# MAINTENANCE STRATEGIES OF MACHINES SUPPORTED BY KNOWLEDGE-BASED SYSTEMS

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**Abstract:** The occurrence of malfunctions, failures, and loss of effectiveness over time is an unavoidable aspect of any industry. In addition, the continuous ability to compete requires the machines to be in the best possible condition with maximum efficiency. In machinery, a good maintenance strategy means better productivity; more reliability and effectiveness; longer service time, and a safe workplace. The goal of the article is to introduce both the main general machine maintenance strategies and main techniques of the knowledge-based approaches in order to build a diagnostic maintenance Expert System, which can be used for all kind of machines. In addition, the article aims to find the most effective strategy to build a maintenance system that monitors marine engines' conditions in real-time and provides the most suitable recommendations based on a knowledge-based approach. Firstly, we briefly introduce different maintenance strategies, then highlight the knowledge-based approaches. After it we demonstrate the possibility of building an Expert System to diagnose different abnormal conditions in marine engines and give a perspective on challenges and potential opportunities. The significance of the article is the elaboration of the Expert System's conception for maintenance of marine engines.

**Keywords:** machines' maintenance strategies, Knowledge-based Systems, Expert Systems, marine engines

## 1. INTRODUCTION

The escalating complexity in the design and construction of engineering facilities and the increasing degree of automation has increased the importance of perfecting the technical investigation process, safety and reliability of these facilities. Maintenance strategies play a vital role in this issue. Knowing the technical condition of the machine at the moment is considered the essential part of the optimal use of condition-based maintenance services, which will improve efficiency. The operator

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(engineer or technician) can make the decision to carry out maintenance (or repair) promptly, which gives the possibility to raise the reliability of the machine (or facility as a whole). The maintenance program's combination of actions has evolved from repair after a malfunction to preventive maintenance to condition-based maintenance and recently to the future view of intelligent predictive and prescriptive systems.

Many relevant articles in the literature were reviewed in this research topic. There are several types of machine maintenance techniques that can be mixed to create different maintenance strategies, e.g. reactive maintenance; preventive maintenance, condition-based maintenance and prescriptive maintenance [1]. A lot of articles discuss the opportunities in using model- and knowledge-based approaches for fault diagnosis. Many existing approaches based on process models and knowledge are reviewed in terms of their basic ideas, weaknesses, strengths, and recent progress [2]. Several papers approach the subject of fault prognosis by predicting future abnormalities so that predictive maintenance and repair can be scheduled. It requires accurate knowledge of how abnormality evolves, and it is considered a future technology with limited known solutions [3-4].

Some papers focus on the possibility of using Knowledge-based Systems to perform a diagnostic process to determine and predict the technical conditions of the machines due to the advanced (improved) effectiveness of these systems. Coraddu at al. built a hybrid condition-based model to predict the engines temperatures during operation to predict multiple engine parameters and train test the hybrid model during operation. As the information and data in these systems are not static but rather increasingly dynamic compared to traditional diagnostic systems based on specific algorithms. Furthermore, the authors show that Machine Learning techniques can be used to establish algebraic and differential equations for complex systems, such as the heating and cooling temperature in engines [5].

Marques at al. propose the Smart Prescriptive Maintenance Framework as a structure for implementing Artificial Intelligence to support a fleet of commercial jets. Includes efficiency checks such as the fleet availability and the direct maintenance cost, and depends on specific operational, engineering, and economic data. The main focus of their article is to study the possibility of benefiting from Knowledge-based Systems by designing a high-quality, low-cost Expert System to diagnose the technical conditions of a ship diesel engine [6]. Krakowski, R. presents examples of unconventional methods of diagnostic systems without disassembling for marine diesel engine and found that the developed diagnostic system would be a good complement to the existing electronic monitoring systems of the marine engine technical conditions [7].

Yazdi at al. propose and test a methodology to overcome some problems in collecting the necessary knowledge from experts for enhancing complex rule-based Expert System [8]. Theissler at al. made a survey and categorized recent research contributions on Machine Learning enable predictive maintenance for automotive systems and one of the most important conclusions was combining the data from multiple sources, which can improve accuracies and enable new applications [9]. Amin at al. present a novel technique to convert the continuous monitoring data into

meaningful evidences to update dynamic Bayesian Network for fault detection and diagnosis which will help improve monitoring system efficiency and reliability [10].
Even though the process of designing a system for marine engines compared to stationary engines (with a stable working system) is linked to many complications such as the difficulty of maintaining a non-stable working system and the impact of diagnostic parameters on external parameters and engine operational parameters more than structural parameters, which reflect the technical condition of the engine.

The goal of the article is to review both the main machine maintenance strategies and the main techniques of the Knowledge-based approaches in order to build a diagnostic maintenance Expert System, which can be used for all kind of machines. In our research we focus mainly on the maintenance of marine engines.
In the article, at first the main general machine maintenance strategies are introduced in Section 2, which are the following: reactive maintenance; scheduled (periodic) maintenance; preventive maintenance condition-based maintenance; reliability-centered maintenance and prescriptive maintenance. After it, the main general techniques of the Knowledge-based approaches (Grids; Decision Trees; Bayesian Networks and Expert Systems) are discussed in Section 3. Then the conception of the Expert System for marine engines are described in Sections 4-5.

## 2. MACHINES' MAINTENANCE STRATEGIES

There are several types of machines' maintenance techniques that can be mixed to create different maintenance strategies [1,11,12].
The main maintenance strategies can be seen in Figure 1.

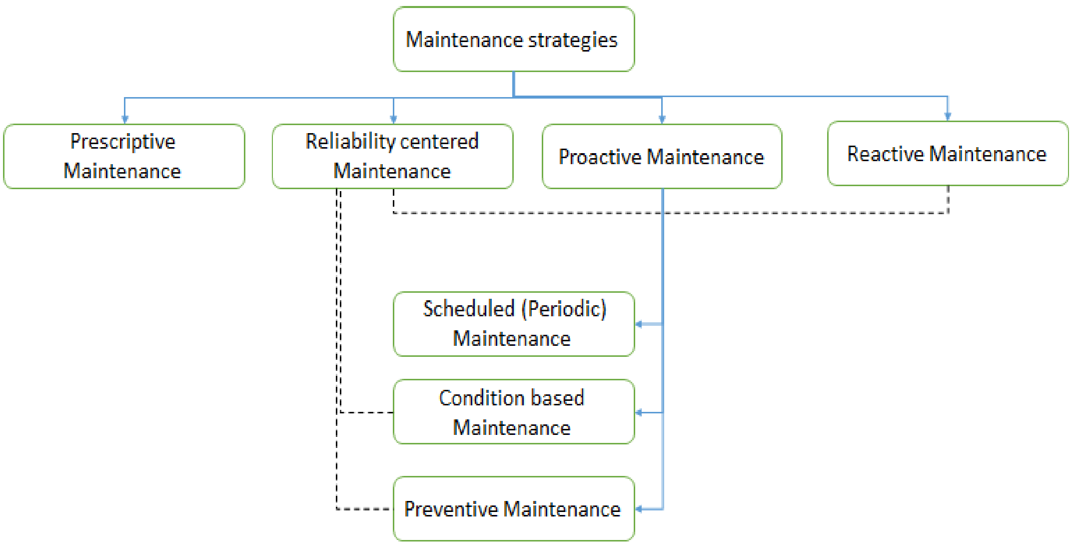


**Fig. 1.** Maintenance strategies

**● Reactive Maintenance**

Reactive maintenance is considered the oldest maintenance method and refers to making repairs or replacements after a breakdown has already occurred, and no action is taken to maintain equipment before it is destroyed.

**● Scheduled (Periodic) Maintenance**

Scheduled maintenance repair will happen for every maintenance issue after a set period, but it does not consider each part structural and operational characteristics.

**● Preventive Maintenance**

Preventive maintenance programs have been developed to prevent catastrophic malfunctions and emergency stops. Its schedules include regularly setting schedules for machine inspection and maintenance regardless of its technical condition, but it allows each part to be inspected separately and have a maintenance plan based on expert analysis. This method helps prevent failure during operation by replacing sensitive parts at an organized time before the end of its expected operational age without considering the environmental and operational parameters.

The two most common types of Preventive maintenance are the following:

- Calendar-based maintenance (for example, end of the week on Friday).
- Runtime-based maintenance (for example after 200 miles).

**● Condition-based Maintenance**

Although Preventive maintenance increases the efficiency and reliability of the equipment and reduces the frequency of unexpected failures. This strategy is costly due to the frequent replacement of expensive parts before the end of their age and the reduction in service time of the machine. In addition, it may cause new failures that may result from disassembly, installation and replacement for parts that expose the machine to tolerances or can result from human errors.

Condition-based maintenance systems include diagnostic and predictive models in order to monitor the condition of the machine based on specific parameters in a way that does not conflict with its regular operation. As it depends on the actual technical condition of the machine, from which the equipment condition is evaluated with the requirements to perform the maintenance or not. If necessary, the appropriate time will be determined for its procedure. In addition, alarms have been added when the operation fails or at the level at which condition must be evaluated, and proper diagnosis can be made. This type of maintenance provides enough time for the operator to take preventive action, look into the current operational status and fix the fault before a failure occurs.

**● Reliability-centered Maintenance (RCM)**

Reliability-centered maintenance systems are multi-selective systems that depend on the combination of Reactive, Condition-based and Preventive strategies. The Reliability-centered maintenance uses these different strategies not only independently but also based on critical and failure modes.

**● Prescriptive Maintenance**

Prescriptive maintenance is the next step to RCM complete implementation, and it is a potential technology that automates the maintenance process by collecting and analyzing machines' data in real-time through Machine Learning and Artificial Intelligence techniques. In addition, we can obtain specialized recommendations from these techniques as to what kind of maintenance work needs to be done and when.

## 3. KNOWLEDGE-BASED APPROACHES

Different knowledge representation methods vary from mathematical relations between outputs and inputs, qualitative data, if/then rules, and conditional probability relations. If flexible methods are used to analyze this knowledge, it is possible to obtain the maximum benefit. A brief overview of this technique will be detailed below [13].

**● Grids**

Grids are based on tables, and despite their many types and ways of use, they have the same principle. It shows a numerical relationship between facts and rules. For example, setting the rules in the first row and facts in the first column, then filling the table with predetermined numbers that indicate whether the rules relate to different facts or not. The following Table 1. represents a Trinary Grid (one of the most common types of grids) and fills the table with the values "1", "2", or "0". Number 1 indicates a causal relationship between the truth and the rule; number 2 indicates that the truth is a consequence of the occurrence of the rule; number 0 indicates that the truth is not related to the rule.

*Table 1.* **Sample for a Trinary Grid**

| | **F1** | **F2** | **F3** | **F4** | **F5** | **F6** |
|---|---|---|---|---|---|---|
| **R1** | 1 | 0 | 1 | 2 | 0 | 0 |
| **R2** | 0 | 0 | 0 | 1 | 2 | 0 |
| **R3** | 0 | 2 | 0 | 1 | 1 | 1 |

**● Decision Trees**

It is a tool for making and analyzing decisions based on a graphic representation of possible options, which helps to make a decision based on specific conditions, and they are called Decision Trees because they start with one box (or one root) that branches into several solutions and steps (Figure 2).

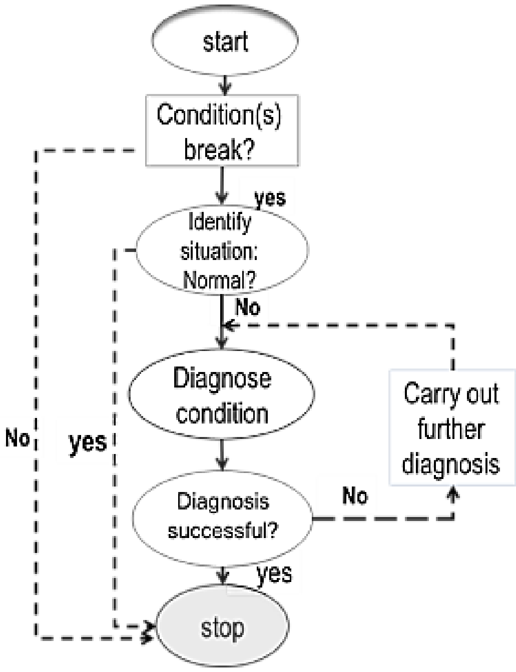


**Fig. 2.** Decision Tree for inference process

● **Bayesian Networks**

Bayesian Networks are a development of Bayesian rule (conditional probability). It is a simple, graphical, structural network that commonly represents knowledge and reasoning with uncertainty. It consists of nodes and links, and it takes several forms: diagnostic inferences, causal inferences, inter-causal inferences, mixed inferences. Each of them forms used in a specific case.

● **Expert Systems**

Expert Systems are interactive systems that simulate the behavior and abilities of one or more experts within a specific field of knowledge. These are used in specific and complex applications to be considered a consultant to the final user. These systems aim to solve complex problems that experts can only address and make decisions by providing inexperienced people with the necessary tools to do work requiring high expertise.

These experts are usually few, rare, and expensive. In addition, to the possibility of the expert person being present in a practical, reliable, well-prepared, able to solve problems in real-time and without prejudices, and available with an unlimited ability to learn and process new information. The different components of an Expert System are shown in Figure 3. from the expert and knowledge engineer to the final operator, including the possibility to modify and add new rules to the knowledge base [14].

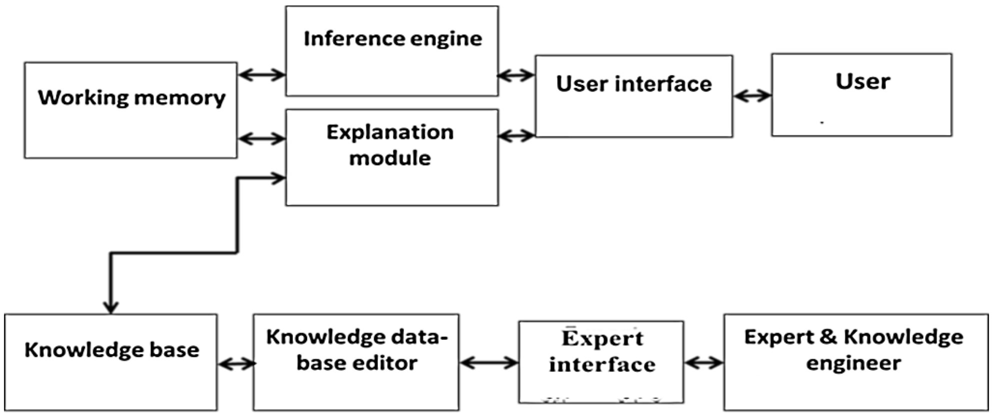


**Fig. 3.** Expert System components

Regardless of what purpose the Expert System was designed for, some characteristics and advantages are present in all Expert Systems:

- Experts are not always available, but the Expert System can be used anywhere and anytime.
- The human expert may have made prejudgment caused by his thinking mechanism.
- The Expert System is faster than a human expert.
- The Expert System reduces maintenance and repair time.
- It has a lower cost than a human expert.
- Easy to modify and develop.
- Advanced efficacy.
- Expert Systems provide the opinions of several experts.
- The Expert System has the knowledge of several experts, which makes the results more effective.
- High accessibility and explanations of how the results were achieved.

## 4. MAINTENANCE OF MARINE ENGINES SUPPORTED BY EXPERT SYSTEM

Effective investment plays a vital role in economic development in any field, and accordingly, the requirements for the continuous work of the main engines of ships and auxiliary engines have increased significance in maritime transport. Economic concerns require an increase in the actual service time between maintenance downtimes and a decrease in these times. Therefore, the most effective way to reach this goal is to rely on flexible forms of technical investment based on techniques that facilitate the fault and failure detection process in various parts of machinery in the ship. In recent years, the interest in this field has grown, and it is considered one of the fundamental issues in investment and has attracted the attention of various organizations, research centers, and companies.

Using Knowledge-based methods to improve marine engines maintenance strategy is not an easy task because of the complex relationship between structural and operational parameters. The significant influence of external effects, engine operating system factors, and the random nature of output parameters changes mean the need for wide use of different methods such as mathematical statistics, probability theory, belief theories, and fuzzy logic to analyze this knowledge. In order to build an effective Expert System that determines the technical conditions of a diesel engine the whole system has to be divided into multiple sub-systems, which would make it easier to study and evaluate.

These sub-systems are the following:

1. *Fuel system:* It includes all the fuel pipes, injectors, fuel pumps, heaters, high-pressure pipes and the fuel itself.
2. *Air system:* It includes all the air pipes, filters, turbocharger, cooler.
3. *Lubrication system:* It includes several independent cycles which are the following:
   - the moving parts inside the engine lubrication cycle;
   - the turbocharger lubrication cycle;
   - the cylinder lubrication cycle.
4. *Cooling system:* Diesel engine cooling systems are divided as follows:
   - Cylinder cooling: It is usually done with fresh or distilled water, and air or salt water may be used in some cases.
   - Cooling the pistons: It is done either with oil or water.
   - Fuel injectors cooling: It is an independent system that uses freshwater or diesel fuel.
   - Exhaust valves cooling: It is needed to ensure the safety of its operation, especially in the case of using heavy fuel.
   - Charging air cooling: It is usually saltwater.
5. *Exhaust system:* It contains exhaust valves and a set of pipes ending in the funnel, through which the exhaust gases pass to the turbine of the turbocharger, economizer, cooler, dampers, surrounding thermal insulators, and a gas treatment system (ideally, but not all engines may necessarily have these components).

Marine engines have many parameters that have their sensors connected to the ship's control panel. Therefore, the parameters that provide as much diagnostic information as possible have been selected to be used as diagnostic parameters; thus, there is no need to add new sensors to the engine. If the selected diagnosing parameters were linked to the rest of the sub-system variables, then as much as new knowledge is added to the knowledge base, the Expert System will be more reliable to use.

After combining different expert opinions, a simple If/Then relationship can create a set of rules for each sub-system that will inform the operator about the best time to repair or replace each part.

## 5. CONCEPTION OF THE EXPERT SYSTEM FOR MAINTENANCE OF MARINE ENGINES

After discussing with a few marine experts about the possibility of using their knowledge to build a maintenance system, we noticed that those experts faced difficulty in dealing with the principle of presenting their opinions with its probabilities for different conditions (probably the first time anyone asked them to talk about their knowledge). That made collecting and linking different opinions to specific rules for each situation more complicated; therefore, we had to make some adjustments.

Table 2 shows a possible solution to obtain knowledge from experts by combining the principles of Grids and Decision Trees methods, where instead of filling the table with numbers, the experts can fill it with their maintenance strategies.

The terms in Table 2 are the following:

- normal – it includes the values of operation parameters in which the machine maintains its efficiency and stability;
- fuzzy – it includes abnormal values in monitored system which indicate defects that lead to failure;
- fault – the machine stop functioning the way intended or designed for it.

*Table 2.* **Knowledge collecting grid (sample for the fuel system)**

| **Parameters (Fuel Pressure)** | **Feeding Pump** | **Injector** | **High pressure pipes** | **High pressure Pump** | **Fuel (daily consumption tank)** | **Combustion process** | **Additional problem may be suggested by expert** |
|---|---|---|---|---|---|---|---|
| **Normal** | (4,5) bar | 200±5 bar | 1000bar | 1000 bar | (90,95) C | . | . |
| **Fuzzy** | < 4 | More than 200+5 | Less than 1000 | . | . | . | . |
| | > 5 | Less than 200-5 | More than 1000 | . | . | . | . |
| **Fault** | low performance | Spring breaking, .. | Unstsable units | . | . | . | . |

The experts explain the conditions during their work and their direct response to marine engines and their strategies. For example, they applied the principle of diagnosis by exclusion in several cases and thus presented their opinions with an absolute probability. In order to combine experts' opinions, a new factor can be created to measure the degree of agreement and disagreement for each opinion.

The opinions of each expert can be weighted with an experience factor related to the number of years the expert worked as a chief engineer on ships. It can be linked to the range (+0.8÷ +0.4) depending on the results shown in Table 3., where only absolute ignorance and absolute knowledge were excluded.

After connecting the years of experience of every human expert to the proposed range, considering that the minimum acceptable number of experience years is five years (min.) and the highest is 20 (max.). The values of the experience factors can be seen in Table 3.

*Table 3.* **Experience factor calculations**

| **Expert** | max | **1** | **2** | **3** | **4** | **5** | **6** | min |
|---|---|---|---|---|---|---|---|---|
| **Experience years** | 20 | 18.115 | 17.667 | 14.878 | 13.518 | 10.510 | 5.737 | 5 |
| **Experience factor** | 0.8 | 0.749 | 0.749 | 0.663 | 0.627 | 0.547 | 0.419 | 0.4 |

If we can define rules with a degree of certainty by linking those experience factors for different technical conditions based on expert agreement or disagreement, then we can organize a set of rules for each sub-system, creating a maintenance system based on human knowledge. This Expert System will improve the monitoring and operating system's efficiency.

## 6. CONCLUSIONS

Using the adequate maintenance strategies and Knowledge-based methods to build a diagnostic maintenance Expert System in the marine industry necessitates three things. Firstly, collaborators (Experts), who are familiar with the worst mistakes that can occur in their work field and how to avoid them, as well as a variety of different conditions that can all be part of the knowledge base. Secondly, a knowledge engineer who is already familiar with the field and studies the most effective ways to extract knowledge from humans. Thirdly, using an appropriate software environment to create the required rules to run the software prototype and work in it.

In the future research Machine Learning techniques can be used to establish algebraic and differential equations for more effective and evolved systems, such as the equations linking changes in the heating up and cooling down of a temperature sensor to another change in the fuel pressure sensor in an engine. Subsequently, the final prototype can be tested in real-time situations to indicate emerging failures early and identify strategies that can be used to perform maintenance. These techniques need to be further developed to support future naval vessel investment.

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