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Tools and methods for ship system reliability modeling and maintenance decision making

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Abstract. The maritime industry is in a continuous state of digital transformation, and with strong cooperation from all stakeholders—ship designers, classification societies, equipment manufacturers, and shipping companies—fully autonomous ships will become a reality within a limited time. Safety and reliability will be one of the primary challenges, ensuring that equipment and ship systems are in a proper working condition during voyages and that all inspections and repairs will be performed only on shore. For that, ship maintenance, like other industries, needs to change its perspective and move toward a "anticipate and prevent" philosophy using tools and methods to forecast technical failures at an early level for effective logistics planning.
This paper presents a new perspective on how reliability analysis like F.T.A, and F.M.E.C.A, and fuzzy set theory can be used together with machine learning and simulation environments to assist maintenance decisions of onboard systems.
The proposed approach creates a new model of automatic equipment evaluation with the aim of early signaling of equipment malfunction, elimination of human errors in operation, early notification for future repair, and improve safety.
Keywords: ship maintenance, FTA, FMECA, machine learning, simulation

1. Introduction

Naval equipment has increased in complexity, as science and technology have allowed the implementation of new features to increase operational safety and increase the level of reliability. However, their failure during the maintenance process, with human error as the main cause, is increasingly common [1].

Ships have an estimated lifecycle of 25-30 years but begin to decrease significantly in performance after 7-8 years after entering service [2]. The consequences of these performance losses contribute to the increase in downtime, unplanned and often significant costs for maintenance and repairs and the failure to fulfill the missions they must perform.

Managing operating data and maintenance data is vital for any equipment to meet performance characteristics over its designed lifecycle [3]. Technological advancement has required the development of automation systems, and by increasing the number of sensors, the data is available in digital format. Thus, expert systems were designed for equipment considered critical for the ship's operability, such as the propulsion system, the electrical energy system and the steering system, which proved their usefulness by increasing the level of reliability and safety of operation of the technique.

Based on the ideas stated above, the research paper proposes several directions for using the operating data to optimize the maintenance process for equipment and auxiliary systems on board the ships. The paper presents the theoretical aspects of the methods and techniques identified through the analysis of the literature: risk analysis methods, simulation tools and artificial intelligence techniques. In the results and conclusions section, the possibilities of capitalization for the optimization of the maintenance process of the equipment on board the ships are presented.

2. Tools and methods for performance data analysis in maintenance

System reliability calculations are important in their design. In addition, the results of the reliability analysis are used to prevent failures by implementing appropriate maintenance policies. Through the analysis of the literature, several methods and tools have been identified that can streamline current maintenance programs. The main objective of risk analysis is to quantify possible events that may endanger a system and its functions. The results of the analysis require the development and implementation of safety measures in order to prevent the occurrence of these causes and reduce the consequences if they do materialize.

Safety and reliability are rigorously evaluated during the design of technical systems. Some of the probabilistic risk assessment include failure tree analysis (FTA), failure mode and effects analysis (FMEA) and event tree analysis (ETA). For probabilistic risk analysis, data on equipment and component failures are required for the purpose of quantitative analysis [4]. Next, the first two methods of analysis, FTA and FMECA, are analyzed.

2.1. Fault tree analysis

Bell Telephone Laboratories originally created the FTA method in 1962 while designing protective measures for the U.S. Air Force's Minuteman intercontinental ballistic missile (ICBM) system. Later, the aircraft manufacturer, Boeing, took the method to the next level, both qualitatively and quantitatively, making it a popular method of analysis, widely used today to analyze the potential for failure of critical systems [5].

The FTA has proven to be an effective tool for analyzing and identifying areas for hazard mitigation and prevention during design, production, operation, or whenever a systematic risk assessment approach is required [6], providing a logical description of the empirical relationships between the peak event or final failure state and its potential causes [7], also serving as a graphical model representing those critical failure events for the system.

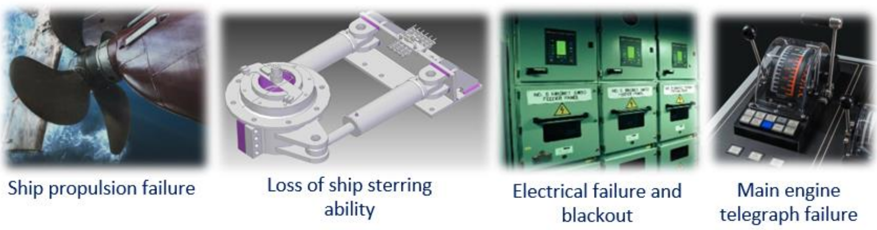

Figure 1. Top events example for ship systems (adapted from [6])

FTA is considered an effective way to describe cause-and-effect relationships using a logic diagram. This is considered the starting point for the qualitative analysis of failure modes and, if the values of failure are known also quantitative analysis could be done. There are five steps to constructing an FTA: (1) defining the problem and identifying the limits (2) constructing the failure shaft, (3) determining the minimum sequences, (4) performing analyses (qualitative and quantitative), and (5) formulating safety measures [7]. Figure 2 identifies the main stages.

Several possibilities for applying the FTA method in different industries, including the maritime one, are discussed in the research [8]. In addition, it revises the application procedure and incorporates fuzzy logic to take into account the interdependence of events.

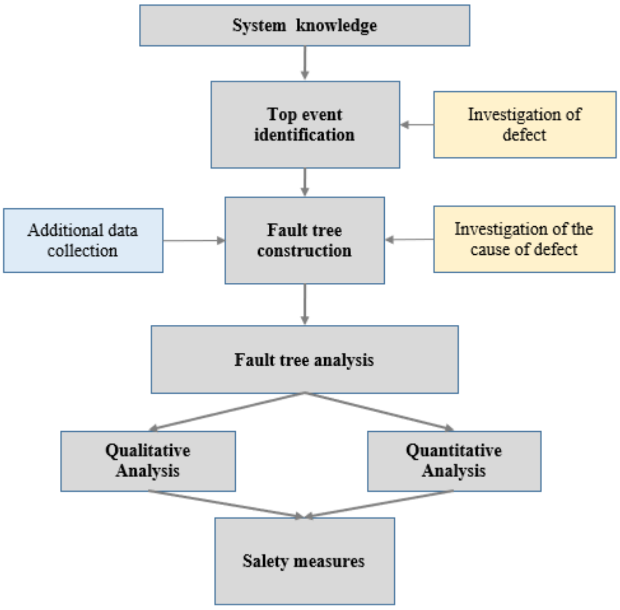

Figure 2. FTA construction process (adapted from [7])

The study [9] provides an overview of the possible failures for propulsion system. By analyzing the impact of disruptive events on the critical components/installations of a ship (the main engine), a method for evaluating the operating time without human intervention and assistance is conducted [10]. The propulsion system found on four identical ships is being analyzed for malfunctions. Important components for the reliability calculation of the system are highlighted, and through the RAM (Reliability Availability, and Maintainability) and FTA analysis, the possibilities for improving the system and the efficiency of the ship are highlighted [11]. However, the FTA method requires the involvement of highly qualified experts and only analyzes the causes of a potential failure, without considering its development [12].

For complex systems, simply observing the tree graph does not identify all possible combinations of events that can lead to failure. However, by supplementing with quantitative analysis, this limitation is eliminated.

When quantitative analysis is performed, the so-called contributors that can lead to the failure of the evaluated system must be classified. This ranking is useful in planning maintenance tasks, allocating resources, and locating weaknesses in a technical system. The ranking techniques are: Birnbaum Importance Measure (BIM), Critical Factor Importance (CIF), Fussell-Vesely Method (FV), Risk Realization Value (RAW), Risk Reduction Value (RRW), and Differential Importance Measure (DIM). These methods are presented in research [13] along with a comparative analysis of the results obtained for a failure tree.

2.2. Failure mode and effect analysis

Failure Mode and Effect Analysis (FMEA) is a systematic method of assessing the impact of various risks, originally used in the aerospace industry in the mid-1960s, specifically for safety issues. While engineers have always analyzed processes and products for potential failures, the FMEA method standardizes the approach and establishes a common language that can be used both within companies and between companies [14]. With the addition of a new analysis, that of Criticality Analysis (CA), the method became known by the acronym FMECA. For an accurate and effective FMEA analysis, it is necessary to have as detailed information as possible about the system regarding: [15], [16]

- the diagrams, the composition table and the list of materials;
- block diagram of the system;
- redundant elements;
- the tasks to be carried out and the links with the other systems;
- performance characteristics, peculiarities of operation and limitations of systems

Even though the two methods have been applied and developed mainly in industrial production (components, subassemblies, machines, etc.), their use in the naval field has also contributed to increasing the level of safety and reliability of technical systems.

To reactively address performance issues, identifying and eliminating the root causes of non-conformities is a common practice. But technical improvements require a proactive approach, and the methodology for implementing the FMEA, shown in Figure 3, can respond to current challenges.

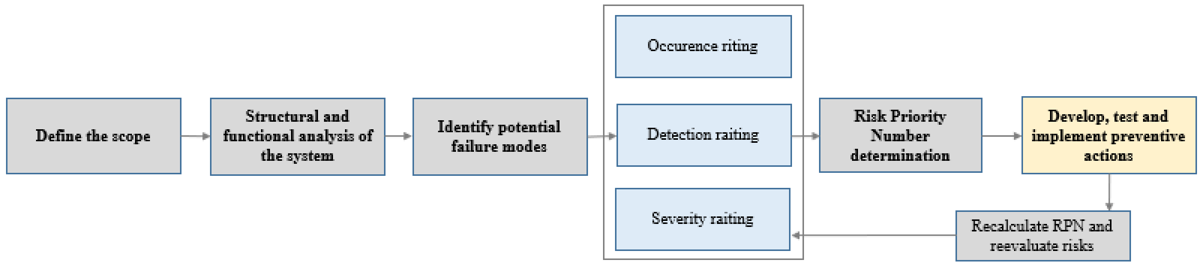

Figure 3. FMECA analysis (adapted from [15] and [17])

FMEA begins with the analysis of the system, the working environment and the operating requirements, as well as changes in the configuration or position of the system and its components during operating regimes. Subsequently, using the data and knowledge about the process or system analyzed, each potential failure mode is evaluated according to the three indicators: occurrence (probability or frequency of failure occurring), severity (consequence of failure) and detection (failure to be observed before producing significant losses). The classification of failure modes is made according to the value of the risk score, RPN, obtained by multiplying the individual scores for the three risk indicators. The general principle of calculating the NPR, namely the prioritization of failure modes, was critical to a large extent because a weight of their importance is not taken into account [18]. After a detailed analysis of the research on improving the FMEA analysis, the following risk assessment tools/techniques/methods were identified: fuzzy logic, Multi Criteria Decision Analysis (MCDA), Analytic Hierarchy Process (AHP), Artificial Intelligence (AI) [19]. For the shipbuilding industry, the method was mainly applied to assess the reliability of installations and maintenance policies.

Recent research papers propose the combined use of the two methods, FTA and FMECA. In the paper [20] the possible failure modes of the water installation on board the ship is studied. Research [21] proposes the use of the integration of the classic FTA and FMEA methods for the risk assessment of technical systems. Authors of research [22] uses the Reliability Block Diagram of the FTA and FMECA methods to modify the design of the ship lubrication plant in order to increase reliability and availability indicators. A recent article proposes the use of DFTA (Dynamic Fault Tree), FMECA and BBN (Bayesian Belief Network) to define component criticality and prioritize maintenance actions in relation to the severity of failures and ship missions [23].

2.3. Fuzzy set theory and application in the field of reliability

In classic forms of risk analysis, failure rates, failure probabilities or other numerical data related to the failure behavior of system components are usually considered known. But in large and complex systems, not all of this data is known due to limited observation and a shortage of statistical data.

The probability of failure of a relatively new component with insufficient historical failure data could theoretically be estimated on the basis of experience or from the data of similar components. Consequently, the safety and reliability of the system could be assessed on the basis of generic statistical data, which can be taken from existing reliability databases. Fuzzy logic offers a flexible method of dealing with imprecision because it operates with vague concepts and helps shape them to solve problems that arise.

Fuzzy logic is a suitable tool that can easily and accurately determine critical elements of the system. It considers each level of risk factors and evaluates them simultaneously to deduce their common contribution to the undesirable event. They can help determine and implement corrective measures to reduce risks [24].

2.4. Modeling and simulation

Modeling and simulation start with model elaboration as close as possible with the real-world corresponding system and used it for development, training, research, improvements or other alternative management strategies and decision-making processes [25].

Through modeling and simulation in the naval field, optimized tools have been created for the virtual representation of equipment, ships, the environment and navigation areas. These programs provide the versatile and realistic functionalities, through detailed situations/scenarios of the ships' architecture, onboard systems, operating procedures and port facilities.

In the naval field, simulation has been used to create tools for the virtual representation of equipment, ships, the environment and navigation areas. These programs offer the versatile and realistic functionalities, through detailed situations/scenarios of the ships' architecture, their onboard systems, operating procedures and port facilities [26].

The simulation training process has a number of benefits, among which we identify: reduced costs, elimination of hazards or damages and repeatability of simulated situations [27]. A study conducted in 2021 on the assessment of the response capacity of shipboard personnel in crisis situations identified that simulation training favors the perception of existing risks on board ships, the development of critical thinking, decision-making under pressure, learning from mistakes and encourages teamwork [26].

Computer-aided simulation uses algorithms, mathematical and logical models that describe the behavior of the real system (or some elements of it) over a period of time and provides a dynamic environment for the analysis of computer models with multiple visualization possibilities (2D, 3D, VR), as can be seen in figure 4.

Figure 4. Maine engine operating console in ERS simulator

An engine compartment simulator is built on mathematical models of the processes that ensure the operation of naval installations and equipment and allows the learner to follow the dynamics of his actions in real time. It offers possibilities to know the structure of each system, machine or device in the compartment, analysis of the operation and diagnostics, in other words a simulated model with characteristics and functionalities as close as possible to the real system [28].

Simulation training is regulated by the IMO and is part of the training process for maritime education graduates. However, the teaching and learning characteristics, value, and impact of this approach are insufficiently researched. One limitation of naval simulation is its focus on common human errors and associated responses, not on the broader application possibilities they could facilitate [29]. In any case, research on the use of naval simulators as teaching-learning tools is expanding and looking at staff motivation, standardization of academic modules, and approaches to crisis management and complex tasks [30], [31].

Naval simulators have been used in research since the appearance of the first models, in fact the research was the second capitalization of the possibilities they have, after the training of the aircrew for the acquisition of skills in operation and management of emergency situations.

In the paper [32] the failures of the fuel supply system of a diesel propulsion engine in two types MAN B&W 5L90MC were studied. The change in time of the values of the operating parameters and the observation of a symptom-failure link by means of a correlation matrix derived from fuzzy logic are analyzed.

The possibility of using simulators in staff training to prevent dangerous situations is also discussed. A study was carried out whereby a potential hazard, such as the explosion of the engine crankcase, occurs as a result of the defect produced in its bearings [33].

Using the naval simulator, the thermodynamic analysis of the combustion process in the propulsion engine and their effect on the performance data was performed. Thus, through the simulated model, the possible malfunctions of the diesel engine are safely identified, without altering the operation of the real installation, as well as the detection of the symptoms of a malfunction in the early phase of manifestation. In addition, a fault database is obtained that can be used in reliability research and for diagnosing the technical condition of the system [34].

A recent paper presents the possibilities of improving maintenance plans, the reliability of the propulsion system and optimizing the operation of the turbocharger during the operation of the main engine by studying the failures of the turbocharging system and analyzing the combustion process [35]

Through high computer processing power and improved features such as product design and user interface, software is much easier to use, reducing the expertise required for effective use [36].

2.5. Machine learning technics

Learning systems that replicate components or the operational state of an industrial process based on available data assigned to a specific state (a class), are increasing in maintenance engineering [37].

While traditional maintenance strategies (corrective and preventive) become ineffective in meeting the level of safety and efficiency required by the industry, equipment prognostics and health management (PHM) known as Condition Based Maintenance (CBM) can overcome these shortcomings [38].

Generally, there are two types of machine learning approaches, supervised, used to train a model by labeled data and unsupervised deals with unlabeled data, which means that the algorithm will identify the unique characteristics of the data and divide them accordingly [39], [40]. Unsupervised learning is useful for data exploration to understand the natural pattern of data, particularly when there is no specific information about significant incidents in the data that can easily indicate error indicators [41].

Different algorithms such as decision trees, discriminant analysis, vector support, kNN classifiers, Bayes naïve classifiers. These algorithms analyze data distributions, find separation hyperplanes, or consider proximity to neighboring points to accurately classify failures [42]. The kNN algorithm has a simple construction and is used for the analysis of new situations by referring to similar situations analyzed before. One method to determine the final accuracy of predictions is the confusion matrix, which compares the actual values with those predicted by the machine learning model.

By integrating ML into naval reliability modeling and maintenance decision-making, ships can increase operational effectiveness, reduce costs, and ensure that critical systems function optimally throughout their lifecycles. ML techniques play a significant role in naval reliability modeling and maintenance decision-making by leveraging data-driven approaches to optimize operations, reduce costs, and enhance the safety and performance of naval systems.

ML models, such as predictive analytics and anomaly detection, enable early identification of equipment malfunctions and potential failures, allowing for proactive maintenance rather than reactive repairs. Additionally, ML aids in CBM, where real-time sensor data is analysed to assess the health of naval systems, reducing unnecessary maintenance activities and extending asset lifespans.

One of the key benefits is improved predictive accuracy. ML models learn from historical data to forecast outcomes such as equipment failures, future demand, or operational risks, enabling proactive measures like predictive maintenance. This helps reduce unexpected downtimes and unnecessary maintenance, improving overall system reliability.

In conclusion, ML helps organizations reduce costs, improve accuracy and increase operational efficiency, making it a powerful tool for solving complex problems across various industries, including naval reliability modeling and maintenance.

3. Integrating proposed tools and methods in maintenance of naval equipment

Considering the theme of the research, in this stage the concept of integrating risk and reliability analysis methods and tools for the optimization of the maintenance program is presented.

Based on the two risk analysis methods, FTA and FMECA, the causal chain of failures, the level of reliability and the possible failure modes for a given equipment on board the ship are assessed. A common problem for reliability analyses is the volume and validity of performance data and the history of technical maintenance work, given the operational characteristics of the vessel. In addition, the complete obtaining of exploitation data can be difficult, due to infrastructure, data security and the level of development of monitoring programs.

Even if in the naval field the legislation requires the existence of remote surveillance and operation systems, there is no possibility of monitoring all the components and all the operating parameters.

Two possibilities have been chosen to reduce the effects of this limitation. For the analysis of reliability data and maintenance history, fuzzy logic is used and for the validity of the performance data, the naval simulator will be used, by creating a simulated model of the system under analysis.

Figure 5 shows the proposal to use the data to create a fault diagnosis model and prioritise the maintenance of the four-stage technique:

- failure shaft analysis and calculation of system reliability based on component reliability data;
- identification of the causes of failures by the FMEA method; collecting data on frequency, detectability and severity, based on expert knowledge and simulating failures on the plant model; calculation of the RPN number by the fuzzy method (FRPN); implementation of Risk-Based Maintenance policies;
- study of the effects of failures on the simulated model; analysis of exploitation data and evaluation based on simulation tools; implementation of Maintenance Policies Based on Operating Conditions;
- storing all relevant information in a common database, for the creation of the machine learning model, integrated data analysis and establishing maintenance execution rules for the analyzed systems.

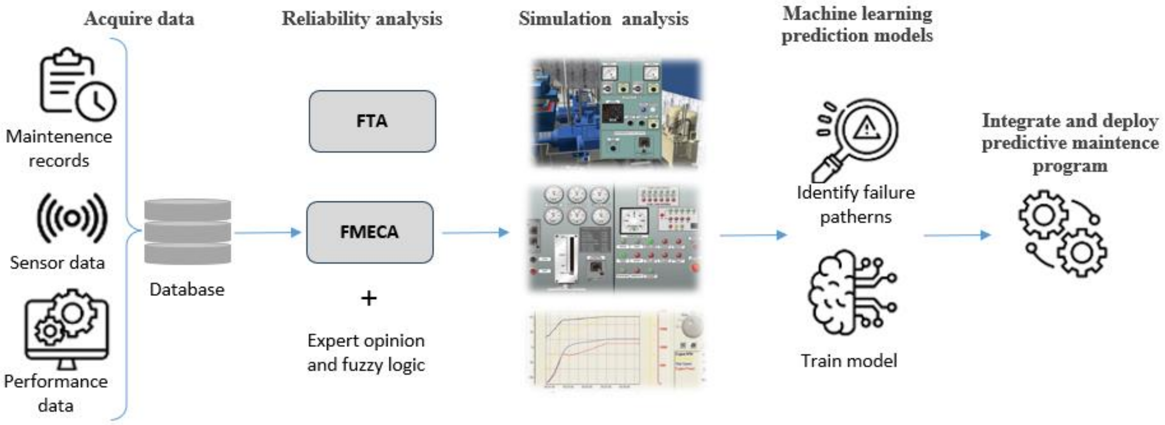

Figure 5. Integrated analysis of performance data, simulation and machine learning to optimize maintenance program

Through machine learning techniques, failure modes, and the level of operating data can be classified for further evaluation and predictions on the functional status of the equipment.

Figure 6 shows the model adapted from the work of [43] and [44], for creating a software program in which machine learning techniques are used. System analysis is necessary to identify critical points and corresponding variables representing the states in which the system may be at any given time. Through integrated analysis, the model can be used for almost any type of facility, not only to improve and/or automate operation, but also to understand the associated relationships and variables. In addition, the results of the FTA and FMEA analyses will be used as inputs for the creation of the machine learning model.

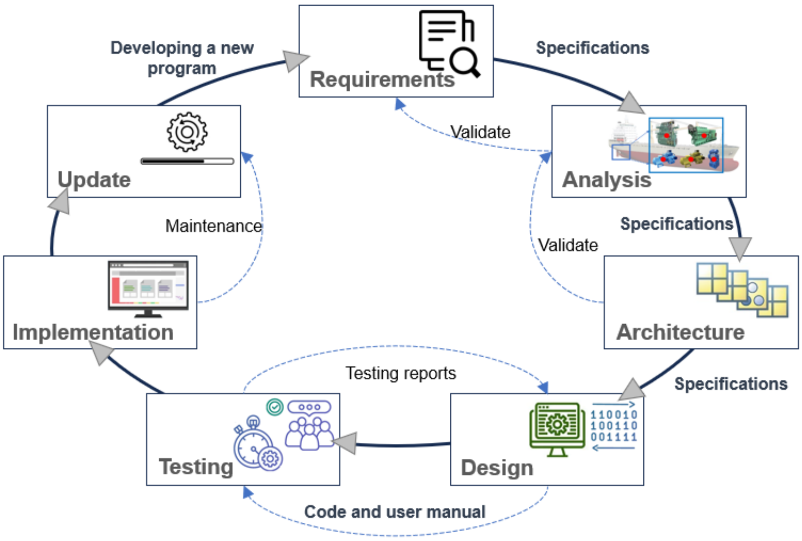

Figure 6 Stages for developing a machine learning model (adapted from [43], [44])

The model continues with the stage of collecting data from the equipment sensors, which convert values from current operation into digital signals transmitted to the control and monitoring system for continuous analysis. The data is stored and can be extracted for further analysis. This raw data must be processed and transformed to distinguish between normal and defective states of the system through techniques such as managing missing values, correcting inconsistent data, normalizing, encoding certain values, removing incorrect values, and removing irrelevant features. This stage is known in the literature as the feature generation process. In general, this process starts from an initial set of measured data and leads to derived values (functions) that will simplify the subsequent phases of learning and modeling. Since it is a comprehensive process that involves several iterations, the resulting database will have a high degree of quality, allowing analyses to be developed to generate reliable results.

In the implementation and testing stages, the program is developed. This is done programmatically, that is, coding the actions that the computer must perform to achieve the goals, with activities that include writing the source code, compiling, editing links, and debugging the program.

After the program is completed, it is put into operation, that is, it is used in the current activities for which it was created. The lifecycle is completed with the update stage through actions to resolve issues that occur during operation, configuration, and updates. All of this is reinforced in application maintenance activities. If subsequent changes to the released version result in improvements in the program's features, a new application development cycle may begin, which involves repeating all the described steps.

4. Conclusions

The paper presented the concept of integrating risk and reliability analysis methods and tools for optimizing the maintenance program. After a brief introduction in the field of naval technical maintenance, the theoretical aspects of each method and the contributions of the research papers that addressed these topics were briefly presented. The main directions through which these methods can be integrated into the study were formulated and the conceptual framework for the implementation of the integrated analysis was presented.

In developing the framework, several methods were considered, including FTA, FMEA, fuzzy evaluation RPN and fault detection through machine learning techniques. ML provides significant advantages by enabling data-driven decision-making and automating complex tasks. It excels in processing large datasets, uncovering patterns, and generating insights that improve accuracy and efficiency. This allows organizations to optimize operations and make more informed, timely decisions.

ML also supports real-time monitoring and anomaly detection. By continuously analyzing data, it can quickly identify unusual patterns or early signs of issues, allowing for immediate corrective actions. This is especially valuable in critical systems, where early detection can prevent costly failures or downtime.

The author considers it necessary to design a program that integrates the results obtained and that can contribute to improving maintenance by assessing the technical condition of the equipment, using performance data, analyzing the causes of failures and operating safely.

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