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Condition-Based Maintenance of HVAC on a High-Speed Train for Fault Detection

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Abstract: Reliability-centered maintenance (RCM) is a well-established method for preventive maintenance planning. This paper focuses on the optimization of a maintenance plan for an HVAC (heating, ventilation and air conditioning) system located on high-speed trains. The first steps of the RCM procedure help in identifying the most critical items of the system in terms of safety and availability by means of a failure modes and effects analysis. Then, RMC proposes the optimal maintenance tasks for each item making up the system. However, the decision-making diagram that leads to the maintenance choice is extremely generic, with a consequent high subjectivity in the task selection. This paper proposes a new fuzzy-based decision-making diagram to minimize the subjectivity of the task choice and preserve the cost-efficiency of the procedure. It uses a case from the railway industry to illustrate the suggested approach, but the procedure could be easily applied to different industrial and technological fields. The results of the proposed fuzzy approach highlight the importance of an accurate diagnostics (with an overall 86% of the task as diagnostic-based maintenance) and condition monitoring strategy (covering 54% of the tasks) to optimize the maintenance plan and to minimize the system availability. The findings show that the framework strongly mitigates the issues related to the classical RCM procedure, notably the high subjectivity of experts. It lays the groundwork for a general fuzzy-based reliability-centered maintenance method.

Keywords: condition-based maintenance; fault detection; fuzzy logic; reliability; reliability-centered maintenance; railway

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1. Introduction

Industrial production is driven by global competition, and radical advances are required in manufacturing technology if companies are to keep up. Industry 4.0 is transforming industrial manufacturing through digitalization and other new technologies (see for instance [1–5]). A main objective is the reduction of down-time by optimizing maintenance policies [6–10]. Reliability-centered maintenance (RCM) is a method used to identify and select failure management policies, including maintenance activities, operational changes, design modifications or other actions to mitigate the consequences of failure [11]. RCM provides a decision process to identify applicable and effective preventive maintenance requirements or management actions to prevent the safety, operational and economic consequences of failures, and to identify the degradation mechanism responsible for those failures. The most important but challenging parts of the RCM process are failure mode effect and criticality analysis (FMECA) and task selection. FMECA is developed using the subjective knowledge of domain experts (for more information about FMECA, see for instance, but not only, [12–15]).

Meanwhile, the decision diagram proposed by the international standard IEC 60300-3-11 [11] for task selection is very generic, and the task choice mostly relies on the experience of the analyst that performs the RCM [16]. The classical risk priority number (RPN), the output of the FMECA, also has many drawbacks, including gaps in the range, duplicates, subjectivity and dispersion [17]. Despite these disadvantages, RCM is a powerful solution, widely used in every industrial field in which service continuity represents a mandatory requirement, and maintenance must be optimized in terms of money and time [18].

Some researchers propose an effective RCM assessment approach using reliability software [19]. In Reference [20], the RCM is applied to the whole system under test instead of focusing on individual components. Other papers use analytical models and a dynamic approach [21,22], while some authors create their own framework for maintenance decision-making [23,24]. Zakikhani et al. [25] propose an availability-based RCM, while in [26] a whole dependability study (RAMS) is introduced to optimize maintenance policy. In Reference [27], the variation trends of the failure rates of components under imperfect maintenance are used to optimize the maintenance of metro trains based on the concept of RCM. Afzali et al. [28] propose a weighted importance reliability index model to prioritize the components in a complete RCM report. In Reference [29], a stochastic RCM is proposed, while other papers introduce genetic algorithms to solve the mathematical problem of RCM optimization [30,31].

Starting from a preliminary work presented in [32], this paper proposes a new approach based on fuzzy set theory to overcome the limitations of traditional FMECA and RCM. It provides a customized decision diagram that uses fuzzy inference rules to mitigate the subjectivity problem of the classical procedure. The three parameters of the criticality analysis are fuzzified using appropriate membership functions; the resulting RPN given by the product of the three indices is a fuzzy number. The proposed decision diagram for the task selection is based on the fuzzy occurrence, severity and detection scores combined with other failure information using a set of if–then rules, one of the most frequently used and efficient fuzzy inference approaches [33–35].

The main contribution of this paper is the introduction of a fuzzy-based decision-making diagram to guide the selection of the optimal maintenance task within the reliability-centered maintenance procedure. The proposed procedure helps to rapidly, easily, uniquely, and unambiguously identify the optimal maintenance policy, while the classical RCM procedure leads the analyst to multiple choices involving high subjectivity in the definition. Moreover, the methodology presented in this work is a diagnostic-oriented decision diagram that favors the choice of condition-based maintenance whenever possible, such as condition monitoring and failure finding procedures.

The paper is organized as follows. Section 2 explains the classical RCM process used by international standard IEC60300 3-11. Section 3 describes the proposed approach to mitigate the subjectivity problems of the standard technique, and Section 4 tests and validates the methodology on a real case study of a railway HVAC system. Finally, Section 5 offers some conclusions.

2. Reliability-Centered Maintenance

Reliability-centered maintenance is an effective way to select the appropriate maintenance policies for every type of system. In compliance with the international standard IEC 60300-3-11, the classical RCM process is divided into five steps [11]:

1. Initiation and planning—establishing a plan of analysis and the operating context;
2. Functional failure analysis—identifying the failure modes, causes, effects and criticalities of each component;
3. Task selection—selecting the appropriate maintenance task and interval;
4. Implementation;
5. Continuous improvement—monitor the effectiveness of the maintenance plan to ensure continuous improvement.

The most critical step of the classical RCM procedure is the selection of the maintenance task (Phase 3). In compliance with international standard IEC60300-3-11 [11], Figure 1 shows how to guide the maintenance task selection in order to identify the optimal maintenance solution for the system under test. The maintenance decision diagram aims to simplify the assessment of the optimal maintenance tasks.

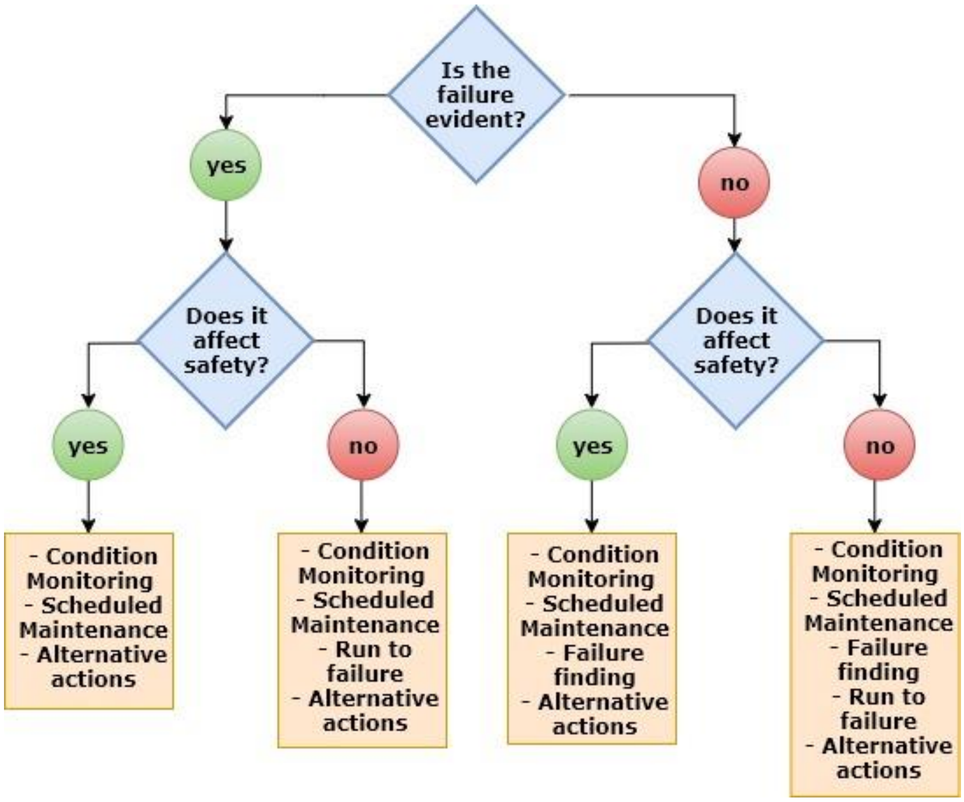

Figure 1. Maintenance decision diagram of classical RCM procedure according to International standard IEC 60300-3-11.

The maintenance policy choice depends on two conditions: if the failure is evident or not, and if the failure will involve consequences for the safety level of the system under test. However, at least four possible task options are given in each orange box; this means the international standard gives the designer a high level of subjectivity. Overall, the diagram is very generic and does not lead to a unique task choice; the designer is free to choose one or another option, based only on his or her expertise.

All possible maintenance tasks taken into account by the standard are explained as follows:

- Failure finding is applicable only to hidden failure. This task can be either an inspection or a function test to determine whether an item would still perform its required function if demanded [36];
- Scheduled maintenance is divided into scheduled restoration and scheduled replacement. This task consists of the scheduled refurbishment or replacement of an item or its components;
- Condition monitoring is a continuous task that allows users to detect the health state of the system by monitoring some contextual parameter that could indicate the degradation and wear-out of the monitored item. Condition monitoring is able to indicate that the failure mode can be expected to occur if no corrective action is taken [37,38];
- No preventive maintenance is performed if no maintenance action is required (i.e., Run to Failure);

- Alternative actions may be performed, as suggested by the designers and maintenance experts.

3. Proposed Approach: Fuzzy-Based RCM

FMECA, based on the fuzzy set theory approach, has been used in a variety of engineering fields to eliminate the drawbacks explained in the introduction section [17,39–41]. In this paper, fuzzy logic is used not only to enhance the features of FMECA and RPN but also to introduce a new approach to maintenance decision-making. The first step is to complete a classical failure modes and effects analysis (FMEA) to identify the failure modes, failure causes and failure effects of the system. The aim of FMEA is to highlight all the criticalities of the system, the causes that could lead to them and all the possible consequences. The second step is to define the linguistic variables of the three risk parameters—occurrence (O), severity (S) and detection (D)—and rank them using fuzzy numbers instead of crisp numbers. The O, S and D indices can be divided into several linguistic terms, each identifiable by a different value. A three-linguistic scale is used in the proposed approach, and each term is fully described in Table 1.

Table 1. Linguistic definition for occurrence (O), severity (S) and detection (D) used in the proposed method.

Occurrence (O)	Severity (S)	Detection (D)
Remote (R)—the mode has a remote probability of occurring	Very low (VL)—the mode has low/no impact on the system	Almost certain (AC)—the mode will almost certainly be detected
Probable (P)—the mode has a medium probability of occurring	Tolerable (T)—the mode causes deterioration in the system	Medium (M)—the mode will probably be detected
High (H)—the mode will likely occur	Critical (C)—the mode leads to serious damage in the system	Absolutely uncertain (AU)—the mode will hardly be detected

The indices are transformed into fuzzy numbers via membership functions. All membership functions are trapezoidal. Figure 2 shows the membership functions related to occurrence, Figure 3 highlights the severity membership functions and Figure 4 illustrates the membership functions of the detection.

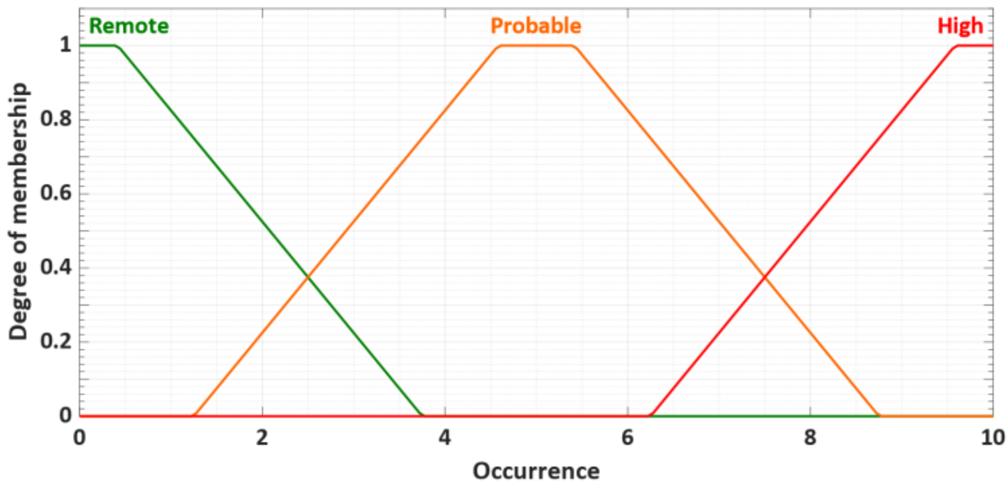

Figure 2. Membership functions for occurrence (O): "Remote (R)", "Probable (P)", "High (H)".

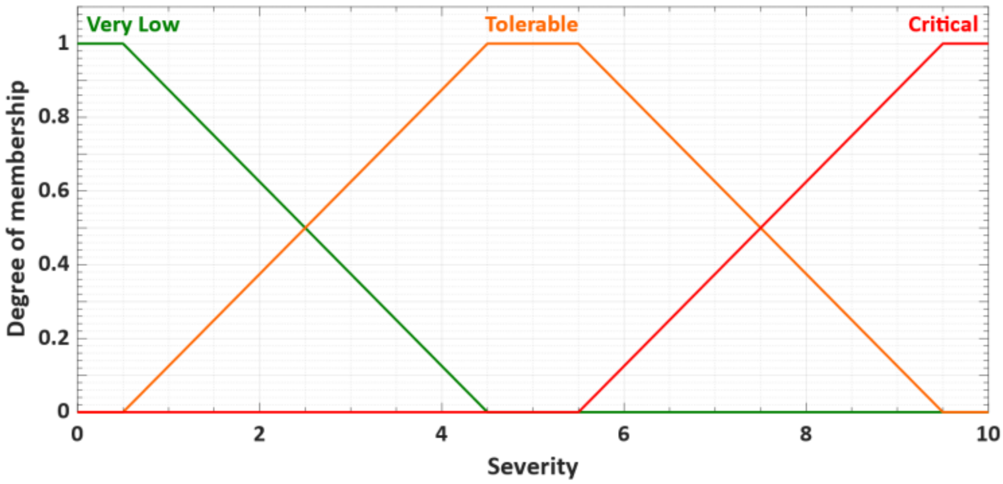

Figure 3. Membership functions for severity (S): "Very Low (VL)", "Tolerable (T)", "Critical (C)".

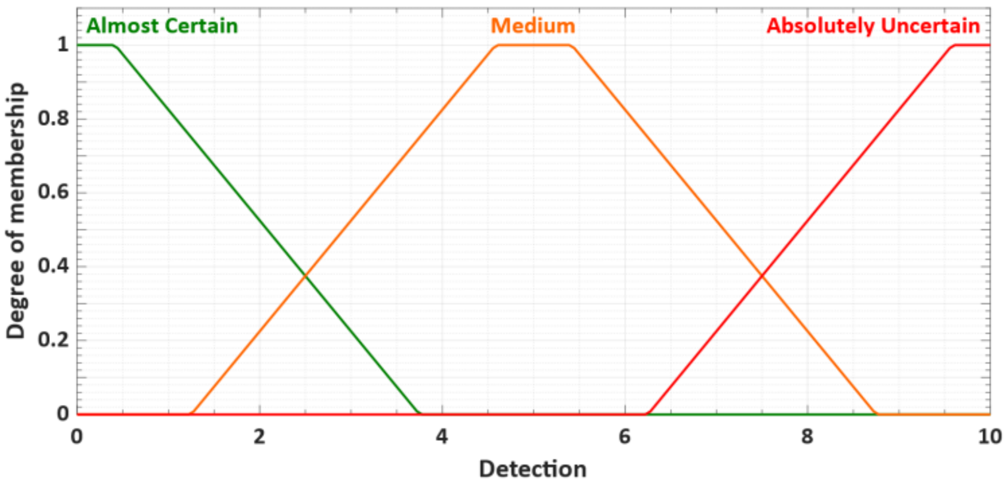

Figure 4. Membership functions for detection (D): "Almost Certain (AC)", "Medium (M)" and "Absolutely Uncertain (AU)".

The main advantage of this approach is that instead of choosing a crisp value within the range of 1 to 10 for each parameter, the designer can choose one of the three linguistic terms. This leads to a better accuracy and a less subjective assessment of the risk level because expert judgment now relies on the linguistic terms.

After the assessment of O, S, and D, the fuzzy FMECA procedure requires the evaluation of the fuzzy risk priority number (RPN) using, for example, if–then rules (see, among others, [33,35,42]), weighted geometric mean [43], OWA operator [44], TOPSIS theory [45] or multicriteria decision method [41]. In this paper, fuzzy if–then rules are used to calculate the fuzzy risk priority number (FRPN). Moreover, the proposed decision focuses on the development of a new maintenance decision diagram. The new customized diagram is shown in Figure 5. In the diagram, the membership functions of O, S and D are identified by different colors, as in Figures 2–4. The proposed maintenance decision diagram is a diagnostic-oriented approach that favors the choice of condition-based maintenance whenever a diagnostic system is applicable. Therefore, the membership function of the detection variable plays a fundamental role in the procedure. For instance, if detection is "Almost Certain—AC" then the proposed procedure suggests the implementation of condition monitoring to diagnose the health-state of the system, and consequently optimize the maintenance policy based on the system's actual conditions.

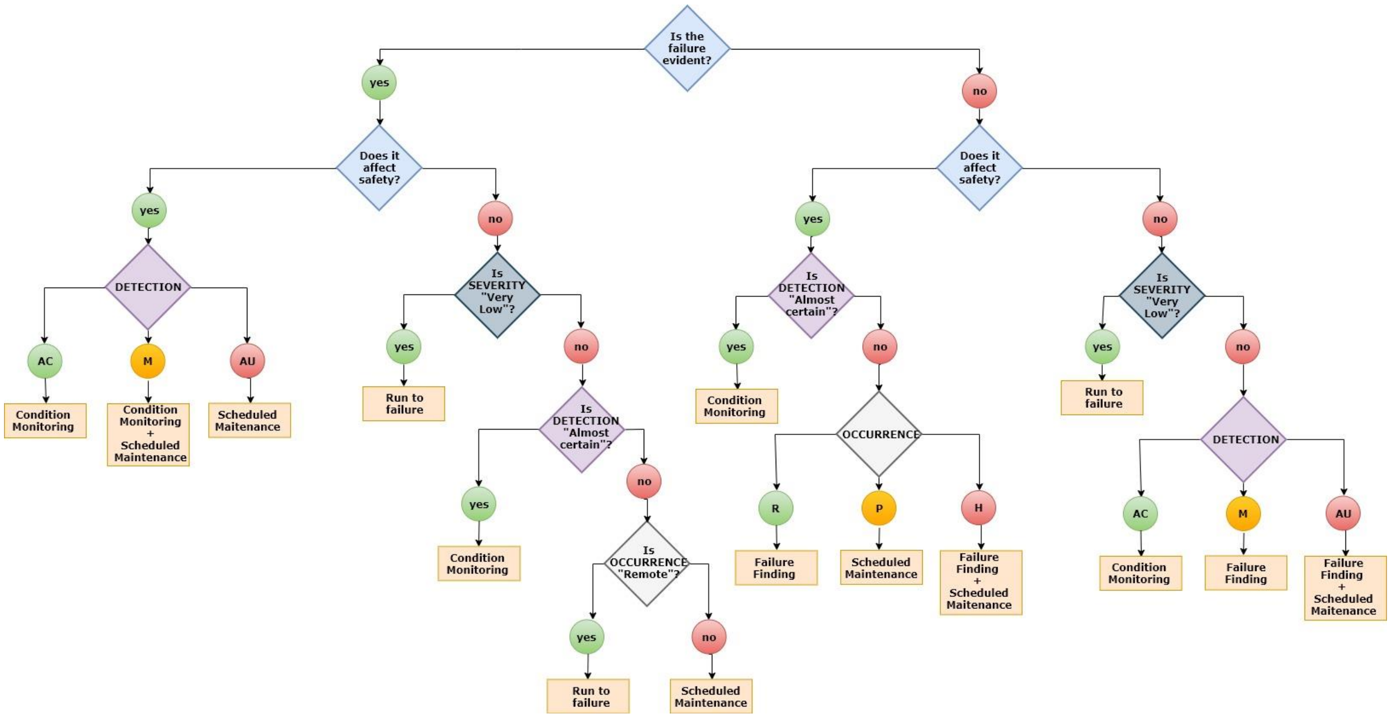

Figure 5. Proposed maintenance decision diagram to assess optimal maintenance task using fuzzy logic.

For the sake of simplicity, the linguistic variables that define each membership function in Figure 5 are abbreviated using only the first letter of each word, as in the captions of Figures 2–4. Different colors have been used to identify the different membership functions.

The information necessary to carry out the proposed procedure is the following:

- Whether the failure is hidden or evident;
- Whether the failure has safety consequences on the system;
- What the membership functions of occurrence, severity and detection are.

Depending on this input information, there is a univocal output, so the set of inputs leads to a specific maintenance task. Designer subjectivity is minimized, and the task is selected in a more deductive and rational way. Furthermore, the proposed methodology is still compliant to the requirements and suggestions of the RCM international standard IEC 60300-3-11. In fact, the top side of the tree remains the same as the decision diagram proposed in then international standard (see Figure 1). The proposed procedure improves the bottom side of the tree introducing the fuzzy linguistic variables to provide a univocal and unique maintenance choice for each analyzed failure mode.

The decision diagram proposed in Figure 5 could be automatized by implementing a set of fuzzy-based if–then rules. Usually, the fuzzy "if–then" procedures presented in the literature are solved using one of the following three types of fuzzy inferences. The Mamdani inference first proposed in [46] results in an aggregation of fuzzy sets that must be defuzzied to achieve the crisp output. The Sugeno inference [47] provides a polynomial function that must be solved to obtain the crisp output value. Finally, the Tsukamoto inference [48] is a hybrid approach based on the previous ones that has not gained much popularity in the literature. In this paper, the Mamdani inference is used since it provides optimal results with low computational complexity, as well as easiness of use. The proposed fuzzy system for maintenance task assessment has five inputs and two outputs. The three inputs (occurrence, severity and detection) are the fuzzy variables described by the three trapezoidal membership functions illustrated in Table 1 and discussed above. The other two inputs are simple Boolean variables with only two states, "Yes" or "No". One is used to divide the failure into "hidden" or "evident"; the other classifies the failure's impact on safety. In other words, the proposed methodology is implemented using a hybrid system merging Boolean and fuzzy logic through a set of fuzzy if–then rules. The two outputs of the fuzzy system are:

- The fuzzy risk priority number (FRPN) assessed combining occurrence, severity and detection. FRPN is described using six trapezoidal membership functions;
- The optimal maintenance task, a linguistic variable assessed using all five inputs according to the decision diagram illustrated in Figure 5.

The proposed fuzzy logic system is illustrated in Figure 6, highlighting the inputs and the outputs. The inference logic uses 9 rules to assess the fuzzy risk priority number and 36 rules to assess the optimal task. Obviously, this number varies if the risk rates O, S and D are described with more membership functions. For the sake of simplicity, this paper analyzes the parameters using only three linguistic variables each; when the number of possible linguistic values is increased, the accuracy of the approach increases, along with its complexity.

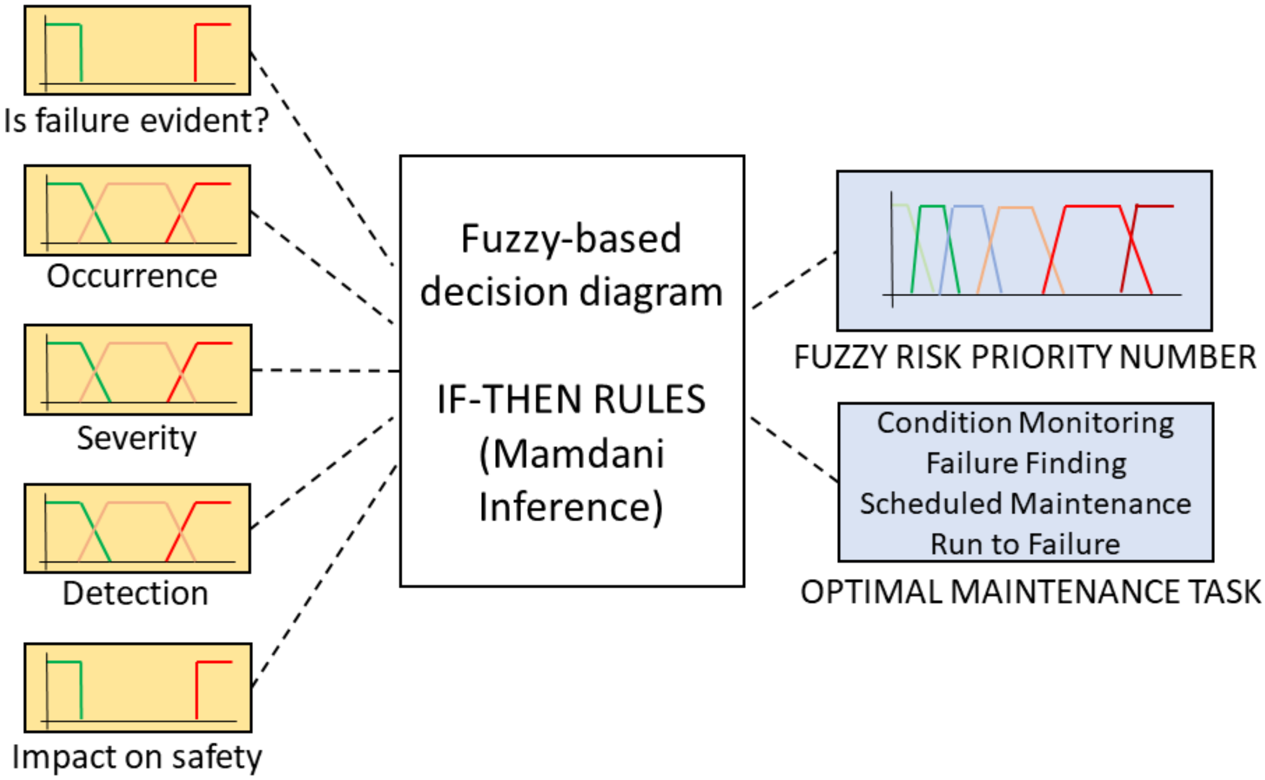

Figure 6. Schematic diagram of fuzzy-based RCM assessment using "if–then" rules.

Two of the implemented rules are illustrated below, the first for the FRPN output and the second for the maintenance task selection:

If (Severity is Critical) and (Detection is Almost certain) and (Occurrence is Remote) then (FRPN is Critical);

If (Failure evident = YES) and (Impact on Safety = NO) and (Severity is Tolerable) and (Detection is Almost Certain) and (Occurrence is remote) then (Optimal task = Condition Monitoring).

4. Case Study: RCM Assessment of HVAC for High-Speed Trains

Heating, ventilation and air conditioning (HVAC) technology is concerned with indoor and vehicular environmental comfort. The objectives of HVAC systems are to provide an acceptable level of occupancy comfort and process function, to maintain good indoor air quality, and to keep system costs and energy requirements to a minimum. Furthermore, one of the main objectives of HVAC is to ensure emergency ventilation and sufficient air exchange [49–52]. In summary, HVAC has to ensure four functionalities: cooling capacity, heating capacity, ventilation capacity and emergency ventilation.

In this section, the proposed fuzzy-based RCM approach has been applied to an HVAC system installed on high-speed trains in order to test and validate the performances of the proposed approach. The complete RCM report is not available; however, the results achieved for the most critical and complex components of the HVAC are illustrated in the following.

Five components are considered in this paper, namely the compressor, the electronic control card (ECC), the watchdog, the IGBT module (insulated gate bipolar transistor) and the UPS (uninterruptible power supply). The compressor draws in the cold gases exiting the evaporator battery at low pressure and compresses them, so they come out as overheated gas at high pressure. It includes a motor, a pump, some internal valves, a thermostat, etc. The ECC is a microprocessor-based electronic board used to manage all the HVAC functionalities, while the watchdog is used to activate the emergency mode. The IGBT is used to drive the compressor motor in order to ensure cooling capacity, and finally the UPS ensures emergency power in order to guarantee emergency ventilation in the case of breakdown of the overhead power line.

The identified failure modes and the notation used to label them are as below.

- Compressor
  - FM_C1: motor does not start on demand.
  - FM_C2: incorrect signal from thermostat.
  - FM_C3: pump gas leakage.
  - FM_C4: sticking internal valve.
  - FM_C5: internal overload motor protection.
- Electronic Control Card (ECC)
  - FM_E1: electronic control failure.
- Watchdog
  - FM_W1: watchdog does not act when the control fails.
- IGBT module
  - FM_I1: short/open circuit.
  - FM_I2: parameter drift.
- UPS
  - FM_U1: no output power.

Table 3 shows all the inputs required by the proposed fuzzy-based RCM approach. Occurrence, severity and detection are expressed in linguistic terms, while the other two inputs are Boolean variables.

Table 2 shows the failure modes and effects analysis carried out for the five components under analysis.

The parameters shown in Table 3 are used as inputs for the proposed framework for maintenance decisions, as illustrated in Figure 5, or the fuzzy system explained in Figure 6 to assess the optimal maintenance task for each failure mode identified during the preliminary FMEA.

The results of the proposed fuzzy-based approach applied to the most critical components of an HVAC system installed in a high-speed train are summarized below.

- FM_C1: "failure finding plus scheduled maintenance". Failure finding is implemented every month; in this way it is possible to obtain a larger interval for the scheduled maintenance (6 months).
- FM_C2: "no preventive maintenance (run to failure)". The failure of the thermostat does not represent critical damage for the system; therefore, corrective maintenance could be implemented.

- FM3_C3: "scheduled maintenance". Operations on the pump are scheduled every 3 months.
- FM_C4: "condition monitoring". The valve is monitored continuously using a position transducer and a pressure transmitter.
- FM_C5: "condition monitoring". Several sensors are implemented to monitor the state of the compressor, including temperature, vibration, pressure and load sensors.
- FM_E1: "condition monitoring plus scheduled maintenance". The electronic board is monitored continuously by a dedicated device equipped with temperature, humidity and vibration transducers. These parameters are extremely useful to identify the health state of electronics. Moreover, the diagnostic device also uses interrogation algorithms and residual life computational algorithms. Furthermore, scheduled maintenance (in the form of visual inspection) is required once a year.
- FM_W1: "failure finding plus scheduled maintenance". Failure finding is implemented every month, while scheduled maintenance (in the form of visual inspection and manual HW/SW testing) is required every year.
- FM_I1: "condition monitoring". The IGBT is monitored continuously using a temperature transducer and two power meters used to provide both input/output voltage and current.
- FM_I2: "failure finding". Failure finding is implemented every month to check the health state of the IGBT.
- FM_U1: "condition monitoring". The UPS is monitored continuously in order to check the health state of the battery using voltage, and current measurements are used to estimate the residual capacity of the battery.

The proposed approach offers a powerful solution because it allows designers to select the optimal maintenance without the need for subjective evaluation. Moreover, it privileges condition-based maintenance tasks, such as condition monitoring and failure finding. Most paths of the decision diagram lead to condition-based maintenance operations. In some cases (see the results obtained for FM_C1, FM_E1 and FM_W1), two tasks are implemented at the same time; one is condition-based maintenance (such as condition monitoring or failure finding), and the other is scheduled maintenance. In fact, in some circumstances, using condition monitoring or failure finding alone is not enough to guarantee high levels of availability. Scheduled maintenance allows designers to improve system performance, but the interval between two consecutive scheduled restorations could be greater because condition-based maintenance is implemented at the same time.

More generally, the proposed approach guides designers to the choice of condition monitoring as long as it is possible to monitor the parameters that influence the component's wear-out. This condition is taken into account using fuzzy detection.

The complete results of the proposed fuzzy-based RCM procedure applied to the whole HVAC system installed on a high-speed train are illustrated in the pie charts in Figure 7.

Figure 7a shows the percentage of each assigned task with respect to the complete HVAC maintenance plan. It is possible to see that condition monitoring and failure finding procedures play a crucial role in the maintenance policies of the HVAC under analysis, with 44% and 25% of the tasks, respectively. On the other hand, only 3% of the failure modes are left to corrective maintenance (Run to Failure) because of the safety implications of many failures related to the ventilation system of the train. Due to the mechanical and hydraulic components included in the system, scheduled maintenance remains a considerable part of the HVAC maintenance plan. However, most of the time, scheduled maintenance is carried out along with condition-based maintenance, such as condition monitoring (10%) and failure finding (7%).

Table 2. Failure modes and effects analysis (FMEA) for an HVAC system installed on high-speed trains. The five considered components are compressor, ECC, watchdog, IGBT module and UPS.

Failure Modes	Failure Causes	Local Effects	Global Effects
Compressor: Increases the pressure of the refrigerant gas			
FM_C1	Motor seizes up Internal failure Blocked compressor Damaged winding	Loss of pumping capacity	Loss of cooling capacity in the cabin
FM_C2	Overheating of compressor Thermostat dirty	Loss of protection	Possible damage of compressor
FM_C3	Mechanical failure Fretting compressor	Loss of refrigerant pumping	Loss of cooling capacity in the cabin
FM_C4	Internal failure Valve dirty	Loss of refrigerant gas pressure	Loss of cooling capacity in the cabin
FM_C5	Motor short circuits Electric overload Compressor motor protection failure	Loss of pumping capacity and shortcircuit of compressor	Loss of cooling capacity in the cabin
Electronic Control Card (ECC): Regulate, monitor and diagnose the HVAC			
FM_E1	Short circuit ECC dirty Defect in printed circuit Overload of the ECC	Incorrect regulation of the temperature by the control card	Loss of cooling capacity in the cabin
Watchdog: Activates the emergency regulation mode			
FM_W1	Hardware failure Software failure	Incorrect regulation of temperature	Loss of emergency regulation capacity
IGBT module: Electronic switch used to control the compressor			
FM_I1	Overcurrent Overtemperature Secondary breakdown	Loss of pumping capacity and short circuit of compressor	Loss of cooling capacity in the cabin
FM_I2	Hot carrier injection Electromigration Temperature instability	Insufficient current to drive the compressor	Loss of cooling capacity in the cabin
UPS: Provides power for emergency ventilation if the overhead power line fails			
FM_U1	Electric failure Ageing battery units	Complete loss of functionality	Loss of emergency ventilation

Figure 7b summarizes the results comparing condition-based maintenance against scheduled maintenance and corrective maintenance. The results confirm how the proposed decision diagram privileges the choice of a diagnostic approach, with 86% of the maintenance task in the proposed plan including condition monitoring or failure finding procedures.

Finally, the results achieved using the proposed fuzzy-based method are compared with the results achieved for a maintenance plan for the same HVAC using the classic RCM, according to the international standard IEC 60300-3-11. For the sake of brevity, only an extract of the comparison is included in Table 4. Upon analyzing Table 4, the superiority of the proposed approach is extremely evident.

Table 3. Input parameters of the proposed fuzzy-based RCM approach. The failure modes refer to the preliminary FMEA report in Table 2.

Failure Modes	O	S	D	Is Failure Evident?	Impact on Safety?
FM_C1	High	Tolerable	Absolutely Uncertain	No	No
FM_C2	Remote	Very low	Almost certain	Yes	No
FM_C3	Probable	Tolerable	Medium	Yes	No
FM_C4	Probable	Tolerable	Almost certain	No	No
FM_C5	Remote	Tolerable	Almost certain	Yes	No
FM_E1	Probable	Tolerable	Medium	Yes	Yes
FM_W1	Probable	Tolerable	Absolutely uncertain	No	No
FM_I1	Remote	Critical	Almost certain	Yes	No
FM_I2	Remote	Tolerable	Medium	No	No
FM_U1	Probable	Critical	Almost certain	No	Yes

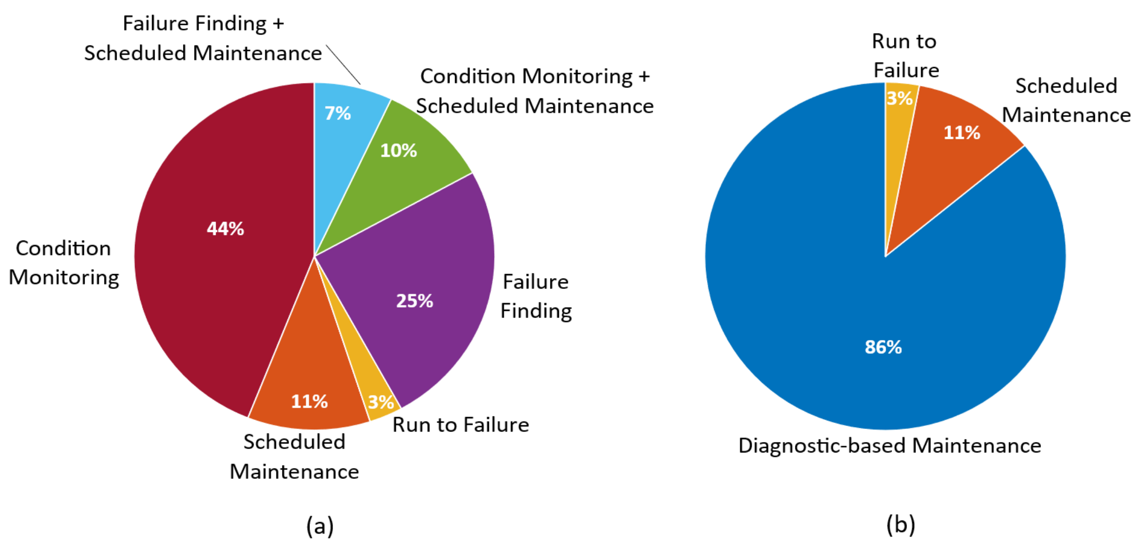

Figure 7. Summary of result achieved by applying the proposed maintenance decision diagram to the complete HVAC system under analysis. (**a**) Overall results of the proposed fuzzy-based RCM procedure. (**b**) Comparison between diagnostic-based maintenance, scheduled maintenance, and corrective maintenance.

Table 4. Extract of comparison between the proposed fuzzy-based RCM and the classic RCM assessed following the guidelines of IEC 60300-3-11.

Failure Mode	Selected Maintenance Task	
	Proposed Fuzzy-Based RCM	Classic RCM: IEC 60300-3-11
FM_C3	Scheduled Maintenance	Condition Monitoring OR Scheduled Maintenance OR Run to Failure OR Alternative actions
FM_I2	Failure Finding	Condition Monitoring OR Scheduled Maintenance OR Failure Finding OR Run to Failure OR Alternative actions
FM_U1	Condition Monitoring	Condition Monitoring OR Scheduled Maintenance OR Failure Finding OR Alternative actions

Using the fuzzy linguistic variables and the if–then rules, the proposed methodology assigns a unique maintenance task to each failure mode, while the classic RCM lets the designer select between at least four or five types of task without any further explanation on how to choose between them.

5. Conclusions

This paper focuses on the reliability evaluation and maintenance policy optimization of an HVAC (heating, ventilation and air conditioning) system used on high-speed trains. The HVAC is a critical subunit because proper air ventilation is mandatory to ensure the railway's safety requirements.

Reliability-centered maintenance is a widely used technique to select maintenance policies for every type of system, but the decision-making diagram included in the international standard IEC 60300-3-11 has a subjectivity problem: for each identified scenario, the standard gives users the possibility of choosing between many different options. This paper proposes an innovative diagnostic-oriented maintenance decision diagram based on classical FMEA and a fuzzy system. The proposed method implements a set of if–then rules that associate only one possible maintenance task to each failure mode identified by the FMEA.

The results of the HVAC case study indicate that the proposed framework is a powerful and effective solution; it can help designers determine the optimal maintenance plan for a system. Condition-based maintenance (both condition monitoring and failure finding) constitutes the largest part of its assessed tasks, with 86% of the tasks selected in the maintenance plan of the HVAC under analysis being diagnostic-based maintenance. As such, the proposed fuzzy-based approach helps to maximize availability and minimize operational cost. Users can monitor the health state of a system with a cost-efficient and cost-effective failure detection tool. Finally, a comparison between the proposed methodology and the classic RCM method emphasizes how the proposed approach mitigates the problem of subjectivity by directly assigning a unique maintenance task to each failure mode, while the IEC 60300-3-11 gives the designer the ability to choose between several options.

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