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Optimization of Maintenance in Supply Chain Process and Risk-Based Critical Failure Situations (Case Study: Iranian Oil Pipeline and Telecommunication Company, North District)

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Abstract

A system's approach depends on the low malfunction of the equipment and processes of that system, and maintenance plays an essential role in achieving this goal. In addition, over time, the equipment quality decreases, and a quality transfer from controlled to uncontrolled mode may occur, characterized by an increase in the rate of return of the product and the tendency to fail. One of the methods that researchers have widely used in analyzing the risk of net operations is the analysis of the effect and failure modes to identify critical failure modes and focus planning and net resources on them. In analyzing the effect and failure modes, one of the essential steps is prioritizing the equipment to determine the critical equipment, as well as determining the fundamental failure modes and prioritizing them to plan the net operation purposefully. This paper aims to dynamically rank equipment in intuitionistic fuzzy environments with interval values to identify and prioritize critical equipment and present a mathematical model for combining optimization of preventive maintenance intervals and control parameters. For this purpose, a model is presented that calculates the dynamic weights of each piece of equipment according to the conditions of each piece of equipment in the indicators of failure probability, failure consequence, and lack of fault detection power. Therefore, dynamic ranking is provided for the equipment. In this research, for dynamic prioritization of equipment, the method of analysis of the ratio of intuitionistic fuzzy gradual weighting with quantitative values (IVIF-SWARA) was presented. Then, a mathematical model was presented for the identified critical equipment. The proposed model can determine the optimal value of each of the four decision variables, i.e., sample size, inspection rotation time, control limit coefficient, and preventive repair intervals of each of the critical equipment of the Northern Oil Pipeline and Telecommunication Company and the total expected cost of integration per unit. Minimize time. The results show that the proposed model is much more flexible in calculating equipment's weight and dynamic rating and provides more logical rating results.

Keywords: Supply chain process, Effect analysis and failure mode, Risk-based maintenance, Process quality, Mathematical optimization.

1 | Introduction

A system's approach depends on the low malfunction of the equipment and processes of that system. Maintenance and process quality play an essential role in achieving this goal. In addition, the equipment quality

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decreases over time, and there may be a transfer of quality from the controlled state to the uncontrolled state, characterized by an increase in the rate of return of the product and the tendency to fail. Maintenance schedules and quality processes are part of the operational policies that result from each system's performance. Despite the common implications of these decisions, which are not very important, model-based approaches are provided to optimize them in a simulated manner. For example, most production scheduling models do not consider the impact of equipment availability due to breakdown or maintenance activity.

Similarly, maintenance planning models seldom consider the effect of maintenance on delivery time and customer needs. However, the maintenance effect can not be measured significantly without calculating the maintenance function that meets the system requirements. One thing that is often overlooked but plays a significant role in keeping the supply chain from crumbling down is maintenance management. In one way or another, you can connect maintenance activities with every stop in your supply chain.to deliver materials/goods to a designated place and on time, your mode of transportation must endure the route without a critical failure.

On the other hand, maintenance delays to meet production requirements may increase process repairs and the risk of equipment malfunction, which may lead to more unacceptable cases and slowdowns. Therefore, considering the quality of the process and maintenance planning can be an effective way to solve some problems. Consequently, if we look at the two separately, given the existing relationships and dependencies between these issues, it will cause problems. One of the essential approaches in any production system is to be aware of the problems of dependencies and relationships between the items in question, and having comprehensive information about the subject and surrounding the existing aspects of the problem can help us in modeling. As a result, our work will have a significant impact. According to the points mentioned, we will realize the importance of integrating maintenance models and the quality of the process.

A study of the maintenance literature shows that a great deal of research has been done on managing physical assets and maintaining and repairing various facilities, equipment, and machinery worldwide [1]. Due to the increasing complexity, equipment, and machinery of these facilities and their increasing variety, new approaches have always been presented to plan maintenance and repairs optimally. According to this literature, Reliability-Based Maintenance (RCM) approaches, Risk-Based Inspection (RBI), and risk-based approaches are the approaches that have made a significant share of studies in recent decades in various industries and organizations. They have tried to use these approaches in planning and evaluating the performance of their maintenance system [2]. As mentioned in the literature, due to its particular importance, the oil and gas industry has tried to use these approaches in various related areas to be effective in net programs [3]. But there are shortcomings in this regard. The main issue is where these approaches are used for systems with different components, and proper prioritization of these components becomes essential for planning. Challenges in this area are:

I. Net approaches based on reliability and RBI in a system are generally studied separately; that is, the application of only one of these two has been studied. Using one of the two in the pipeline and oil transfer systems can not lead to proper planning to maintain the entire system.

II. Many studies have been performed in the literature based on reliability-based notes, RBIs, or risk-based notes. What is clear, however, is that these studies have focused more on individual equipment and items or parts of a system's processes and less on the net operations required throughout the system.

III. Also, no study was found to plan and evaluate the net system of all pipelines and telecommunications.

Overall, as far as the researcher is concerned, no study has examined risk-based methods for simultaneously modeling notes based on RBI with integrated notes based on reliability. In the field of oil pipelines and telecommunications, no approach was found that could be used to plan and evaluate the performance of the entire transmission system net system. In the case of oil pipelines and telecommunications, most inspections are traditional, and based on the intervals defined in the company's maintenance instructions, inspections are performed to detect defects that do not use RBI logic. As a result, inspection programs are not as effective as they used to be, leading to increased breakdown rates. Also, in some cases, due to a lack of timely inspection, repair costs to return the damaged equipment to operating condition are higher than normal. Based on the criticisms of the methodology for calculating the number of risk prioritization, the question arises: what is the appropriate method for prioritizing equipment? The main problem that the researcher faces is how to combine risk-based notes, reliability-based notes, and RBI in an integrated model for note and inspection of the entire oil pipeline and telecommunication system and dynamic prioritization. Did all the equipment create this model to increase its effectiveness?

For this purpose, this article is organized as follows. In Section 2, while stating the background, the research gap is described. Section 3 introduces the research methodology, and the analysis of the intuitionistic fuzzy gradual weighting ratio with interval values (IVIF-SWARA) is explained. In Section 4, the mathematical optimization model is presented. The basis of the new FMEA approach was introduced under uncertainty, and an integrated algorithm was used to apply this method. Section 6 includes a case study on applying the proposed approach in prioritizing equipment and critical failure situations for pipeline and telecommunications equipment to demonstrate capability. The implementation of the proposed model is presented in Section 7. The results of the proposed model are presented in Section 8. The results of this paper are presented along with suggestions for future research.

2 | Literature Review

After 2000, risk-based notes (RBM) became known for including RBI within the paradigm of reliability-based notes (RCM) and status-based notes (CBM). Subsequently, risk-based notes were used in various industrial fields [4]. Technical risk analysis identifies, characterizes, quantifies, and assesses an event's damage. This approach combines probability and consequence and can be defined as quantitative or qualitative equations [5]. The risk-based net strategy that emerged in industrial facility management in the 1990s provides new insights into integrated asset management. This approach has used the level of risk as an indicator for planning activities and has been considered by researchers in recent years. To fully understand the study area, the research background was described, which includes studies on maintenance and repair (score based on reliability and note based on risk, status monitoring, and prevention), studies on inspection and RBI, and the studies on equipment prioritization methods and the use of mathematical modeling techniques are given in *Table 1*.

Ghasemi and Babaeinesami [6] have done a study on the optimization of equipment used in the fire stations, minimizing the time to arrive at the incident through the management of referral calls to 125 Sari Fire Station Center so that the referral call to the nearest fire station does not remain unanswered as much as possible. There will be no need to refer to another station. This research simulated the resources required at Sari's fire station using Enterprise Dynamic software. In the following, the distribution functions of failure in the existing fire engines are calculated using the same method, and the obtained information is simulated. The result indicates an improvement of 20% in relief time by adding one source in Sari Fire Station Center. Pourghader Chobar et al. [7] presented a novel multiobjective model for hub location problems with dynamic demand and environmental issues. The model aims to minimize the routing cost between production centers and retailers, along with emitting pollution from vehicles as little as possible. As the proposed model is bi-objective, minimizing costs and pollution emission, two Pareto-based solution methodologies, namely the Non-Dominated Sorting Genetic Algorithm (NSGA-II) and Non-Dominated Ranking Genetic Algorithm (NRGA), are used. Lotfi et al. [8] proposed a novel viable Medical Waste Chain Network Design (MWCND) by a novel two-stage robust stochastic programming that considers resiliency (flexibility and network complexity) and sustainable (energy and environment) requirements. Lotfi et al. [9] explored a Robust, Risk-aware, Resilient, and Sustainable Closed-Loop Supply Chain Network Design (3RSCLSCND) to tackle demand fluctuation like the COVID-19 pandemic. For this purpose, a two-stage robust stochastic multiobjective programming model expresses the proposed problems in formulae. Lotfi et al. [10] indicated resilience and sustainable Supply Chain Network Design (SCND) by considering Renewable Energy (RE)

(RSSCNDRE) for the first time. A two-stage new robust stochastic optimization is embedded for RSSCNDRE.

In the maintenance literature, extensive research has been done based on decision-making in fuzzy environments to select the appropriate net strategy for each equipment and prioritize the equipment to identify critical equipment. Recently, new generalizations of intuitionistic fuzzy sets, intuitionistic fuzzy sets with interval values, and hesitant fuzzy sets have been considered by researchers in this field due to their high ability to describe vague and uncertain information [11]-[19].

Among the new approaches, intuitionistic fuzzy sets with interval values than fuzzy sets and intuitionistic fuzzy sets provide a more accurate description of fuzzy information, and this approach is gaining more and more attention [12]. Therefore, considering that intuitionistic fuzzy sets with interval values compared to fuzzy sets and intuitionistic fuzzy sets provide a more accurate description of fuzzy information [12], this theory will be used in the critical equipment selection process. Based on the research, no case has been found by the researcher who has used the reliability-based note and RBI in a comprehensive framework to determine the note and inspection strategies and their critical level. In this paper, while determining the critical level of oil pipeline and telecommunication equipment, the RCM logic has been used to determine their critical level by integrating this logic in the RBI of fixed equipment and creating an integrated prioritization. Attempts will be made to use RCM and RBI simultaneously in a risk-based net platform. The main innovations of this research are the underlying dynamic weighting model, along with the presentation of a combined methodology for reliability-based notes and RBI in the context of risk-based notes. The following summary has been made based on the reviews in the research literature and the reviews and reviews:

I. A hybrid framework for the simultaneous application of reliability-based notes and RBIs in the context of risk-based notes is based on integrating different methodologies.

II. To determine the characteristic constant weights, hesitant fuzzy preferential relations based on the definition of normalization and algorithm will be used in this field [20]. The Euclidean distance function will be defined in hesitant fuzzy sets to improve this algorithm.

III. To determine the dynamic weight of each option, the dynamic weighting method will be used based on the situation in the intuitionistic fuzzy environment with interval values. This method will be presented by the researcher for the first time.

IV. Based on the results of theoretical literature and critique of various approaches, the combined IVIF-SWARA approach in an intuitionistic fuzzy environment with interval values will be used to determine the prioritization of equipment. To optimize the IVIF-SWARA hybrid approach, in this study, the intuitionistic fuzzy power heron aggregation operator with interval values will be used to aggregate information [12].

No study has used the FHPR method to calculate the maintenance area. Also, no studies have used the general framework used in paragraph four, and the dynamic weighting model based on the condition and its combination with the intuitionistic fuzzy heron operator with interval values and the SWARA method is performed for the first time in this study.

Considering that the primary purpose of conducting research is to study a subject in a field method to solve a problem and to satisfy a specific need, it can be said that the said research is in the field of applied research in terms of purpose. On the other hand, considering that in this research, library study methods and references to documents are used to provide a detailed description and analysis of the system status, it can be said that the present study is a descriptive-analytical research based on the data collection method—a case study of oil pipelines and telecommunications in the country's North. Also, in terms of the nature of the data, this research combines quantitative and qualitative methods. In the field of determining the necessary data for weighting the equipment evaluation indicators, collecting information about the evaluation of each equipment based on the specified indicators, and evaluating critical equipment failure cases, a statistical sample, which was selected through purposive judgment, is used. The composition of the community of research experts includes experts in the field of net and operations, experts in the field of support, and managers of the collection, and a total of 20 people.

The methods used for data analysis were both quantitative and qualitative. Qualitative analysis is used to show all aspects of the system in identifying the system and its consequences. Here, FMEA tables and equipment tree structure are used in qualitative analysis to determine the effects and failure modes.

Optimization model design. Now, after determining the critical equipment and prioritizing each failure mode in this section, a mathematical model was designed to optimize the process of repairing and maintaining the crucial equipment of the country's oil pipelines and telecommunications, described in the following steps. In order to obtain any integrated model, it is necessary to examine all the relations and features related to the integrated subjects and be aware of all the dependencies in them to be able to relate them to each other. In this section, the problem in question and the integrated model's description are discussed, the proposed model is formulated, and the total cost function is calculated.

Consider a production or service system or process involving fixed-rate equipment on an ongoing basis. Also, consider a device with a component. Equipment failures in this model are divided into the following two failure modes:

I. Fault mode of the first type (〖FM〗 _1): equipment failure is determined immediately.

II. Type II failure mode (FM_2): equipment failure after production or service due to the transfer of the average process in the process quality discussion is determined.

A similar classification is used by Lad and Kulkarni [21]. They defined the error and defect of the equipment tool when the equipment fails or the equipment works and the process recurrence rate increases. This means that if an error occurs, it does not need to be detected immediately, and the equipment stops working, but this may affect the quality of the process. For example, in a polishing machine, if the belt is cut, the machine stops working immediately. But if a part in the machine loosens, the machine still works but may be of lower quality.

It is necessary to consider these types of errors in terms of the costs of the error, which may be in certain circumstances in planning maintenance decisions. Errors belonging to the second category can be considered as minor errors. They can be defined by Mojabi and LoVetri [22] as a degradation in the performance of a device without a complete error. Therefore, the problem is integrating the maintenance and process quality policy design parameters. Let us now consider the following hypotheses:

- *Corrective maintenance and repairs are inherently minimal, i.e., after the corrective activity, the life of the equipment does not change, and the time of corrective activity is also considered part of the equipment's life.*
- *Maintenance is inherently flawed, meaning it does not entirely solve the problem, and we may run into problems again.*
- *For quality control, we consider only one characteristic: this characteristic (CTQ).*
- *The process starts from the controlled state. The mean and standard deviation of CTQ are μ and σ, respectively.*
- *A definite error, which occurs randomly, causes the mean process when σ remains constant from μ_0 to* $\mu-1=\delta[+\mu]-0.$

The symbols used in the research model are described below.

Parameters

$ARL2_E$	Average equipment life when equipment is out of control due to external and environmental reasons.
$ARL2_{\frac{M}{C}}$	Average equipment life when the equipment is out of control due to depreciation.
$ARL1$	Average equipment life when equipment is in control mode.
K	Control limit coefficient.
C_{1P}	Cost of stopping the process.
$C_{Re\,j}$	The cost of reworking the process.
$C_{resett\,in\,g}$	The cost of restoring the process to its original state.
prd_E	Overall estimated time.
$[C_{CM}]_{FM_1}$	Expected cost of maintenance and repair due to the first case error.
C_{PM}	Expected cost of preventive maintenance.
$E[T_{cycle}]$	Process duration.
T_1	The time required to determine the occurrence of a specific cause of failure.
$E[T_{restore}]$	Time required to return the process to its original state or repair the equipment if the process has gone out of control due to environmental or equipment depreciation.
$[TCQ]_{process-failure}$	Cost of quality degradation due to process defects.
λ_1	Equipment failure rate for environmental and external reasons.
λ_2	Equipment failure rate due to depreciation.
C_{FCCM}	Fixed cost of maintenance and corrective repairs.
C_{FCPM}	Fixed cost of preventive maintenance and repairs.
LC	Cost of labor maintenance and repairs.
MT_{CM}	Average time required for maintenance and corrective repairs.
MT_{PM}	Average time required for preventive maintenance and repairs.
N_f	Average number of equipment failures.
t_{PM}	Interval for maintenance activities.
β_E	Probability of type II error due to external.
$\beta_{\frac{M}{C}}$	Probability of the second type of error due to equipment depreciation.
P_{FM_1}	Probability of first failure.
P_{FM2}	The possibility of a second breakdown occurs.

λ	Process failure rate.
PR	Production rate (distribution) of equipment.
n	Sample size.
T_S	Sampling time.
α	The first type of error.
h	Time interval between sampling.

The mathematical model is described below. If FM_1 occurs, the equipment will stop immediately. Corrective operations are performed to repair the equipment. Therefore, the cost of maintenance and repair $[C_{CM}]_{FM_1}$ includes the cost of idle time and repairing and restoring the equipment to its original condition. The effects of FM_2 are a function of equipping and increasing the return level of the process. In other words, FM_2 affects the process rate of return. It is assumed that whenever FM_2 appears, the process will stop immediately, and corrective action will be taken to repair and restore the process to normal. In addition to errors due to FM_2, the process may be degraded due to external reasons (E) such as environmental impacts, operator errors, misuse of tools, etc., which were fully described in the equipment tree structure section in the previous sections. Slowly, in other words, the process goes back out of control if an external event (E) occurs.

Finding FM_2 or external reason (E) is achieved by monitoring the process. In this work, a control chart mechanism is considered to monitor the process. Assume that the control parameters of the control diagram, sample size (n), sampling time interval (h), and coefficient (k) exist to determine the distance between the center line of the control limit. Therefore, the total cost of process failure due to $[TCQ]_{process-failure}$ including equipment unemployment cost, process return cost due to process transfer, repair cost, sampling and inspection cost, and deviation cost Target for CTQ.

In addition to corrective action, the machine is subject to preventive maintenance and repairs to minimize downtime, etc. In this dissertation, incomplete maintenance and repairs are considered. That is, after a preventive repair operation, the equipment achieves a state between the initial good state and the pre-repair state. The number of defects decreases after PM. That is, both defects FM_1 and FM_2 are reduced. A reduction in FM_2 reduces quality costs associated with off-mode operations. Preventive maintenance, however, consumes some of the resources and time that can be spent on production. The cost of PM C_PM includes the cost of process unemployment and the cost of preventive maintenance activities. As mentioned, the issue discussed in this article is to determine the optimal values of the decision variables (n, h, k, t_{PM})so as to minimize the total cost per unit of time $([TCT]_{Maintenance*Quality})$.

It should be noted that the life of the equipment is reduced after preventive maintenance and repairs depending on the factor of repair and return. Total cost per unit of preventive maintenance time and control chart policy $([TCT]_{Maintenance*Quality})$, ratio of total cost of quality control $[([TCQ]_{process-failure})$, (total cost of maintenance and repairs) preventive (C_PM) and total cost of machine failure $([C_{CM}]_{FM_1})$ at the time of assessment, cost incurred due to FM_2 includes process quality control cost. The total per unit time for the integrated model is as follows:

$$[TCT]_{Maintenance*Quality} = \frac{1}{prd_E}([[C_{CM}]_{FM_1} + C_{PM} + [TCQ]_{process-failure}),$$

$$[TCT]_{Maintenance*Quality} = f(n, h, k, t_{PM}), prd_E,$$

is planned and evaluated time according to the analysis of what is to be done,

$$Z_1 : \mathrm{Min}[TCT]_{\mathrm{Maintenance*Quality}},$$
$$\text{s.t.}$$
$$a_1 \leq n \leq b_1,$$
$$a_2 \leq h \leq b_2,$$
$$a_3 \leq k \leq b_3,$$
$$a_4 \leq t_{PM} \leq b_4,$$
$$n, h, k, t_{PM} \geq 0,$$

where a_i and b_i are the upper and lower values of the decision variables. In the following, we will describe the three cost functions of the objective function. Expected cost models for preventive maintenance and maintenance and corrective maintenance due to FM_1 and process defect costs due to FM_1 as well as for external reasons are calculated for the given estimated time.

3 | Dynamic Equipment Prioritization Method

This method will be used to determine the dynamic weight of each option. The assumptions used to model this method are based on the requirements of the three indicators of failure probability (O), failure outcome (S), and failure to detect failure (D) in order to plan maintenance and repairs as follows properly:

I. Information about the fixed weights of the indicators O, S, and D (the first step of this method) is collected for a situation where the hypothetical equipment is at its lowest point in terms of all three criteria; that is, the probability of failure is close to zero, the consequence of failure is close to zero, and the inability to detect failure is close to zero. In this case, the experts are asked to express their views on the weight of the indicators according to this hypothetical equipment. This hypothesis allows us to ask experts to present their opinions based on the same hypothetical equipment. Fixed weights are initial weights that can be changed depending on the condition of the equipment.

II. It is assumed that the effect of O, S, and D weights is different based on the condition of each equipment in O and S indices. Thus, in equipment that has a very high failure consequence, the final weight for this indicator is higher than the calculated initial weight. The same is true of the breakdown index. In the field of the net, when the consequence of failure or the probability of failure increases, the effect of these indicators on the criticality of the equipment/failure mode increases, and this means the need to increase the weight of these indicators in equipment where the probability of failure, consequence Malfunction or both. For example, if the failure consequence is too high for equipment/failure mode, the sensitivity of company managers to manage the net and properly inspect this equipment to prevent failure because the failure will result in irreparable damage. Therefore, this equipment should be identified by the model as critical equipment, while even if the failure detection power is high, this equipment may not be essential. Modeling based on this assumption allows the creation of dynamic initial weights based on the state of each equipment/failure state in the O, S, and D indices.

III. Considering that with increasing the consequence or probability of failure of equipment/failure mode, the weight of consequence and probability of failure increases, it is natural that this issue reduces the weight of the inability to detect failure. In this model, the parameter of the minimum allowable weight of the failure detection index is considered in order to control the excessive reduction of this index by calculating the dynamic weighting constant (λ). In fact, the final weight of this index varies between the minimum allowable weight of the failure detection index and the constant weight of this index. The result will be as follows:

$$LW_D \leq W_{D_i}(F) \leq W_D.$$

IV. In this model, it is assumed that the weight of the two indices, O and S, does not fall below the value of the fixed weight calculated in the first step. For this purpose, after calculating the initial dynamic weights of the three indices O, S, and D, an algorithm is defined that calculates the final dynamic weights of the field and does not allow the reduction of these two indices from the estimated constant weight value. The final weight of these two indices is always greater than their constant weight. The results will be as follows:

$$W_{O_i}(F) \geq W_O,$$
$$W_{S_i}(F) \geq W_S.$$

The researcher has proposed this method for the first time, and its algorithm is as follows.

Step 1. Calculate the fixed weights of O, S, and D indices using different weighting methods. In this step, O, S, and D indices are calculated based on different weighting methods in the literature. The researcher, in calculating the fixed weights of O, S, and D indices, has presented an improved Hesitant Fuzzy Preferred Relations (HFPR) method, which, in order to summarize the information, only gives the results of this study. The proposed approach will be presented in another article.

Step 2. Calculate the accuracy functions SC_{O_i}, SC_{S_i} related to the failure probability index and failure outcome for each equipment/failure mode related to the aggregated evaluation matrix. In this step, the accuracy functions SC_{O_i}, SC_{S_i}, related to the failure probability index and failure outcome for each equipment/failure mode related to the aggregated evaluation matrix are calculated.

$$K(\tilde{a}) = \frac{\mu^L + \mu^U(1-\mu^L-\nu^L) + \mu^U + \mu^L(1-\mu^U-\nu^U)}{2},$$
$$K(\tilde{a}) \in [0,1].$$

Step 3. Calculate the minimum allowable weight of the failure detection index. The minimum permissible weight of the failure detection index LW_D is the value from which the weight of the failure detection index is not less. This index is calculated according to the decision maker's preference and as a coefficient of the average of the total weights of failure results and probability of failure and is calculated as follows:

$$LW_D = \beta * (W_S + W_O)/2,$$

where $\beta = [0,1]$ is considered. Ws and Wo are also the constant weight of the failure consequence and the probability of failure calculated in step one, respectively.

Step 4. Calculate the dynamic weighting constant (λ). The dynamic weighting constant (λ) is calculated using the solution of the following linear equation in which we have

$$W_D(LW_D - 1) + (LW_D * W_S * \lambda) + (LW_D * W_O * \lambda) = 0,$$

where W_S, W_O, and W_D are the fixed weight of the failure consequence and the constant weight of the probability of failure and the constant weight of the failure detection power calculated in step one, respectively, and LW_D is the minimum allowable weight of the failure detection index.

Step 5. Calculate the initial dynamic weights of the three indicators O, S, and D. The initial dynamic weights of the three indicators, O, S, and D, are calculated as follows:

$$W_{O_i}(p) = (W_o * (\lambda^{SC_{O_i}}) / ((W_o * (\lambda^{SC_{O_i}}) + (W_s * (\lambda^{SC_{S_i}}) + W_D)))),$$

$$W_{S_i}(p) = (W_S * (\lambda^{SC_{S_i}}) / ((W_o * (\lambda^{SC_{O_i}}) + (W_s * (\lambda^{SC_{S_i}}) + W_D)))),$$

$$W_{D_i}(p) = 1 - W_{O_i}(P) - W_{S_i}(P),$$

where $W_{O_i}(P)$ initial weight calculated for the failure probability index of option i: $W_{S_i}(P)$ initial weight calculated for the failure outcome index of option i: $W_{D_i}(p)$ initial weight calculated for the failure detection index of option i, λ, dynamic weighting constant, SC_{oi}, SC_{si} respectively, the accuracy functions related to the failure probability index and failure consequence for each equipment/failure mode and W_S, W_O, W_D are the constant weight of the failure outcome, the constant weight of the probability of failure, and the constant weight of the failure to detect failure, respectively.

Step 6. Calculate the final dynamic background weights. The final dynamic weights of the fields corresponding to the specifications of each equipment/failure mode are as follows:

I. If $W_{O_i}(p) \geq W_O$ and $W_{S_i}(p) \geq W$ then $W_{O_i}(F) = W_{O_i}(p)$ and $W_{S_i}(F) = W_{O_i}(p)$ and $W_{D_i}(F) = W_{D_i}(p)$.

II. If $W_{O_i}(p) \succ W_O$ and $W_{S_i}(p) \prec W_S$ then $W_{O_i}(F) = W_{O_i}(p) - (W_S - W_{S_i}(P))$ and $W_{S_i}(F) = W_S$ and $W_{D_i}(F)D_i = W_{D_i}(P)$.

III. If $W_{O_i}(p) \prec W_O$ and $W_{S_i}(p) \succ W_S$ then $W_{S_i}(F) = W_{S_i}(p) - (W_O - W_{O_i}(P))$ and $W_{O_i}(F) = W_O$ and $W_{D_i}(F) = W_{D_i}(P)$.

Calculation of aggregated evaluation: matrix using intuitionistic fusion power heronian aggregation operator with interval values based on the formula of the Heronian aggregation operator, we calculate the aggregated evaluation matrix with the following interval values (IVIFPWHA):

$$\mathrm{IVIFPWHA}^{p,q}(\tilde{a}_1, \tilde{a}_2, \ldots, \tilde{a}_n) = \left[\begin{array}{l} \left[\begin{array}{l} (1-(\prod_{i=1}^{n}\coprod_{j=1}^{n}(1-(1-\tilde{a}_i)^{\frac{nv_iw_i}{\sum_{k=1}^{n}v_kw_k}})^p(1-(1-\tilde{a}_j)^{\frac{nv_iw_i}{\sum_{k=1}^{n}v_kw_k}})^q))^{\frac{2}{n(n+1)}})^{\frac{1}{p+q}}, \\ (1-(\prod_{i=1}^{n}\coprod_{j=1}^{n}(1-(1-\tilde{b}_i)^{\frac{nv_iw_i}{\sum_{k=1}^{n}v_kw_k}})^p(1-(1-\tilde{b}_j)^{\frac{nv_iw_i}{\sum_{k=1}^{n}v_kw_k}})^q))^{\frac{2}{n(n+1)}})^{\frac{1}{p+q}} \end{array}\right] \\ \left[\begin{array}{l} 1-(1-(\prod_{i=1}^{n}\coprod_{j=1}^{n}(1-(1-\tilde{c}_i)^{\frac{nv_iw_i}{\sum_{k=1}^{n}v_kw_k}})^p(1-\tilde{c}_j^{\frac{nv_iw_i}{\sum_{k=1}^{n}v_kw_k}})^q))^{\frac{2}{n(n+1)}})^{\frac{1}{p+q}}, \\ 1-(1-(\prod_{i=1}^{n}\coprod_{j=1}^{n}(1-(1-d_i)^{\frac{nv_iw_i}{\sum_{k=1}^{n}v_kw_k}})^p(1-d_j^{\frac{nv_iw_i}{\sum_{k=1}^{n}v_kw_k}})^q))^{\frac{2}{n(n+1)}})^{\frac{1}{p+q}}, \end{array}\right] \end{array}\right].$$

4 | Case Study

This chapter implements the proposed mathematical model. For this purpose, the equipment of oil pipelines and telecommunications in the Northern region of the country has been considered for a case study. For this purpose, the relevant equipment is first identified. A total of 25 devices have been identified. In order to collect information, 20 experts were identified. In order to collect the desired information, weigh the desired indicators, and rank the specified equipment, organized interviews have been designed, and the desired information has been collected. In order to analyze the data, HFPR and calculation of relations in Excel software have been used to calculate the constant weights of the indicators. In order to dynamically prioritize equipment and identify critical equipment, as well as to prioritize failure modes to identify essential modes of failure and determine the critical extent of equipment and failure modes, the model presented in Section 3 is fully coded in MATLAB software and a robust model using this software is designed to analyze information. Using this software, 25 identified prioritization equipment and critical equipment were first identified. Then, based on the complete description of each piece of equipment and its structure, all failure cases are identified for each piece. In order to identify failure cases initially, the Offshore Reliable Data Handbook (OREDA) was used. Then, by holding several meetings with experts, this information was reviewed, the necessary corrections were made, and the final failure cases were extracted. After identifying the failure modes, using MATLAB software and the designed model, the critical equipment failure modes are classified. After determining the required limit, the essential modes of failure are identified.

Step 1. Using the intuitionistic fuzzy power heron aggregation operator with interval values to aggregate opinions about options.

Step 2. Normalize the preference values.

In order to facilitate the presentation of information by the team of experts, the linguistic variables of *Table 1* were used. Information about the status of each piece of equipment is shown in *Tables 1*, O, S, and D.

Table 1. Linguistic terms and intuitionistic fuzzy numbers with interval values [12].

Linguistic Terms	Intuitive Fuzzy Numbers with Interval Values
Absolutely high	[0.99,0.99],[0.01,0.01]
Highly high	[0.90,0.90],[0.10,0.10]
Too high	[0.75,0.85],[0.05,0.15]
Top	[0.60,0.75],[0.10,0.20]
Over average	[0.45,0.60],[0.15,0.25]
Medium	[0.50,0.50],[0.50,0.50]
Medium to low	[0.35,0.45],[0.40,0.55]
Down	[0.25,0.35],[0.50,0.60]
Very low	[0.15,0.20],[0.60,0.75]
Extremely low	[0.10,0.10],[0.90,0.90]

Table 2. Opinions of the team of experts on the status of each piece of equipment in indicators O, S, and D.

Equipment Name	Probability of Failure (O)				Consequence of Failure (S)				Inability to Detect Failure (D)			
Reston turbine	0.35	0.45	0.4	0.55	0.9	0.9	0.1	0.1	0.35	0.45	0.4	0.55
Diesel generator	0.35	0.45	0.4	0.55	0.9	0.9	0.1	0.1	0.35	0.45	0.4	0.55
Compressor	0.35	0.45	0.4	0.55	0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5
Control valves	0.35	0.45	0.4	0.55	0.9	0.9	0.1	0.1	0.45	0.6	0.15	0.25
Strainer	0.45	0.6	0.15	0.25	0.6	0.75	0.1	0.2	0.5	0.5	0.5	0.5
Underground tanks	0.45	0.6	0.15	0.25	0.6	0.75	0.1	0.2	0.5	0.5	0.5	0.5
Storage containers	0.45	0.6	0.15	0.25	0.6	0.75	0.1	0.2	0.5	0.5	0.5	0.5
Flowmeter	0.45	0.6	0.15	0.25	0.6	0.75	0.1	0.2	0.5	0.5	0.5	0.5
Pressure transmitter	0.5	0.5	0.5	0.5	0.25	0.35	0.5	0.6	0.15	0.2	0.6	0.75
Shotgun switches	0.5	0.5	0.5	0.5	0.25	0.35	0.5	0.6	0.15	0.2	0.6	0.75
UPS system	0.5	0.5	0.5	0.5	0.15	0.2	0.6	0.75	0.15	0.2	0.6	0.75
PLC control system	0.5	0.5	0.5	0.5	0.15	0.2	0.6	0.75	0.15	0.2	0.6	0.75
Cold cutter	0.25	0.35	0.5	0.6	0.25	0.35	0.5	0.6	0.25	0.35	0.5	0.6
Hot branching machine	0.5	0.5	0.5	0.5	0.9	0.9	0.1	0.1	0.5	0.5	0.5	0.5
Paint and metal thickness gauge	0.5	0.5	0.5	0.5	0.9	0.9	0.1	0.1	0.5	0.5	0.5	0.5
Movable and fixed cranes	0.5	0.5	0.5	0.5	0.25	0.35	0.5	0.6	0.5	0.5	0.5	0.5
One-way valves in between	0.25	0.35	0.5	0.6	0.45	0.6	0.15	0.25	0.25	0.35	0.5	0.6
LBVs of pipelines	0.25	0.35	0.5	0.6	0.45	0.6	0.15	0.25	0.25	0.35	0.5	0.6
Terminal installation metering system	0.45	0.6	0.15	0.25	0.25	0.35	0.5	0.6	0.45	0.6	0.15	0.25
Electro-motor	0.25	0.35	0.5	0.6	0.9	0.9	0.1	0.1	0.25	0.35	0.5	0.6

Table 2. Continued.

Equipment Name	Probability of Failure (O)				Consequence of Failure (S)				Inability to Detect Failure (D)			
Battery bank	0.25	0.35	0.5	0.6	0.5	0.5	0.5	0.5	0.25	0.35	0.5	0.6
Cathodic protection station	0.25	0.35	0.5	0.6	0.5	0.5	0.5	0.5	0.25	0.35	0.5	0.6
Industrial computer	0.25	0.35	0.5	0.6	0.5	0.5	0.5	0.5	0.25	0.35	0.5	0.6
Hot line telecommunication system and radio room	0.25	0.35	0.5	0.6	0.5	0.5	0.5	0.5	0.25	0.35	0.5	0.6
F&G system	0.25	0.35	0.5	0.6	0.5	0.5	0.5	0.5	0.25	0.35	0.5	0.6

Table 3. Final ranking of equipment based on IVIF-SWARA method.

Ranking	$\tilde{w}_j$	Equipment Name	Row
1	□□□□□□□□□	Reston turbine	1
2	□□□□□□□□□	Diesel generator	2
3	□□□□□□□□□	Compressor	3
4	□□□□□□□□□	Control valves	4
5	□□□□□□□□□	Strainer	5
6	□□□□□□□□□	Underground tanks	6
7	□□□□□□□□□	Storage containers	7
8	□□□□□□□□□	Flowmeter	8
9	□□□□□□□□□	Pressure transmitter	9
10	□□□□□□□□□	Shotgun switches	10
11	□□□□□□□□□	UPS system	11
12	□□□□□□□□□	PLC control system	12
13	□□□□□□□□□	Cold cutter	13
14	□□□□□□□□□	Hot branching machine	14
15	□□□□□□□□□	Paint and metal thickness gauge	15
16	□□□□□□□□□	Movable and fixed cranes	16
17	□□□□□□□□□	One-way valves in between	17
18	□□□□□□□□□	LBVs of pipelines	18
19	□□□□□□□□□	Facility metering system	19
20	□□□□□□□□□	Electro-motor	20
21	□□□□□□□□□	Battery bank	21
22	□□□□□□□□	Cathodic protection station	22
23	□□□□□□□□	Industrial computer	23
24	□□□□□□□□□	Hot line telecommunication system	24
25	□□□□□□□□□	F&G system	25

Since the three indicators, O, S, and D are designed in such a way that the information of all three is of profit type, there is no need to normalize the comments matrix. And in the second step, $T(\tilde{a}_k)$ must be calculated. In the fourth step, the calculation of the power weight vector was put on the agenda. In the fifth step, the aggregated evaluation matrix was calculated using the intuitionistic fuzzy power weight of intuitionistic fusion power (IVIFPWHA) using the Heronian aggregation operator. Now, we can calculate the dynamic weights based on the situation in the intuitionistic fuzzy environment with interval values. In this regard, the following steps were performed in order. The first step is to calculate the accuracy functions SC_{o_i} SC_{s_i} related to the failure probability index and failure outcome for each equipment. In this step, the accuracy functions SC_{o_i} SC_{s_i} related to the failure probability index and failure outcome for each piece of equipment related to the aggregated evaluation matrix are calculated. In the second step, the minimum allowable weight of the failure detection index was calculated. In this study, the value of β is considered equal to 0.25. Then, the final dynamic weights were calculated based on the status of the three indices O, S, and D. Finally, the risk prioritization of each equipment was computed using the IVIF-SWARA method, which, due to the large volume of calculations, the tables were always refused and only the final table was given.

As can be seen, the Reston turbine equipment was identified as the most critical equipment of oil pipelines and telecommunications in the North of the country, which was followed by a model to optimize the maintenance program of this crucial equipment.

According to the results of the dynamic prioritization model of critical equipment, Reston turbine equipment was recognized as the most critical equipment for oil pipelines and telecommunications. According to experts, the time of preventive maintenance is 7 units, and the time of corrective maintenance is 12 units. The process was also assumed to be under control.

Table 4. Value of problem parameters.

C_V	C_F	$T_{resetting}$	T_1	T_0	T_s	$\delta_{M/C}$	δ_E	Parameter
50	100	2	1	1	0.33	0.6	1.5	The amount of
PR	C_{reset}	LC	C_{LP}	C_{FCPM}	C_{FCCM}	$C_{false-Alare}$	$C_{Re\,j}$	Parameter
10	5000	500	400	1000	10000	1200	2500	The amount of

According to the problem data, these data were implemented in the model, and the proposed model was solved by GAMS software. Finally, the optimal variables were calculated as follows:

I. Preventive and corrective maintenance cost model.

$$p := \frac{1398.4 \times x^{0.8703} + \dfrac{227500000}{x}}{7000}.$$

II. Cost model due to quality degradation due to process defects.

$$q := \frac{1}{7000}\left((1200) \times \left(\frac{e^{-(0.012429+0.000003121\times x^{0.8703})} \times h}{1-e^{-(0.012429+0.000003121\times x^{0.8703})} \times h}\right) \times 2 \times \left(\frac{1}{\sqrt{2\times\pi}}\right) \times e^{-\frac{1}{2}\left(y^2\right)} dy\right),$$

$$\begin{aligned} z_2 := {} & h \times ((1/(1-(\int_{-\infty}^{k-(0.6\times\sqrt{n}} \frac{1}{\sqrt{2\times\pi}}) \\ & \times e^{-\frac{1}{2}(y^2)} dy) - (\int_{-\infty}^{-k-(0.6\times\sqrt{n}} \frac{1}{\sqrt{2\times\pi}}) \\ & \times e^{-\frac{1}{2}(y^2)} dy)) \times \frac{(0.02185\times x^{0.8703})}{87+(0.02185\times x^{0.8703})}) \\ & +(1/(1-(\int_{-\infty}^{k-(1.5\times\sqrt{n})} (\frac{1}{\sqrt{2\times\pi}}) \times e^{-\frac{1}{2}(y^2)} dy) \\ & -(\int_{-\infty}^{-k-(1.5\times\sqrt{n})} (\frac{1}{\sqrt{2\times\pi}}) \times e^{-\frac{1}{2}(y^2)} dy)) \\ & \times \frac{87}{87+(0.02185\times x^{0.8703})})) - \frac{h}{2} + 1 + (\frac{1}{3}\times n), \end{aligned}$$

$$z_3 := (\frac{(0.02185 \times x^{0.8703})}{87 + (0.02185 \times x^{0.8703})}),$$

$$z_4 := (z_1 \times z_2) \times z_3,$$

$$z := \frac{z_4}{7000}.$$

III. Return cost when the process gets out of control due to an external and environmental factor.

$$ul := (10 \times (1 - (\int_{-\infty}^{3-1.5} (\frac{1}{\sqrt{2 \times \pi}}) \times e^{-\frac{1}{2}(y^2)} dy)$$

$$-(\int_{-\infty}^{-4.5} (\frac{1}{\sqrt{2 \times \pi}}) \times e^{-\frac{1}{2}(y^2)} dy)) / 1 - ($$

$$\int_{-\infty}^{k-(1.5 \times \sqrt{n}} (\frac{1}{\sqrt{2 \times \pi}}) \times e^{-\frac{1}{2}(y^2)} dy) - ($$

$$\int_{-\infty}^{-k-(1.5 \times \sqrt{n}} (\frac{1}{\sqrt{2 \times \pi}}) \times e^{-\frac{1}{2}(y^2)} dy)) \times 2500),$$

$$u_3 := (\frac{87}{87 + (0.02185 \times x^{0.8703})}),$$

$$u_4 := (u_1 \times u_2) \times u_3,$$

$$u := \frac{u_4}{7000}.$$

IV. Expected cost of sampling in a period.

$$\succ t_1 := (100 + (50 \times n)),$$

$$t_2 := ((\frac{7000}{87 + (0.02185 \times x^{0.8703})})$$

$$+((\frac{e^{-(0.01229 + 0.000003121 \times x^{0.8703}) \times h}}{1 - e^{-(0.01229 + 0.000003121 \times x^{0.8703}) \times h}}) \times 2 \times ($$

$$\int_{-\infty}^{-k} (\frac{1}{\sqrt{2 \times \pi}}) \times e^{-\frac{1}{2}(y^2)} dy))),$$

$$t_3 := h \times ((1 / (1 - (\int_{-\infty}^{k-(0.6 \times \sqrt{n})} \frac{1}{\sqrt{2 \times \pi}})$$

$$\times e^{-\frac{1}{2}(y^2)} dy) - (\int_{-\infty}^{-k-(0.6 \times \sqrt{n}} \frac{1}{\sqrt{2 \times \pi}})$$

$$\times e^{-\frac{1}{2}(y^2)} dy)) \times \frac{(0.02185 \times x^{0.8703})}{87 + (0.02185 \times x^{0.8703})})$$

$$+(1 / (1 - (\int_{-\infty}^{k-(1.5 \times \sqrt{n})} (\frac{1}{\sqrt{2 \times \pi}}) \times e^{-\frac{1}{2}(y^2)} dy)$$

$$-(\int_{-\infty}^{-k-(1.5 \times \sqrt{n})} (\frac{1}{\sqrt{2 \times \pi}}) \times e^{-\frac{1}{2}(y^2)} dy))$$

$$\times \frac{87}{87 + (0.02185 \times x^{0.8703})})) - \frac{h}{2} + 1 + (\frac{1}{3} \times n),$$

$$t_4 := \frac{(t_2 + t_3)\times t_1}{h},$$

$$t = \frac{t_4}{7000}.$$

V. Expected cost.

$$\succ e := \frac{10000}{7000}\left(\frac{87}{87 + (0.02185 \times x^{0.8703})}\right).$$

VI. Expected cost of maintenance and repair activities due to error FM_2 and finding and repairing a specific cause due to a malfunction.

$$\succ g := \frac{64000}{7000}\left(\frac{0.02185 \times x^{0.8703}}{87 + (0.02185 \times x^{0.8703})}\right).$$

VII. With (Optimization).

$$[\text{ImportMPS, Interactive, LPSolve, LSSolve, Maximize, Minimize, NLPSolve, QPSolve}],$$
$$\text{NPSolve}(p + q + ((u + z + t + g + e)), n = 10..100,$$
$$k = 3..4.5, h = 5..50, x = 400..700),$$
$$(n^*, k^*, h^*, t_{PM}{}^*) = (12, 1.80, 6, 652),$$
$$(f^*(12, 1.80, 6, 652) = 112.$$

This section provides an analysis of the data and their impact on decision variables and the total cost function. Each of the parameters of the above table is implemented on the model in two levels of 10 and 20% increase, and their effect on the decision variables and the objective function are investigated. The results are given in *Table 5*.

Table 5. The rate of change of some problem parameters at the level of + (10%) and + (20%).

Parameter	Initial Value	+(%10)	+(%20)
δ_E	1/5	1/65	1/8
$\delta_{M/C}$	0/6	0/66	0/72
T_0	1	1/1	1/2
T_1	1	1/1	1/2
$T_{resetting}$	2	2/2	2/4
C_{Rej}	2500	2750	3000
C_v	50	55	60
C_F	100	110	120

As can be seen in the *Table 6*, by increasing the parameters δ_E and $\delta_{M/C}$ by 10 and 20%, the value of the objective function and the decision variables change significantly. Still, by changing the other parameters, we do not see a significant change in the model. This shows the importance of preventing the process from going out of control, changing the mean and standard deviation of the desired quality characteristic, and paying attention to critical equipment.

In this model, preventive maintenance operations reduce the number of cases that are out of control of the system, and by determining the optimal values of preventive maintenance intervals and quality parameters, the total cost function is minimized. According to the above case, compared to the case where maintenance is ignored, the cost function is much less. It can be concluded that considering preventive maintenance along with the quality of the process will be very fruitful.

Table 6. Values of our decision variables and objective function at + (10%) and + (20%) levels.

Parameter	n	h	k	t_{pm}	$f(n,h,k,t_{pm})$
$\delta_E = 1/65$	11	7	1/90	653	118
$\delta_E = 1/8$	10	6	1/92	655/5	120/5
$\delta_{M/C} = 0/66$	12	8	1/85	654	119
$\delta_{M/C} = 0/72$	11	8	1/9	654	117
$T_0 = 1/1$	12	6	1/8	652	112
$T_0 = 1/2$	12	6	1/8	652	112
$T_1 = 1/1$	12	6	1/8	652	112
$T_1 = 1/2$	12	6	1/8	652	112
$T_{resetting} = 2/2$	12	6	1/95	651	113
$T_{resetting} = 2/2$	12	6	1/9	652	114
$C_{Rej} = 2750$	13	6	1/85	650	113
$C_{Rej} = 3000$	13	5/5	1/85	651	115
$C_F = 110$	12	6	1/8	652	112/5
$C_F = 120$	13	8	1/85	652	114/5
$C_V = 550$	11	9	1/8	651	113
$C_V = 600$	11	9	1/8	650	114

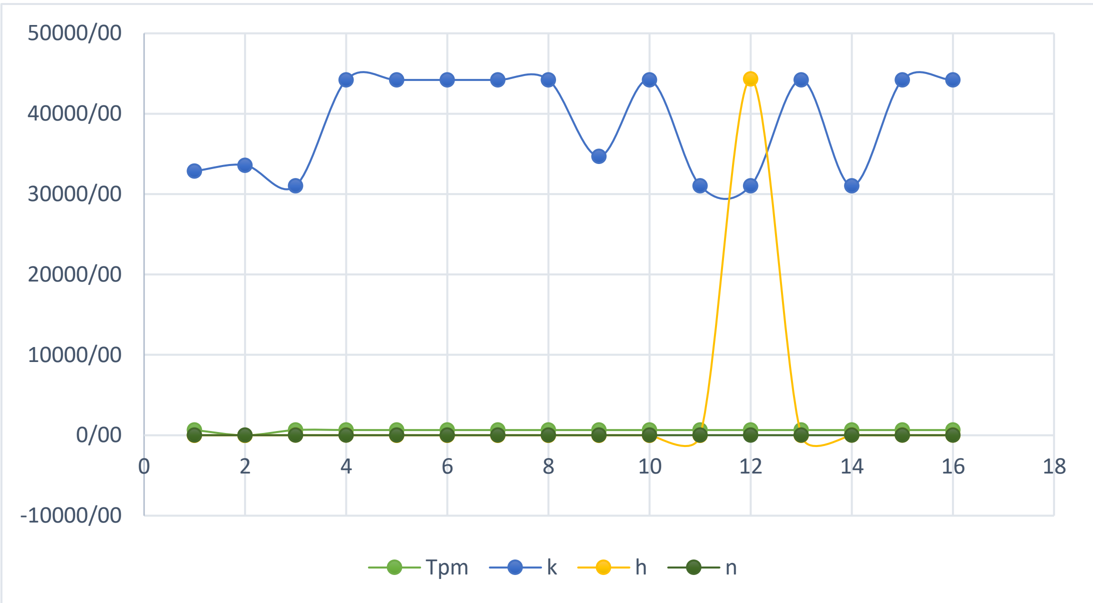

Fig. 1. Sensitivity analysis status of the integrated model.

5 | Discussion

In this study, fixed weights are first identified for ranking. Fixed weight data of indicators O, S, and D (first stage) are collected for the condition that the hypothetical equipment is at the lowest point in terms of all three criteria; that is, the probability of failure is close to zero, the consequence of failure is close to zero, and the inability to detect failure is close to zero. In this case, the experts are asked to express their views on the weight of the indicators according to this hypothetical equipment. Then, using the modified HFPR method, in three steps of fixed weights, three indicators of failure outcome (S), failure probability (O), and failure detection power (D) are identified. The results of the calculations are as follows:

$W_O = 0.35,$

$W_S = 0.425,$

$W_D = 0.245.$

But the second challenge is the different effects that O, S, and D can have on the failure of each device. In the conventional method, the effect of these three indicators is assumed to be the same in different situations. In order to meet this challenge, the researcher has proposed a dynamic weighting model based on an intuitionistic fuzzy state with interval values. The use of this model has enabled the researcher to be able to create dynamic weights for each equipment and each failure mode, according to its condition, and therefore, in a completely flexible way, the different effects of the three indicators O, S, and D on the ranking. Make any equipment or failure mode possible. Using the dynamic weighting model based on the intuitionistic fuzzy state with the values of the intervals mentioned in the general ranking model as one of its steps, the initial dynamic weights and the final dynamic weights have been calculated. According to the conditions of use and structure of the equipment, these equipment were identified in the form of 8 main categories. The most critical Reston turbine was placed, and a mathematical model for optimizing maintenance was developed for this equipment.

Maintenance is connected to every single step of the supply chain. While different industries will have varying maintenance needs, it is interesting to see how crucial good maintenance is in keeping a healthy supply chain.

In this research, an integrated model is presented so that the two aspects of maintenance and repair and process quality are considered in a combined system. In this model, all maintenance and repair features and process quality are presented in the form of an integrated model and solved with GAMS software. The proposed model determines the optimal value of each of the four decision variables. That is, equipment inspection size (n), equipment inspection frequency (h), control limit coefficient (k), and preventive maintenance intervals (t_PM), which minimize the total expected cost of integration per unit of time. A numerical example of compressor equipment as the most critical equipment for oil pipelines and telecommunications was shown to illustrate the impact of cost parameters on the process of combining process quality and economically preventive repair. Also, in this dissertation, the integrated model was compared with its independent model by a numerical example, and it was observed that the difference in the total cost and the advantage is enormous.

In this study, it is assumed that process failure follows exponential distribution. The process failure time distribution can be supposed to be another distribution. Also, only one qualitative characteristic is considered. Suppose the problem can be modeled with more qualitative characteristics. In this study, hesitant fuzzy preferential relations have been used to calculate the weight of fixed indices. It is suggested that other approaches to weight calculation, such as the use of intuitionistic fuzzy preferential relations, etc., be used to calculate fixed weights and compare the results with the results of this study. In this research, in the last stage, the combined IVIF-SWARA approach has been used to prioritize the equipment. Therefore, instead of this method, other methods, such as the TOPSIS method, can be used in the intuitionistic fuzzy environment with interval values , and the results can be compared with the results of the present study.

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