters increases the expected number of failures, which reduces system reliability and the MTBF (see Table 13). Therefore, by considering non-cathodic protection, unplanned downtime costs will be increased.

9. Conclusions and future research directions

Based on the PAM requirements, in this paper, the authors develop a mathematical PM scheduling model for the Gas distribution steel networks which can face failure modes depending on its life, usage, or stochastic. In the proposed model, the authors tried to establish a balance between risk, cost, and performance of the CPS in a case study. The efficiency of the proposed model was proved at 10 metrics by a numerical study and a real case of the CPS in the KHGC. In this research, three main contributions are proposed: (I) The first contribution is modeling the NLIBP model with three activities such as repair, replacement, and inspection then comparing the proposed and actual cost of the problem. (II) The second contribution is providing a decision-making model related to OPM and an allocated budget regarding outsourcing and insourcing. (III) The third contribution is providing a comprehensive model along with a developed computational GA and NSGA-II for single and multi-objective problems respectively that evaluates the cost and risk while maintaining the performance. In three times executions of the code, the proposed model showed a good capability in obtaining the near-optimal solution. When a single-objective PM scheduling was used in the case study, it resulted in about 19% reduction at TMC, in the conditions of the lowest risk of cathodic protection, and obtained reliability and availability of the system by about 90% and 95%, respectively. Also, in the multi-objective optimization problem, based on the TMC, different decision-making alternatives were provided to managers in terms of risk, reliability, and availability. To investigate the effect of the λ and K parameters, sensitivity analysis was done. The compared analysis indicates that an increase in the λ and K parameters causes a decrease in system reliability due to system shutdown as well as an increase in TMC due to the increase in unplanned failure. Therefore, optimum values of the λ and K parameters were obtained by the MLE method for 20 transformers, and the effectiveness of the results was validated with the Kaplan-Meier curve. Further extension of the proposed model to develop the NLIBP for a multi-component machine with different failure modes and policies is a suitable case for future study.

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