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Operating Environmental Condition Effect on Reliability-Centred Maintenance

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Abstract

Implementing maintenance protocols for industrial machinery is essential since a well-thought-out plan may support and improve machinery dependability, production quality, and safety precautions. Implementing a maintenance plan that considers the equipment's actual functional behavior and the effects of failures will be easier and more practical. Engineers must consider environmental conditions when studying in hostile environments such as mine. The major goal of this study is to create a mining equipment maintenance program that is as effective as possible while incorporating risk and performance indicators and taking environmental factors into account. The study uses the “reliability-centered maintenance” method, which combines the reliability operating index and risk. The Cox model also includes the risk factors associated with environmental conditions in the reliability analysis. The proposed approach was implemented in a 5-758 Komatsu dump-truck case study at the Sungun copper mine in Iran. The reliability-centered maintenance approach is implemented for dump-truck in three scenarios based on risk factors: 1- baseline, 2- First semi-annual, cheap maintenance, and 3- second semi-annual, expensive maintenance. All failure modes are low-risk, making corrective maintenance appropriate. In Scenario 1, electrical-electrical, electrical-start, mechanical, and pneumatic-related failures are low-risk, making corrective maintenance suitable. In Scenario 2, corrective maintenance is recommended for pneumatic-related failure. In Scenario 3, the fuel-related failure has a high criticality number and failure intensity, indicating a high-risk situation. Time-based preventive maintenance is the most appropriate strategy for this scenario.

1. Introduction

Open-pit mining with a high production rate needs a large equipment. The mine's harsh environmental and operating conditions (risk factors) impact equipment performance. Unexpected stoppages will increase maintenance costs, reduce profits, delay orders, etc. Also billions of dollars are spent annually on producing different kinds of equipment for use in the global mining industry, and this cost is over-growing [1]. Appropriate maintenance increases the system's lifetime and reduces capital costs, etc. Maintenance has various strategies such as Preventive Maintenance (PM), Corrective Maintenance (CM), Conditional-based Maintenance (CBM), Reliability-centered Maintenance (RCM), etc. Reliability-centered maintenance can combine reliability and risk. *Reliability is the system's probability of carrying out a needed operation in the determined condition at a specific time with the provision of required external resources* [2]. Since the mid-1960s, the reliability indicator has been gradually introduced into the field of mining engineering [3]. Several researchers have conducted studies on the maintenance of mining equipment by reliability including dump trucks, dump truck tires, drum shears, rotary drilling machines, and Load-Haul-Dumpers (LHDs).

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However, many of these studies have not considered the risk of equipment failure [4]–[14].

A Fault Tree Analysis (FTA) approach was initially employed to enhance the risk assessment of maintenance planning. The FTA method was first used in 1962 by the Bell Telephone Laboratory to study safety in missile launch systems. In 1995, Wu Chao analyzed unexpected fires in more than ten mines due to the presence of the sulfide mineral, identified 17 key factors, and finally proposed a mathematical model for predicting combustion risk [15]. Chao and Dishing studied the application of free-to-air technologies for coal dust suppression spray systems, combining particle collection models and theoretical and practical results [16]. FTA was used to identify critical items in system success and potential causes of failure [17]. In 2005, Sharma *et al*. used fuzzy logic due to the quality of most of the information used in the “Failure Mode and Effects Analysis (FMEA)”. In this study, a paper mill's risk priority number (RPN) was calculated using this method, and its risk was analyzed. The results showed that it was possible to remove the limitations of the traditional FMEA method with this method and combine experts' information and opinions in calculating the intensity, probability of failure, and identification [18]. Gupta and Bhattacharya analyzed the reliability of an underground coal mine conveyor belt using FTA [19]. Beamish *et al*. used FTA to identify the root causes of coal fire accidents [20]. Nouri Qarahasanlou proposed maintenance to prevent equipment failure at Azarabadegan Cement Plant [21].

National Aeronautics and Space Administration (NASA) used the FMEA model in 1963 but Ford Motor Company proposed it in 1977 [22]. Gupta *et al*. used RCM to prioritize mechanical equipment failure modes, selecting the appropriate strategy for each failure [23]. Rezaee *et al*. used FMEA to identify failures, effects, prevention, and control methods in Iran's stone industry [24]. Mottahedi *et al*. demonstrated the causes of coal bursts, guiding safe mining [25]. Shahani *et al*. conducted research utilizing the FTA approach on the gas explosion in Pakistani underground coal mines in 2019. The primary factors that led to this hazardous mishap were examined. Reforms in structural management and safety are necessary to lower the risk of fatal and non-fatal accidents, gas explosions, and other mishaps [26]. To rank each failure mode of a forage crushing machine and improve its dependability, Zhai *et al*. worked on a case study of the 9R-40 forage crushing machine in 2020. They used the "failure modes, effects, and criticality analysis (FMECA)" approach. Based on the results, the rotor is the main component affecting the system reliability, and must be addressed to improve forage crushing machines. [27]. In 2021, Xu *et al*. used the fuzzy FTA to investigate the hardware reliability of a gas monitoring system in a coal mine in Shaanxi, China. Industrial computers and monitoring substations, power, sensor, and communication line failures were the leading causes of hardware failure in coal mine gas monitoring systems. A management system based on human factors is needed to mitigate human factors [28]. FMEA and the "analytic hierarchy process (AHP)" method was used in 2021 by Rahimdel *et al*. to identify and rank the failure scenarios in a rolling stock utilized in a Swedish iron ore mine. The research identified hazardous failure modes and their importance [29]. In 2022, Jiskani *et al*. used the combination of the z-number concept, fuzzy theory, and FTA to analyze the risks associated with mine health and safety (MHS) in the surface mines' workplace, equipment, and environment. The FTA method found that blasting, explosive fumes, and dust were more likely to occur. Staff incompetence, improper safety perimeter setting, and non-implementation of regulations threaten mine health and safety [30].

One of the most successful methods for fusing risk and reliability is the RCM strategy. It is divided into two sections: the risk section, which assesses the likelihood, impact, and consequences of the failure, and the operating conditions of the system's reliability. The literature study indicates that most studies base the first half of their conclusions on experts' judgments, while the second portion is based on time data such as the mean time to failure (MTBF). However, more thorough reliability studies in actual settings (e.g. references: [31]–[35]) show that this indicator is significantly impacted by contextual factors (i.e. risk factors). Part 3 of the article includes a case study that uses RCM to examine the reliability-centered maintenance of a 5-785 Komatsu dump truck. Therefore, any use of this index including determining the system's state, making judgments about the system, scheduling maintenance, etc. In this situation, RCM is carried out on a 5-785 Komatsu Dump Truck within a pre-determined time frame and following its working environment. There are three sections to the paper. Reliability and maintenance including FTA, FMEA, and FMECA, are briefly covered in Part 1. The methodology framework is described in Part 2, which consists of defining the system boundaries, gathering data, formulating risk factors, identifying significant component functions using the FTA approach, calculating system reliability, performing FMEA, performing FMECA, and using RCM logic to determine the appropriate maintenance strategy (step 6).

2. Reliability-cantered Maintenance Methodology

Maintenance significantly impacts a system's performance, and many different maintenance strategies can be used to improve it. One of these strategies is Reliability-centered Maintenance (RCM), presented in Figure 1. The American aviation industry first proposed RCM in the 1960s, providing a practical approach to determining the appropriate maintenance strategy for a system. The main goal of RCM is to focus on the system's critical functions and eliminate unnecessary maintenance actions to reduce maintenance costs [36]. RCM is based on analyzing the structure of failures in the system using tools such as FTA, FMEA, and FMECA [23], [37]. The stages of the RCM program are shown in Figure 1, and the RCM steps are as follows [37], [38]:

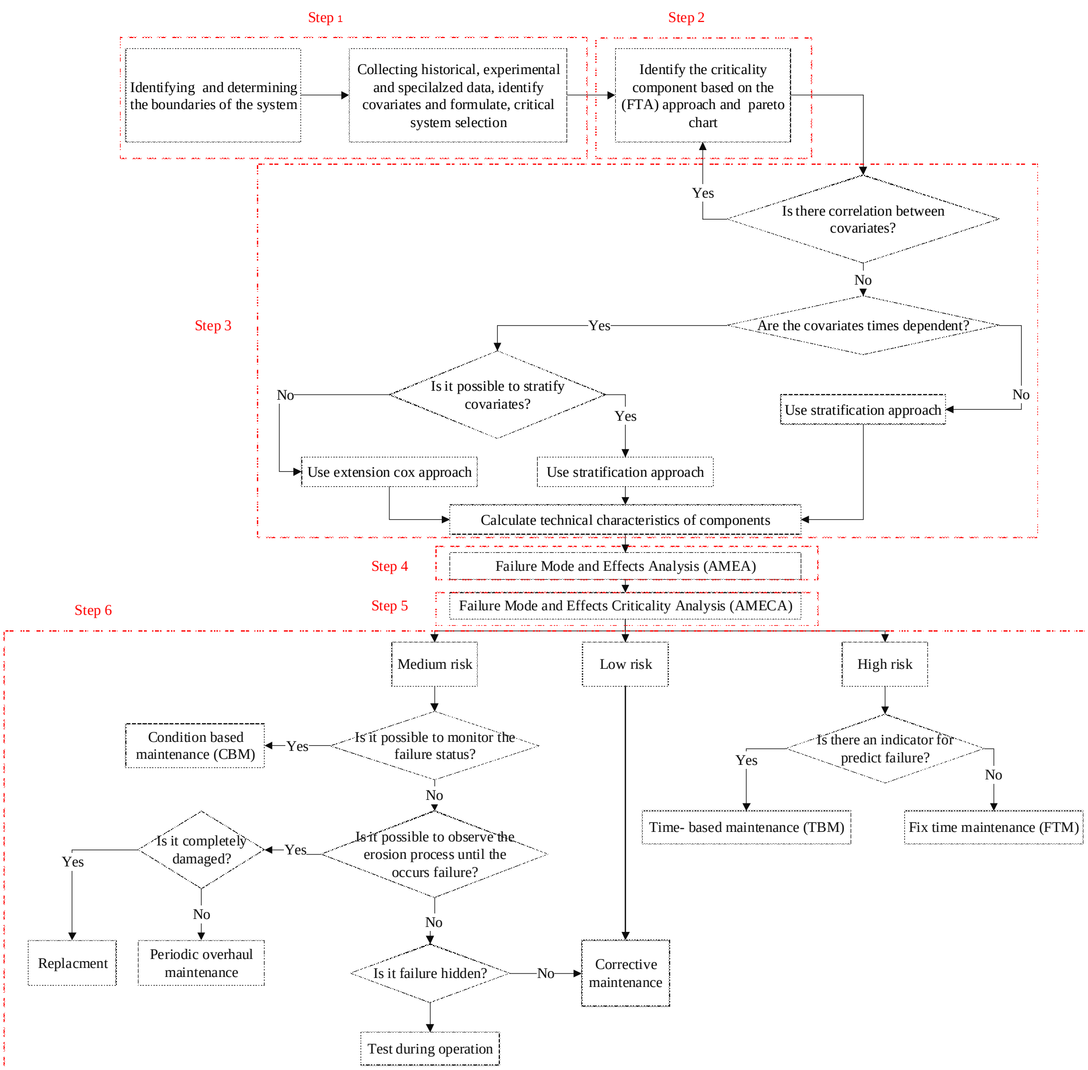

Figure 1. Reliability-centered maintenance analysis [23].

Step 1: System boundaries, data collection, and risk factors formulation

Step 2: Identify the significance functional of the component based on the FTA approach

Step 3: Calculation of system reliability

Step 4: FMEA

Step 5: FMECA

Step 6: Use RCM logic to decide on the appropriate maintenance strategy

In the following, each RCM step will be implemented for the system under study.

2.1. System boundaries, data collection, and risk factors formulation

The RCM approach's first phase entails establishing the system boundaries and gathering and assembling temporal data and risk variables. Categorical (scaled) risk factors and qualitative variables are the two basic categories into which risk factors can be sub-divided. Qualitative variables with binary or more categories such as the type of rock or the operating shift are examples of definite risk factors. For instance, when Barabadi *et al*. took operator skill into account, high competence was denoted by one and poor skill by -1 [39]. Quantitative variables with a specified scale and a potential for linear or non-linear change are continuous risk factors. Temperature and humidity are two examples of ongoing risk variables. In contrast to categorical risk factors, continuous risk factors do not need to be categorized, and can be used immediately in the analysis [40].

2.2. Identify significance functional of component based on FTA approach

The system is divided into various subsystems and components during the analysis stage. The sub-systems and components that experience the most failures are identified as critical. To achieve this, FTA and Pareto diagrams can be utilized.

2.3. Calculation of system reliability

Once the critical system is identified, its reliability must be determined. In this regard, the Weibull distribution function is one of the widely-used and flexible statistical functions that can cover extensive changes or coincidences in the data of these two indicators. In the following sources, some of its applications and various expansions under the title of the Weibull family can be found [41]–[45]. In 2004, Murthy reviewed the types of the Weibull models and discussed 40 varieties of this function and their relationship with the 2-parameter Weibull distribution [46].

The Weibull Probability Plot has unique forms for most Weibull family functions (WPP). For instance, the 2-parameter Weibull is represented as a straight line in this diagram but the 2-fold Weibull mixture has an S shape [44], [46]. This study conducts reliability analysis crucial in operational applications-using multiple Weibull mixture distribution function models. According to Buar, this function can be added to the system to increase reliability even when the system's structure is unknown [47]. The discrete or finite mixture that results from the linear integration of two or more functions may have normal, exponential, Weibull or other distributions. A simple description of this function can be expressed as follows: the analyzed population consists of n ≤ 2 sub-populations, and the contribution of each in the total function is ω_i, and its value for the whole population is [48]:

$$\sum_{i=1}^{n} \omega_i = 1 \Rightarrow; \tag{1}$$

$$i = 1,2,\dots,n; 0 < \omega_i < 1$$

Therefore, for a random variable t from the population, the reliability function of the mixture distribution can be expressed as follows:

$$R_m(t) = \sum_{i=1}^{n} \omega_i R_i(t) \tag{2}$$

$$i = 1,2,\dots,n; 0 < \omega_i < 1$$

In the case of 2-parameterization Weibull (shape parameter (β) and scale (η)) of all the distribution functions of the sub-populations, the form of the reliability function will be as follows:

$$R_m(t) = \sum_{i=1}^{n} \omega_i exp\left[-\left(\frac{t}{\eta_i}\right)^{\beta_i}\right] \tag{3}$$

$$i = 1,2,\dots,n; 0 < \omega_i < 1$$

In this equation, if n = 2, the distribution function is called the "two-fold Weibull mixture".

However, this function is unaffected by the environment. Regression techniques should be used to account for the impacts of environmental factors. In general, the Cox proportional hazard model (PHM), the stratified Cox regression model (SCRM), and the extended Cox regression model (ECRM) are the three reliability-based risk factor analysis methods. The proportional hazard assumption (PH assumption) of the risk factors guides the choice of each model [49].

Cox proportional hazard model: In 1972, Cox presented a medical non-parametric regression model for patients' survival analysis. In engineering named reliability, the common form PHM in Equations (1) and (2) are expressed [40]:

$$\lambda(t,z) = \lambda_0(t)\exp\left(\sum_{i=1}^{n} \alpha_i z_i\right) \quad (1)$$

$$R(t,z) = (R_0(t))^{\exp\left(\sum_{i=1}^{n} \alpha_i z_i\right)} \quad (2)$$

λ *(t, z)* and *R(t, z)* are the failure and reliability functions, and z is the row vector comprising the risk factor parameters (revealing the degree of influence that each risk factor has on the failure function), α is the unknown parameter of the model or regression coefficient of the corresponding n risk factors, $\lambda_0(t)$ and $R_0(t)$ are baseline hazard rate and baseline reliability dependent on time only and $exp\sum_{i=1}^{n}(\alpha_i z_i)$, the exponential function is more used for risk factors terms and also can be used [linear form $1+\alpha z$, the log-linear $exp(z\alpha)$, and the logistic form $(1+exp(z\alpha))$] [50]. When a risk factor is time-dependent, the component's failure rate will vary depending on the different values of the risk factor. Equation **Error! Reference source not found.** states that risk factors are time-independent if the hazard ratio is constant for two observations with different z-values, I and j [51], [52]:

$$HR = \frac{\lambda_1(t,z_1)}{\lambda_2(t,z_2)} = \frac{\lambda_0(t,z_1)\exp(\alpha_1 z_1)}{\lambda_0(t,z_2)\exp(\alpha_2 z_2)} = e^{(\alpha_1(z_{i1}-z_{j1})+\ldots+\alpha_n(z_{in}-z_{jn}))} \quad (3)$$

Graphical and theoretical models can check the PH assumption. A theoretical model such as Schoenfeld residuals is used for the goodness-of-fit (GOF), and a graphical model is defined [50].

If the (PH) assumption for the risk variables is violated, which occurs when they are time-dependent and require more than one baseline function to calculate the hazard rate or reliability, then non-proportional hazard models such as SCRM or ECRM can be applied.

Stratified Cox regression model: This model uses statistical techniques or prior knowledge to account for varied levels of time-dependent risk factors. A level of risk factor represents each stratum. The number of baseline functions in the SCRM, where each stratum represents a baseline function, is a key difference between the stratified Cox regression model and the PHM. The general forms of the stratified Cox regression model for reliability and hazard rate, respectively, are expressed in Equations **Error! Reference source not found.** and **Error! Reference source not found.** [53]:

$$\lambda_s(t,z) = \lambda_{0s}(t)\exp\left(\sum_{i=1}^{n} \alpha_i z_i\right), \quad s = 0,1,\ldots.r \quad (4)$$

$$R_s(t,z) = (R_{0s}(t))^{\exp\left(\sum_{i=1}^{n} \alpha_i z_i\right)}, \quad s = 0,1,\ldots.r \quad (5)$$

$\lambda_s(t,z)$ And $R_s(t.z)$ are the observed hazard rate and reliability in each stratum, $\lambda_{0s}(t)$ and R_{0s} are the baseline hazard rate and reliability in each stratum, *s* shows the stratum number, and *n* indicates the risk factor number.

Extended Cox regression model: This model, an expanded version of the fundamental PHM, is used to examine risk factors that are both time-dependent and time-independent simultaneously. The Cox regression model can be used with the non-proportional hazard assumption, all equations that are already defined can be used if replaced with *z (t),* and Equations **Error! Reference source not found.**) and **Error! Reference source not found.**) can be modified to [54]:

$$\lambda(t,z) = \lambda_0(t)\exp\left(\sum_{j=1}^{n} \alpha_j z_j(t)\right) \quad (6)$$

$$R(t,z) = (R_0(t))^{\exp\left(\sum_{j=1}^{n} \alpha_j z_j(t)\right)} \quad (7)$$

λ *(t, z)* and *R (t, z)* are the failure and reliability functions, z is the row vector consisting of the risk factor parameters (indicating the degree of influence which each risk factor has on the failure function), α is the unknown parameter of the model or regression coefficient of the corresponding n risk factors. The general form ECRM is used simultaneously for time-dependent and time-independent risk factors, and it can be written as Equation **Error! Reference source not found.**).

$$\lambda(t,z(t)) = \lambda_0(t)\exp\left[\sum_{i=1}^{n} \alpha_i z_i + \sum_{j=1}^{m} \alpha_j z_j g_j(t)\right] \quad (8)$$

where $\lambda_0(t)$ is baseline hazard rate, α_i and α_j are the unknown parameters of the model or regression coefficients of the corresponding risk factors, z_i and z_j are row vectors consisting of the risk factor parameters (indicating the degree of influence that each risk factor has on the failure function), n number of time-independent risk factors, m number of time-dependent risk factors, and $g_j(t)$ is a function of time that can be fixed as well as *log (t)* or a random function of time [40].

It is vital to include the impact of environmental factors at this point in the Weibull family functions. Regression and the Weibull family functions must be combined to achieve this. B. Ghodrati's method can be expanded to account for the effect of external factors on the mixture function because the baseline functions follow a Weibull distribution [55], [56]. He proved that the risk factors are only effective in the scale parameter (η) value, and do not change the shape parameter (β). These changes can be defined with new parameters of shape (β_{si}) and scale (η_{si}) for introducing the influence of environmental conditions. If β_{oi} and η_{oi} are the shape and scale parameters of each fold in the fitted baseline functions, respectively, then [55]–[57]:

$$\beta_{si} = \beta_{0i}$$

$$\eta_{si} = \eta_{0i}\left[exp\left(\sum_{i=1}^{n} z_i\alpha_i\right)\right]^{-\frac{1}{\beta_{0i}}} \quad (9)$$

As a result, the reliability function (R_{sm}) and maintainability function (M_{sm}) are presented as follows by entering the effects of risk factors:

$$R_{sm}(t) = \sum_{i=1}^{n} \omega_i exp\left[-\left(\frac{t}{\eta_{si}}\right)^{\beta_{si}}\right] \quad (13)$$

$$i = 1,2, \dots, n; 0 < \omega_i < 1$$

2.4. Failure mode and effect analysis

FMEA is a methodology that aims to identify potential failure modes for a process or product before they occur to assess the associated risks. The FMEA process should, in theory, be a systematic procedure that discovers and assesses potential system dangers and their impacts. In the end, the procedures should be documented. It should also identify steps that might decrease or eliminate the possibility of probable failures. The timing of this procedure is among its most important characteristics. It is a tool for preventing defects rather than resolving them after issues have arisen. This study's proposed algorithm for using FMEA is shown in Figure 2. Prioritization in this method aims to allocate limited resources to the most significant items in terms of risk. Also in Table 1 prioritization quality scale by RPN is shown. The RPN scale was chosen for this study after integrating the findings of a review of [58]–[63] references, the classification of failure modes, and feedback from experts such as maintenance managers, technical managers, and HSEE professionals. Generally speaking, each company's organizational culture and risk tolerance level should be considered while developing a risk management strategy.

2.4.1. Failure mode, effects, and criticality analysis

The FMECA approach, a kind of expanded form of FMEA, was used to determine the failure critical following the discussions and some of the inadequacies in the output of FMEA to RPN. In addition to the FMEA tasks, this technique also includes a stage of analysis known as "crisis analysis" [64]. Critical analysis is divided into quantitative and qualitative categories in the US Military Standard Booklet. The methodology described in the US military controversy was applied in this article following the unwavering principles of American standards [62].

Quantitative analysis of critical: The following factors should be provided in a quantitative analysis of the amount of crisis [65], [66]:

- Determine reliability and unreliability
- Identify the share of the unreliability of each case (item) in total failure

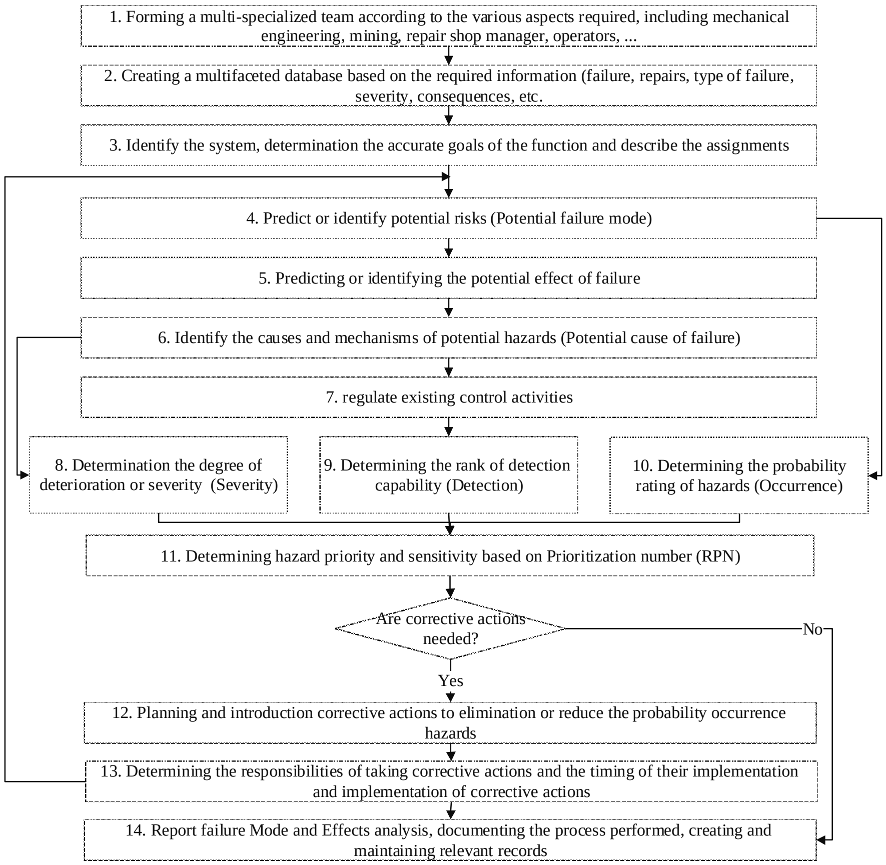

Figure 2. Implementation algorithm of Failure Mode and Effects Analysis [65], [66].

Table 1. Prioritization quality scale by RPN.

RPN	Description	Criteria by color
0-30	Low priority	Green
30-300	Medium priority	Yellow
> 300	High priority	Red

- Rate the probability of loss (or severity) due to failure. The critical value of each potential failure condition will be obtained from Equation (9) [49], [64], [67]:

$$C_{mode} = \beta_{mode} . \alpha_{mode} . F(t)_{component} \quad (10)$$

C_{mode} shows the failure mode criticality value, and β_{mode} shows the probability of damage (severity) in the assignment with the occurrence of this state of failure, which must be specified according to Table 2.

Table 2. Probability of effect of failure.

Failure effect	Value of damage
Actual detriment	1
Probability detriment	0.1-1
Possible detriment	0-0.1
Without effect	0

α_{mode} is the share of failure mode in the occurrence of component failure, which is the sum of the failure mode m in a component is equal to one $\left(\sum_{i=1}^{m} \alpha_{mode_i} = 1\right)$. Unreliability or the possibility of component failure at time t. In Equation (10), the following equation can be used, assuming a constant failure rate over a specified period for the assignment (t) of a component:

$$F(t)_{component} = 1 - e^{-\lambda_c . t} \approx \lambda_c . t \quad (11)$$

Therefore, Equation (9) with the assumption (10) will be re-written in Equation (11):

$$C_{mode} = \beta_{mode} . \alpha_{mode} . \lambda_c . t \quad (12)$$

In the analysis of different systems, the assumption that the failure rate is constant is rarely established, and in fact, each failure mode and each component has its failure function. Therefore, if determining the probability of each failure state and assuming that m is a different state of failure (which is true in most cases), the best way to determine the amount of crisis is as follows in Equation (12):

$$C_{mode_i} = \beta_{mode_i} \frac{\frac{F(t)_{mode_i}}{F(t)_{component}}}{\sum_{i=1}^{m} \frac{F(t)_{mode_i}}{F(t)_{component}}} \tag{13}$$

The critical value of an item with m failure mode will also be obtained from the sum of the crisis values:

$$C_{Item} = \sum_{i=1}^{m} C_{mode_i} \tag{14}$$

Crisis numbers are similar to risk prioritization with RPN; a standard scale can be used to qualify crisis analysis. Table 3 provides examples of quality values. Although this table is immature, it provides a visual comparison in prioritization, which is further completed with the help of the criticality matrix in the continuation of the qualitative analysis of the criticality of this issue.

Table 3. Qualification scale, risk prioritization with crisis number.

Criticality value	Description	Criteria by colour
0-0.4	Low priority	Green
0.4-0.6	Medium priority	Yellow
0.6 <	High priority	Red

Qualitative analysis of critical : For qualitative analysis of the amount of crisis, the following factors should be provided:

- Intensity rate of potential impact effects due to failure (S)
- Determine the probability of occurrence for each potential failure condition (F)
- Comparison of failure states and their prioritization in the criticality matrix. The matrix consists of an arbitrary classification of failure intensity (S) with different levels of probability of occurrence (F) or critical number (C) for different failure states. The criticality matrix makes it possible to identify and compare each failure mode with other modes according to the severity of the failure.

2.5. RCM logic for appropriate maintenance strategy detection

The sixth step of the flowchart shown in Figure 1 is connected to this one. In Step 5, the risk was prioritized quantitatively or qualitatively into three categories: high, medium, and low, denoted by green, yellow, and red for each approach. Based on studies conducted in earlier research, the maintenance techniques are currently split into three categories: CM, PM, and CBM. Figure 1 shows the RCM decision logic system. It should be said about the preventive strategy is one of the most widely used strategies in industrial equipment; one of the most important goals of PM is to improve system reliability. Therefore, for the systems for which this strategy is to be used, if the reliability after performing the PM, denoted by the symbol R_{PM} (t), the reliability function can be calculated from the following Equation **Error! Reference source not found.**:

$$R_{PM(t)} = \begin{cases} R(t) & 0 < t < T_{PM} \\ R^n(T_{PM})R(t - nT_{PM}) & nT_{PM} \le t < (n+1)T_{PM}, \quad n \ge 1 \end{cases} \tag{15}$$

In Equation **Error! Reference source not found.**, T_{PM} is the time interval for performing PMs. Based on Equation **Error! Reference source not found.**, the reliability function of this paper as Weibull function will be as Equation **Error! Reference source not found.**:

$$R_{PM(t)} = \begin{cases} \sum_{i=1}^{n} \omega_i exp\left[-\left(\frac{t}{\eta_i}\right)^{\beta_i}\right] & 0 < t < T_{PM} \\ \sum_{i=1}^{n} \omega_i exp\left[-n\left(\frac{T}{\eta_i}\right)^{\beta_i}\right] exp\left[-\left(\frac{t-nT}{\eta_i}\right)^{\beta_i}\right] & nT_{PM} \le t < (n+1)T_{PM}\,, \quad n \ge 1 \end{cases} \tag{16}$$

3. Case Study

The 5-785 Kumatso dump truck machine is the subject of this study's case study. It occurs at the Azarbayjan Molybdenum-Copper Mine in Iran, also called the Sungun Copper Mine, located northwest of the nation.

3.1. System boundaries, data collection, and risk factors formulation

Time data and risk indicators from 5-785 Komatsu dump trucks were gathered over six months, and an example of this data is shown in Table 4. Five different subsystems comprise each dump truck, and an FTA diagram has been created to show how these subsystems interact. The FTA diagram for the Komatsu dump truck sub-systems is shown in Figure 3.

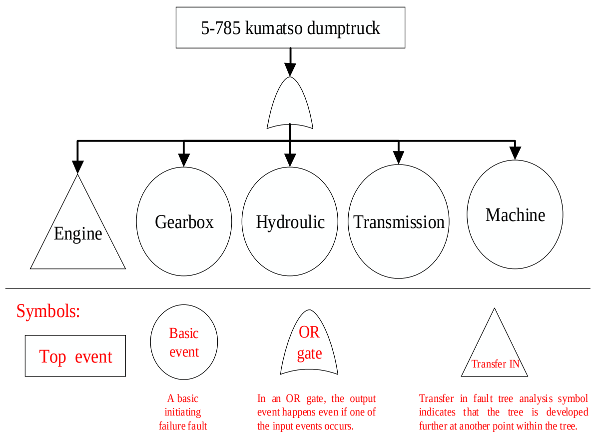

Figure 3. 5-785 Komatsu dump truck FTA chart.

Table 4. Example of the Komatsu dump truck data.

N	Risk data		Failure data							
	Cause of failure	Cost ($)	The time between failure (TBF)	Status	Haulage distance (m)	Haulage height (m)	Operations capacity (m3)	Humidity (%)	Temperature (C)
1	Lamp failure	3	386	S	183950	2500	980	80	2
2	Compressor hose failure	53	6.5	F	7350	62.5	18	72	6
3	..	..	..	..	.	.	.	…	.

In Table 4, Haulage distance (m) and Haulage height (m) indicate the transportation distance traveled and the height increase (or decrease) from the loading point to the unloading point.

The engine subsystem was identified as a critical component based on analysis of failure data from 5-785 Komatsu dump trucks. The FTA diagram for the engine system is presented in Figure 4.

Among engine sub-systems, the fuel subsystem has the most frequent failures. The Pareto chart is shown in Figure 5 component of the engine system.

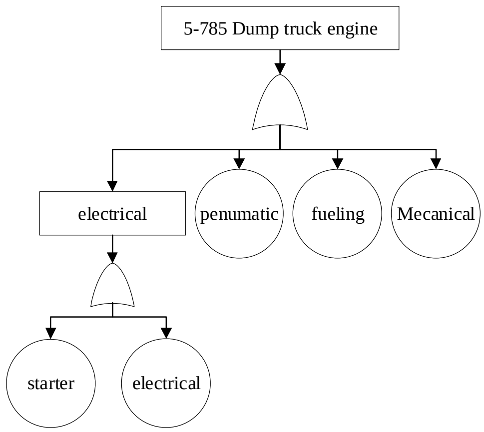

Figure 4. 5-785 Dump truck engine FTA diagram.

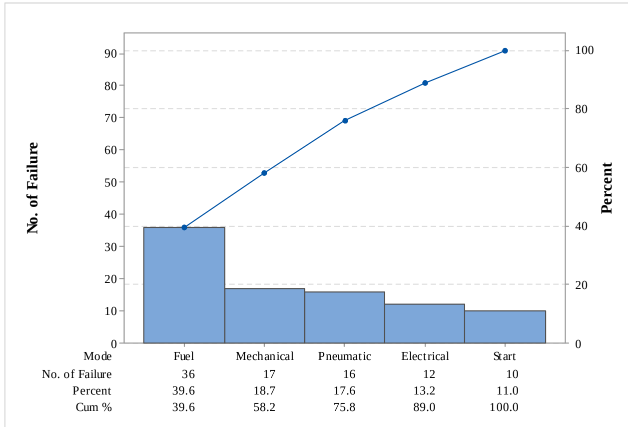

Figure 5. Diagram of dump truck engine breakdown mode.

3.2. Calculation of system reliability based on risk factors

This section estimates engine system sub-system reliability based on various risk factors. The techniques include PH assumption testing, correlation testing, and reliability modeling.

3.2.1. Risk factors correlation test

The risk factors should be examined to see whether they correlate after sorting and quantifying the data. This can be accomplished using the Pearson correlation test. At a 95% confidence level, the correlation test results between the risk factors revealed no significant correlation between them. Table 5 displays the engine system's correlation test findings, which also contain the following risk factors:

- "Precipitation (m)" (continuous risk factor): The amount of precipitation that could affect the state of the roads is represented by this parameter.
- "Slope" (continuous risk factor): This parameter shows the height ratio carried to the distance hauled.
- "Temperature (C)" (continuous risk factor): The ambient temperature has a direct effect on the operation of the machine and the operator's skill.
- "Weather conditions" (discrete risk factor): This risk factor has been divided into four parts based on the weather conditions: clear and sunny (4), partly cloudy (3), cloudy (2), and heavy fog (1)."

3.2.2. Proportional hazard assumption

The theoretical model as residual Schoenfeld is used for quantitative risk factors (continuous) and qualitative risk factors (qualitative). In this study, used to estimate regression coefficients, we used test z for eliminated risk factors found to have no significant value from the subsequent calculations. The corresponding regression coefficient estimates were obtained and tested for their significance based on test z and p-value (obtained from the table of normal unit distribution). We used the p-value of 5% as the upper limit to check the significance of risk factors. In the theoretical model, if the p-value is more significant than 0.05, the PH assumption is established, and risk factors are time-independent. The results of the PH assumption are shown in Table 6.

Table 5. Correlation of risk factors.

Failure Mode	Statistics	Risk factors correlations				
		Sky Condition (z_1)	Slope (z_2)	Capacity per hour (z_3)	Rain per hour (z_4)	Temperature per hour (z_5)
Electrical-Electrical	Pearson correlation	-0.321	-.093	.264	-.101	-.085
	p-value	0.145	.681	.236	.654	.706
Electrical-Start	Pearson correlation	-0.428	.082	.060	-.343	-.348
	p-value	0.217	.821	.870	.332	.324
Fuel	Pearson correlation	-0.093	-.033	-.167	-.147	-.214
	p-value	0.590	.848	.329	.391	.210
Mechanical	Pearson correlation	0.134	.342	-.213	-.225	.260
	p-value	0.609	.179	.412	.385	.313

Pneumatic	Pearson correlation	0.110	-.017	.187	-.338	-.078
	p-value	0.686	.949	.488	.200	.773

Table 6. Results of a theoretical model for PH assumption for engine system.

Failure mode	Statistics	Sky condition (1)	Sky condition (2)	Sky condition (3)	Slope	Capacity per hour	Rain Per Hour	Temperature per hour
Electrical-Electrical	Pearson correlation	0.496	0.355	-0.040	-0.123	0.071	0.213	0.091
	P(PH)-value	0.084	0.235	0.897	0.688	0.817	0.484	0.767
Electrical-Start	Pearson correlation	-0.423	-0.276	0.157	-0.389	0.160	-0.106	-0.169
	P(PH)-value	0.297	0.508	0.710	0.341	0.704	0.802	0.690
Fuel	Pearson correlation	-	-	-	-	-	0.027	0.029
	P(PH)-value	-	-	-	-	-	0.877	0.869
Mechanical	Pearson correlation	-	-	-	-	0.055	-	-
	P(PH)-value	-	-	-	-	0.834	-	-
Pneumatic	Pearson correlation	-	-	-	-	-0.419	-0.399	-
	P(PH)-value	-	-	-	-	0.228	0.253	-

3.2.3. Reliability model selection

As was already mentioned, the Weibull family of functions is used in this article. The reliability function is calculated using Equation **Error! Reference source not found.**, and the results of the Kolmogorov-Smirnov goodness-of-fit test are shown in Table 7. For instance, the formula for the mechanical failure mode's reliability is:

Table 7. Fitted functions and goodness of fit (GOF) test results on system failure data.

Failure mode	Distribution	Risk factors model	Estimation of parameters and portion												Goodness of Fit	
			Sub-population 1			Sub-population 2			Sub-population 3			Sub-population 4				
			Portion	Beta	Eta (Hr)	Portion	Beta	Eta (Hr)	Portion	Beta	Eta (Hr)	Portion	Beta	Eta (Hr)	K-S Test: P(Critical<D)	P-value
Electrical-Electrical	Weibull-Mixed (2-fold)	Proportional hazards model (PHM)	0.37	2.24	42.92	0.63	0.76	79.51	-	-	-	-	-	-	0.03%	99.97%
Electrical-Starter	Weibull-Mixed (2-fold)	Proportional hazards model (PHM)	0.53	0.67	16.29	0.47	2.26	132.47	-	-	-	-	-	-	0.00%	100.00%
Fuel	Weibull-Mixed (4-fold)	Proportional hazards model (PHM)	0.20	1.63	8.38	0.31	7.99	22.50	0.19	6.77	44.63	0.31	2.13	113.79	0.00%	100.00%
Mechanical	Weibull-2P	Proportional hazards model (PHM)	1.00	1.31	31.32	-	-	-	-	-	-	-	-	-	0.00%	100.00%
Pneumatic	Weibull-Mixed (2-fold)	Proportional hazards model (PHM)	0.12	0.92	13.72	0.88	1.38	32.15	-	-	-	-	-	-	0.01%	99.99%

$$R_{Mechanical}(t) = 100\%.exp\left[-\left(\frac{t}{31.322}\right)^{1.313}\right] \quad (21)$$

The reliability of various failure modes is depicted in Figure 6. This graph that represents the system performance over 100 hours shows how the feeding of the graph wave caused a failure mode and how the function changed for various contributions to each fold of the Weibull mixture function.

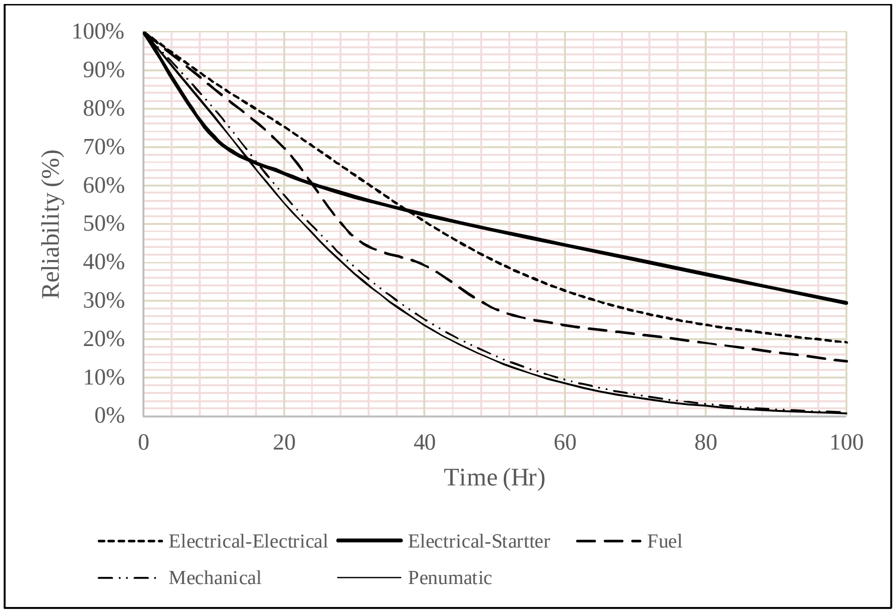

Figure 6. Reliability of various modes of system failure.

"Baseline functions" are the fitted functions from the previous phase with the average risk factor values. These functions will be modified in this stage based on the effects of risk variables (the effects of environmental conditions) (Equations **Error! Reference source not found.** and **Error! Reference source not found.**). According to theory, the following reliability and maintainability functions apply to mechanical failure modes:

$$R_{sMechanical}(t) = 100\%.exp\left[-\left(\frac{t}{31.322[exp(-2.779z_5)]^{-\frac{1}{1.313}}}\right)^{1.313}\right] \quad (22)$$

Two scenarios are investigated in Table 8 to determine the effects of risk factors. These scenarios include three reliability and maintainability risk factors each, along with the appropriate values (z_i) taken from the data bank. In order to assess the type of maintenance needed for minor and significant failures, information from the data bank is also employed, accounting for both cheap and expensive maintenance. Figure 7 shows the reliability graph for system failure over an 8-hour operation period for the baseline mode and the two scenarios. The figure clearly shows that the first scenario's reliability is much higher than the second scenario and the baseline mode, emphasizing the influence of environmental factors on reliability.

Table 8. Defined scenarios for reliability and maintainability.

Scenarios No.	Scenarios		Reliability			Maintainability		
			Capacity per hour	Rain per hour	Temperature per Hour	Maintenance condition	Rain	Temperature
1	First semiannual	Cheap maintenance	2.600	0.039	0.485	1.000	0.950	
2	Second semiannual	Expensive maintenance	2.587	0.028	-0.017	2.000	0.700	

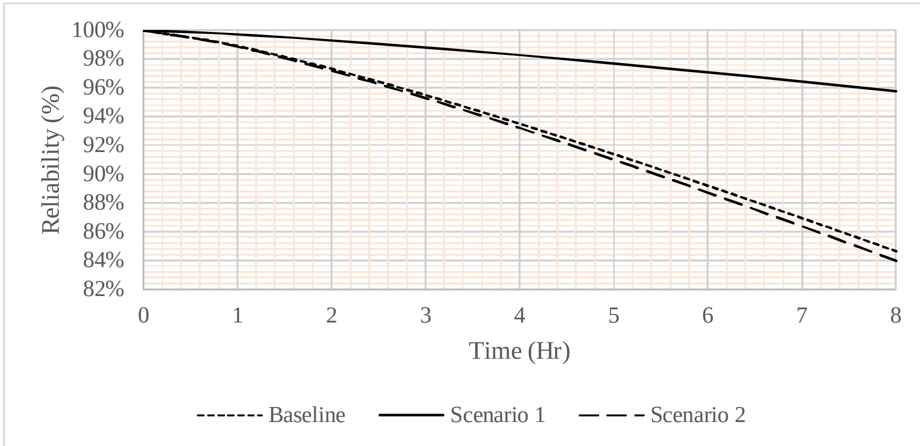

Figure 7. Reliability of system "Mechanical" failure mode.

3.3. Dump-truck FMEA

This step aims to identify potential subsystems that can be at high risk. In this part of the analysis, according to the flowchart in Figure 2, the effects and causes of various failure modes for the engine system are shown in Table 9. Also the calculation of RPN is shown in Table 10. To determine the Si, Oi, and Di values for the specified failure modes, which were categorized into four groups (Electrical, Pneumatic, Fuel, and Mechanical), a questionnaire was developed based on the Automotive Industry Action Group (AIAG) standard and distributed to experts. The average values of their responses were then considered in calculating the Si, Oi, and Di values [58]–[60].

Table 9. Effects and causes of occurrence of various failure modes.

Electrical		**Pneumatic**	
Cause	**Effects**	**Cause**	**Effects**
Electrical connections are not good.	Short circuit connection and fire	Compressor high-pressure hose failure	Performance drop of the brake system, excessive compressor operation
Start breakdown	Do not turn on the device	Unloader valve	Air pump and brake system failure
Battery failure	Starter failure and startup problems, especially during the cold season		
Bulb failure	Accidents and deadly events, especially in shifts two and three		
Cost ($)	2104	Cost ($)	1253
Fuel		**Mechanical**	
Cause	**Effect**	**Cause**	**Effect**
The failure of the extra fuel pump and the fuel injection pump chamber failure	Air leak in the fuel system- The device has not started	Crack in spiral turbojet crust	Loss of engine power-Unusual engine smoke
The fuel injection pump failure	Loss of engine power- The disruption of air and fuel combination-Device not started	Exhaust brake failure	Muffler Brake (engine brake) failure-Excessive air pump operation
Fuel pump sensor	Loss of engine power-Disruption in governor function	Belt tensioner Failure	break or loose of belt
Cylinder Injector Needle Failure	Engine shake-Loss of engine power	Lubrication line tubes and hoses failure	Oil leak - The engine oil pressure drop in case of excess leakage
coupling failure	An unusual sound from the engine - the disruption of the fuel pump's period	Seal & Oring failure	Mixing oil and water
Electronic Governor Failure	The problem of fuel intake in a motor-Failure of the operator at High engine rpm	Complete turbocharger failure	Sudden engine power drop-Smoke emission from the exhaust
Burnout of injection tubes	Pressure drop in fuel circuit-engine misfire	Radiator core failure	Water leak - Engine hot
Gasket failure	Inlet pressure drop of the combustion chamber		
Air leaks the fuel system	Hard engine start		
Cost ($)	4359	Cost ($)	467

Table 10. Calculation of RPN.

Function	Failure	Effect	Si	Cause	Oi	Control	Control type	Di	RPNi
Electrical-Electrical									
Provide electricity	Electrical failure	Short circuit connection, fire (5), start failure and startup problem, especially during the cold season (6), accident and deadly events, especially in shifts two and three (10)	10	Electrical connections problems, battery failure, bulb	5	Preventive maintenance	Prevention	5	250
Electrical-Start									
Start Engine	Start Failure	Do not turn on the device (9)	9	Start breakdown	5	Preventive maintenance	Prevention	5	225
Mechanical									
Supply mechanical power	Mechanical failures	Loss of engine power-unusual engine smoke (4), muffler brake (engine brake) failure-excessive air pump operation (6), break or loss of the belt (4), oil leak - The engine oil pressure drops in case of excess leakage (5), mixing oil and water (6), sudden engine power drop-smoke emission from exhaust (6), water leak-engine hot (5)	6	Crack in spiral turbojet crust, exhaust brake failure, belt tensioner failure, lubrication line tubes, and hoses failure, seal & oring failure, complete turbocharger failure, Radiator core failure	5	Preventive maintenance	Prevention	5	150
Pneumatic									
Supply of compressed air	Pneumatic Failures	Performance drops of the brake system, excessive compressor operation (8), Air pump and brake system failure (5)	8	Compressor high-pressure hose failure, unloader valve	5	Preventive maintenance	Prevention	5	200
Fuel									
Supply of fuel	Fuel supply system failures	Air leak in the fuel system-device not started (5), loss of engine power- disruption of air and fuel combination-device not started (7), disruption in governor function (5), an unusual sound from the engine-the disruption of the fuel pump's period (5), problem in fuel intake in an engine-failure of the operator in high engine rpm (4), pressure drop in fuel circuit-engine misfire (8), the inlet pressure drop of the combustion chamber (7), hard engine start (4), engine shake-loss of engine power (7)	8	The failure of the extra fuel pump and the fuel injection pump chamber failure, the fuel injection pump failure, the fuel pump sensor, cylinder injector needle failure, coupling failure, electronic governor Failure, burnout of injection tubes, gasket failure, air leaks of the fuel system	5	Preventive maintenance	Prevention	5	200

3.3.1. Dump-truck FMECA

In this part of the analysis, quantitative and qualitative approaches to the engine system are evaluated.

3.3.1.1. Quantitative analysis of system crisis value

In Table 11, the criticality calculations for 5 hours of system operation are performed using Equations **Error! Reference source not found.** and **Error! Reference source not found.**. The system, after 5 hours of operation, is in critical condition. Table 11 lists the priority for the system and failure modes (the last column). Electrical-start and total electrical failure modes are in high and medium priority modes, respectively. It should be mentioned that all calculations at this stage of the work consider the probability of the impact of failure (β) with the actual loss (1).

Table 11. System criticality value for 5 hours.

Items & modes	Operating time (Hr)	Probability of failure	Criticality	Priority
1. Dumptruck motor system	5 Hr	0.430027	1	1
1.1- Electrical	5 Hr	0.253349	0.49553	1.1.2
1.1.1- Electrical-Electrical	5 Hr	0.075047	0.280218	1.1
1.1.2- Electrical-Starter	5 Hr	0.192769	0.719782	1.1.1
1.2- Pneumatic	5 Hr	0.102331	0.200151	1.2
1.3- Fuel	5 Hr	0.069553	0.13604	1.4
1.4- Mechanical	5 Hr	0.086036	0.168279	1.3

The above analysis has a serious issue because it is a static analysis. But as a system operates and the environment changes, its performance indicators vary over time, affecting the essential values. The critical values of various failure modes during 50 hours of system operation are shown in Table 10 and Figure 7 in three scenarios (basic, scenario 1, and 2). In the basic scenario, the electric-start system failure is initially identified as the most significant for the first 15 hours of operation, as illustrated in Table 12, which classifies it as a low-priority mode. However, after 15 hours, its importance diminishes, and a fuel-related failure becomes the most pressing issue.

On the other hand, the pneumatic failure crisis. However, after 15 hours, its significance diminishes, and a fuel-related failure becomes the most pressing issue. Contrarily, the pneumatic failure situation worsens, and after around 30 hours, both fuel and pneumatic failures rank as the most serious system failures. The findings emphasize the major differences between static and dynamic studies and how the crisis value evolves. Figure 8 illustrates how environmental factors affect the severity of the crisis in scenarios 1 and 2. In scenario 1, the mechanical and pneumatic failure modes are rated second and third in the crisis, whereas the fuel failure mode is prioritized throughout the operation. The fuel failure mode is given a lower priority in scenario two and the baseline. The criticality value of the fuel failure mode in the three states is better illustrated in Figure 9.

Table 12. Value of the critical states of failure in different scenarios.

	Failure mode	Operating time									
		5	**10.00**	**15.00**	**20.00**	**25.00**	**30.00**	**35.00**	**40.00**	**45.00**	**50.00**
Baseline	**Electrical-Electrical**	0.14	0.14	0.13	0.12	0.12	0.12	0.13	0.13	0.13	0.13
	Electrical-Start	0.36	0.36	0.22	0.19	0.15	0.14	0.13	0.13	0.12	0.12
	Fuel	0.20	0.20	0.26	0.26	0.25	0.26	0.27	0.27	0.27	0.27
	Mechanical	0.14	0.14	0.15	0.18	0.23	0.22	0.21	0.21	0.22	0.22
	Pneumatic	0.17	0.17	0.24	0.25	0.24	0.25	0.26	0.26	0.26	0.26
Scenario 1	**Electrical-Electrical**	4.54E-04	4.94E-04	5.42E-04	4.53E-04	4.45E-04	4.98E-04	5.38E-04	5.70E-04	6.12E-04	6.70E-04
	Electrical-Start	4.05E-03	3.89E-03	3.83E-03	2.88E-03	2.56E-03	2.59E-03	2.54E-03	2.46E-03	2.42E-03	2.44E-03
	Fuel	0.79	0.70	0.63	0.68	0.68	0.64	0.62	0.61	0.60	0.58
	Mechanical	0.09	0.14	0.17	0.15	0.15	0.17	0.18	0.18	0.19	0.20
	Pneumatic	0.12	0.16	0.19	0.17	0.17	0.18	0.19	0.20	0.20	0.21
Scenario 2	**Electrical-Electrical**	2.59E-04	2.17E-04	2.15E-04	2.19E-04	2.22E-04	2.48E-04	2.83E-04	3.20E-04	3.61E-04	4.07E-04
	Electrical-Start	1.26E-05	9.32E-06	8.28E-06	7.61E-06	6.96E-06	7.04E-06	7.30E-06	7.55E-06	7.80E-06	8.08E-06
	Fuel	0.18	0.19	0.18	0.20	0.26	0.26	0.25	0.25	0.26	0.27
	Mechanical	0.38	0.39	0.40	0.39	0.37	0.37	0.37	0.37	0.37	0.36
	Pneumatic	0.44	0.42	0.42	0.41	0.37	0.37	0.38	0.37	0.37	0.36

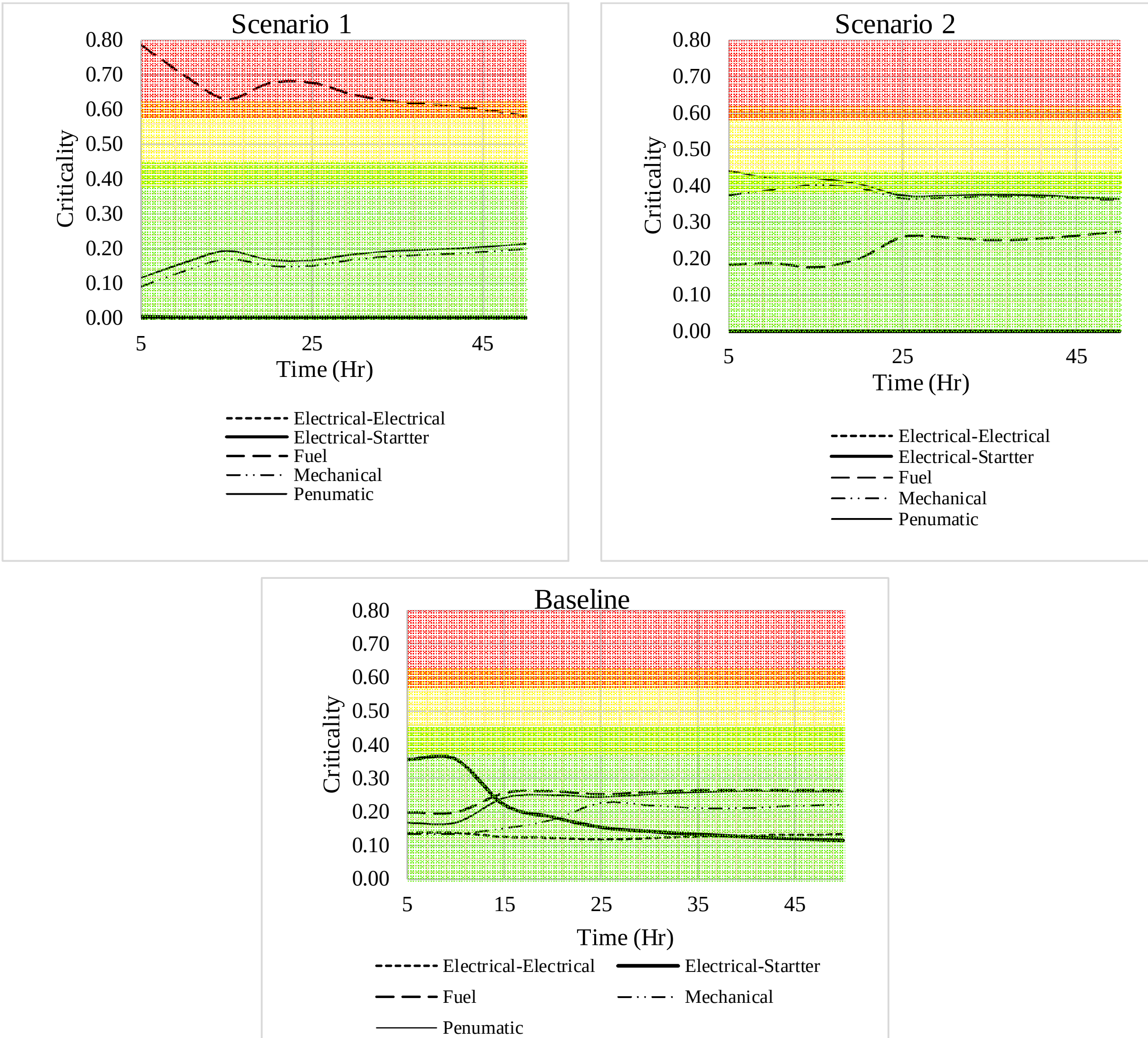

Figure 8. Critical value of failure mode for different scenarios.

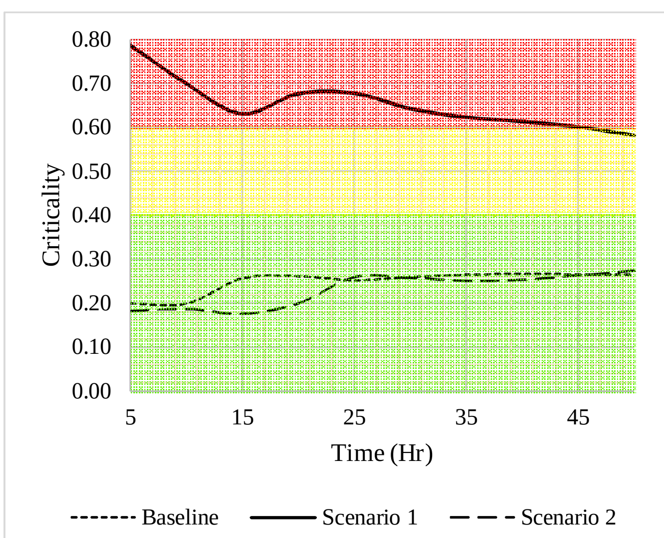

Figure 9. Fuel criticality value in three scenarios.

3.3.1.2. System qualitative analysis of critical

The qualitative matrix for the failure priority analysis over the system's five hours of operation is shown in Figure 10. Critical numbers are represented on the matrix's vertical axis, with greater values increasing from bottom to top. The matrix is colored green, yellow, and red and is separated into three priority zones. The matrix's upper left corner is marked to show a rising crisis level. This matrix categorizes the electrical-start failure scenario as high-priority (red) and demands extra focus. While pneumatic and mechanical failure modes are categorized as low priority (green), the electrical-electronic failure mode is categorized as a medium priority (yellow). The restrictions outlined for the quantitative mode still apply because this technique is static.

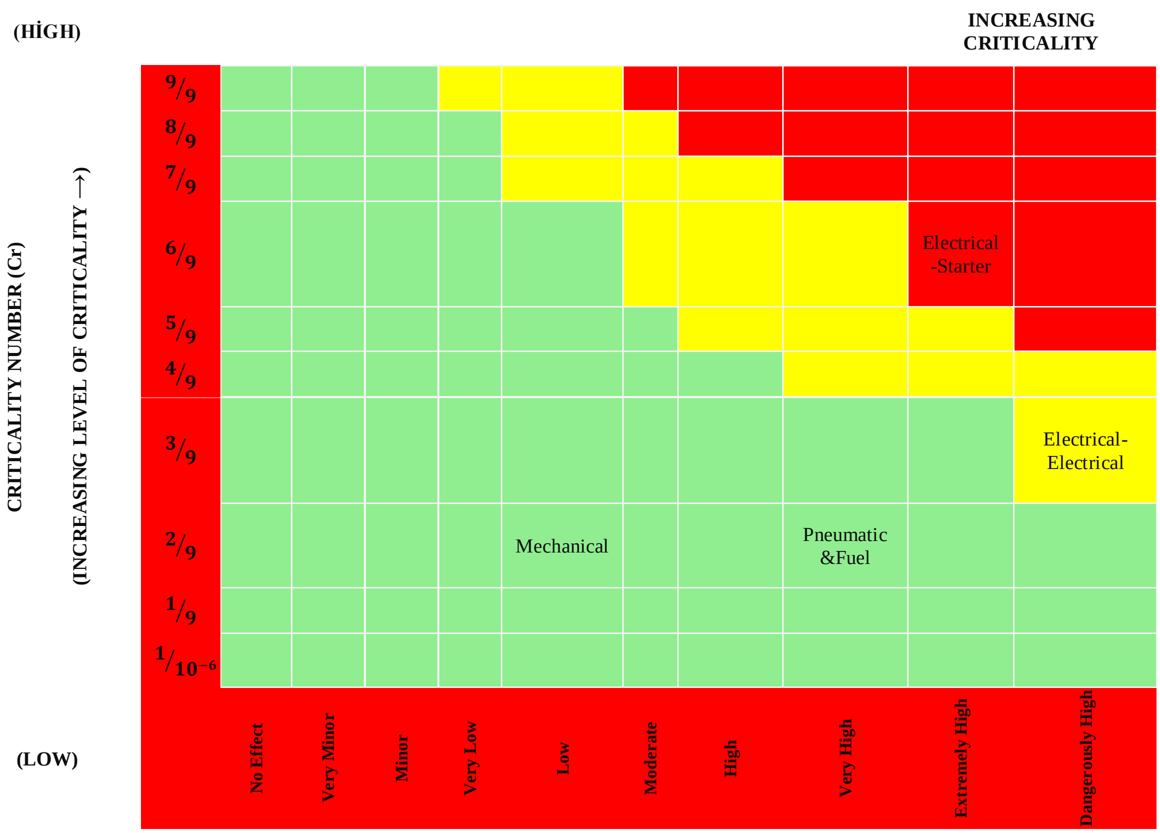

Figure 10. Qualitative criticality matrix for different failure modes (intensity-criticality).

3.3.2. Select appropriate strategy for engine system with RCM logic

Different maintenance strategies are suggested for the system based on the outcomes of the three scenarios (basic, 1, and 2) in steps 6 and 5 of Figure 1. All failure modes are present during the operation time in the fundamental scenario, as depicted in Figure 8a. As a result, corrective maintenance will only be carried out after a failure, following the algorithm of Figure 1's step 6. Due to its high criticality number and failure intensity, the pneumatic failure mode in Scenario 2 is the only one that moves into the middle zone, and only corrective maintenance is suggested. All other modes remain in the green zone. Therefore, condition-based maintenance utilizing barometers and the proper sensors is advised for the pneumatic mode since the system operates with pressure, making monitoring the system's status possible.

Corrective maintenance is advised for the low-risk electrical-electrical, electrical-start, mechanical, and pneumatic failure modes in Scenario 1. However, preventive maintenance based on time is advised for the fuel failure mode due to its high criticality number and failure intensity. Equation **Error! Reference source not**

found. was used to examine the impacts of preventive maintenance, and the findings are shown in Table 13 and Figure 11. The maintenance window is 10 hours, and the reliability value is 80 percent. Implementing the first preventative maintenance will show the effects of enhanced reliability.

Table 13. Effect of preventive maintenance implementation on reliability.

PM number	0	1	2	3	4	5
T_{PM}	0	10	20	30	40	50
R	100.00%	80.60%	60.09%	42.95%	30.15%	20.63%
R_{PM}	100.00%	80.60%	79.25%	78.72%	78.23%	77.74%

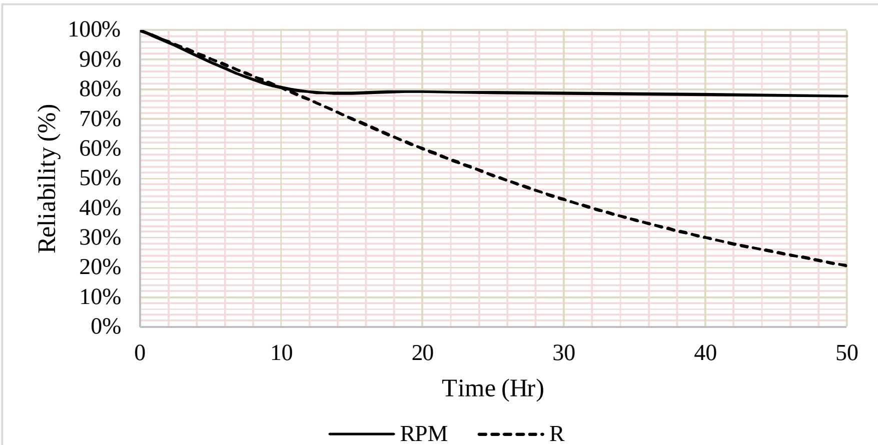

Figure 11. Reliability changes as a result of preventive maintenance performance.

The system's reliability will be maintained at roughly 80% if the maintenance is carried out on schedule with intervals of 10 hours, which was the major objective of the maintenance to reach the same figure.

4. Conclusions

The industry uses various methods to examine maintenance techniques, making it challenging for researchers and managers to choose the best method. Integrating risk with operational indicators such as reliability to provide the appropriate maintenance strategy is one of the biggest issues. Reliability-centered maintenance (RCM), which entails six steps, is one of these solutions. Data collection and establishing the system's boundaries are the first steps in RCM. According to fault tree analysis, the engine system was selected as the purpose system in the second step (FTA). The electrical failure mode comprises two components: electric-electric and electric-starter and the engine system also contains pneumatics, fuel, and electricity. The third stage's findings indicate no discernible interdependence between the variables. The reliability curve shows how risk factors affect the system's effectiveness. Effective risk factors include discrete risk factors (maintenance condition) and continuous risk factors (slope, capacity per hour, precipitation, and temperature). Two alternative scenarios and a baseline were employed to study the system's performance and assess the impact of risk factors on performance. FMEA risk analysis was utilized in the fourth phase to rank failures according to RPN. Electric-electric (250), electric-starter (225), pneumatic (200), fuel (200), and mechanical are the order of priority with RPN (150). The FMECA was utilized in the fifth phase to statistically and qualitatively evaluate risk. After five hours of operation, the system is in critical condition, according to the quantitative system risk analysis. The electrical start and total electrical failure modes are also at high and medium priority levels. According to the rating for the critical number, the electric-start system is the most critical system failure in the basic scenario for up to around 15 hours of operation. The failure linked to refueling is highly prioritized after 15 hours of operation. After roughly 30 hours, both failures become the most serious as the pneumatic failure situation worsens. The impact of environmental conditions (risk variables) on the crisis level may be seen in the analysis of scenarios 1 and 2. In Scenario 1, fuel failure precedes pneumatic and mechanical failure during operation. In Scenario 2, the pneumatic failure is at the highest critical level, while the fuel failure mode is given lower priority. Based on the outcomes of the earlier stages of RCM, various maintenance methods were put forth in the final step. In the fundamental case, all subsystems are low-risk throughout the operation, and rectification maintenance is advised after a failure. Due to the critical number and extremely high failure intensity in Scenario 2, only the pneumatic failure mode is found in the middle zone. Condition-based maintenance utilizing barometers and the relevant sensors is advised. The mechanical, pneumatic, electrical-start, and electrical-electrical failure modes in Scenario 1 are suited for proper maintenance because they provide little danger. It is advised to do maintenance as a time-based preventive for the fuel failure mode, which has a high criticality number and high failure intensity. The outcome shows that preventive maintenance increases system reliability.

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نگهداری و تعمیرات متمرکز بر قابلیت با درنظرگیری تاثیرات شرایط محیطی

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چکیده:

اجرای پروتکل‌های نگهداری و تعمیرات (نت) برای ماشین‌آلات صنعتی ضروری است، زیرا یک برنامه سنجیده شده‌ای است که می‌تواند قابلیت اطمینان ماشین آلات، کیفیت تولید، اقدامات ایمنی و پشتیبانی را بهبود بخشد. اجرای یک برنامه نت دربرگیرنده رفتار عملکردی واقعی تجهیزات و اثرات خرابی، آسان‌تر و کاربردی تر خواهد بود. لذا مهندسان هنگام مطالعه در محیط‌های خشن مانند معدن باید شرایط محیطی را در نظر بگیرند. در این راستا هدف اصلی این مقاله ایجاد یک برنامه نت برای تجهیزات معدنی است که تا حد امکان موثر بوده و در عین حال شاخص‌های عملکرد، ریسک و عوامل محیطی را در نظر بگیرد. در این مطالعه از روش «تعمیر و نگهداری مبتنی بر قابلیت اطمینان (RCM)» استفاده شده که ترکیبی از شاخص عملیاتی قابلیت اطمینان و ریسک می‌باشد. در این مدل همچنین از رویکرد کاکس شامل فاکتورهای ریسک که دربرگیرنده شرایط محیطی است برای تحلیل قابلیت اطمینان استفاده شد. رویکرد پیشنهادی برای مطالعه موردی دامپتراک کوماتسو 5-758 از معدن مس سونگون در ایران بکار رفت. این رویکرد برای دامپتراک در سه سناریو بر اساس فاکتورهای ریسک اجرا شده است: 1- حالت اساسی، 2- نیمه اول سال ، نت ارزان، و 3- نیمه دوم سال، نت گران. در این مدل برای حالت های خرابی با ریسک پائین از نت اصلاحی استفاده شد. در سناریوی 1، خرابی‌های الکتریکی-الکتریکی، استارت الکتریکی، مکانیکی و پنوماتیکی ریسک پائین نیز از نت اصلاحی مناسب می‌باشد. در سناریوی 2، نت اصلاحی برای خرابی مربوط به پنوماتیک توصیه می‌شود. در سناریوی 3، خرابی مربوط به سوخت دارای عدد بحرانی و شدت خرابی بالایی است که نشان دهنده وضعیت پرخطر بوده و نت پیشگیرانه مبتنی بر زمان مناسب‌ترین استراتژی برای این سناریو می‌باشد.

کلمات کلیدی: ریسک، قابلیت اطمینان، مدل رگرسیون کاکس، نگهداری و تعمیرات متمرکز بر قابلیت اطمینان، معدن مس سونگون.