Fuzzy Predictive Maintenance for Railway Transport Networks

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Abstract: In railway systems, every equipment item requires maintenance, which in turn can affect the availability of a certain machine and the planned transport schedule. This paper aims to provide a method for integrating the maintenance operations into railway transport networks based on fuzzy logic. The proposed approach allows the insertion of daily or weekly preventive and corrective maintenance operations when the rolling stock is available, in order to minimize downtimes, avoid disastrous scenarios and preserve the transport network's stability and safety. Two algorithms were established for inserting the planned machine recovery tasks into the Sahel metro's availability periods, with or without the modification of the initial scheduling solution. Further on, an illustrative example is provided in order to highlight the efficiency and accuracy of the newly developed approach for a real railway system. The findings of this paper reveal that fuzzy logic can also be applied to sustain the travel process in the degraded modes of operation, while guaranteeing satisfactory traffic quality and safety levels for the customers by incorporating experts.

Keywords: Fuzzy logic, Maintenance scheduling, Safety, Railway transport networks.

1. Introduction

Maintenance is an indispensable activity within a company, its primary objective being to guarantee the operational functionality of the industrial system.

The most traditional and pervasive approach to maintenance is the "fix it when it breaks" strategy.

Traffic volume and customer expectations have increased gradually over the last few years. Significant efforts are being made to enhance the capacity and quality of the transportation system. The management of these systems is becoming challenging in light of the safety requirements (Mellouli et al., 2024; Huang et al., 2020).

The issue of maintenance scheduling in the context of unforeseen occurrences is of paramount importance for the effective deployment of real-time scheduling systems.

The objective of this paper is to present a methodology for maintenance scheduling based on fuzzy logic in a railway system that inserts an unexpected event into the systematic maintenance scheduling proposed by the train builder.

The remainder of this paper is structured as follows. Section 2 locates the proposed scheduling approach among the state-of-the-art approaches, while Section 3 gives a comprehensive account of the maintenance approach under consideration, including a detailed overview of its underlying principles and an in-depth analysis of its framework.

Section 4 sets forth a novel approach that incorporates fuzzy logic and maintenance scheduling.

Further on, Section 5 presents an illustrative example to demonstrate the strength of this approach, along with a discussion of the findings. Finally, Section 6 presents the conclusion of this paper and possible future research directions.

2. State of the Art

In the context of railway transportation networks, breakdowns are inevitable, particularly in modern Electric Multiple Units (EMUs). Researchers and manufacturing practitioners are keen to keep these units in perfect working order. Few research projects have focused on Integrated Maintenance Scheduling (IMS) to enhance EMU availability (Çınar et al., 2020). Some research projects have focused on the railway transport systems maintenance to save time and enhance the rail-based public transportation service quality (Arena

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et al, 2021), (Mahmoud et al., 2021), (Binder et al., 2021).

Veloso et al. (2022) outlines the MetroPT dataset, the outcome of a predictive maintenance project with the Porto metro, an urban public transport service in Portugal. The data was gathered in order to apply machine learning methods for online anomaly detection and fault prediction. Multiple analog sensor signals, and digital signals and the GPS information provide a readily usable background for the future development of machine learning methods. Similar applications using deep learning are mentioned in (Davari et al., 2021a).

The study of Davari et al. (2021b) proposes a data-driven predictive maintenance framework for an air production unit (APU) system of a Porto metro by deep learning based on a Sparse Autoencoder (SAE) network ensuring the abnormal data detection and reducing false alarms rate. In this study two SAE network versions have been implemented in order to introduce analogue and digital sensor data, and the experimental findings demonstrate that faults related to air leak problems are accurately predicted by the analogue sensor data, whereas digital sensor data identifies other fault patterns.

Another study using a thermographic approach is that of Karakose & Yaman (2020) for predicting the maintenance of electric railroads, using a complex fuzzy system. This approach is based on a complex fuzzy approach, since maintenance estimation methods for railway systems are subject to seasonal weather conditions, environmental factors, daylight and, above all, periodical effects such as the train's velocity.

Ciani L. et al. (2021) present an innovating fuzzy method for human factor evaluation in safety-critical systems for solving traffic problems in railway applications. Fuzzy logic enables the evaluation of model parameters based on linguistic variables closer to the human learning process and simplifies the process. In this study, fuzzy logic deals with incomplete and uncertain data and minimizes the analyst's subjective evaluation. The proposed algorithm's output is generated by fuzzy interval arithmetic, the α-cut theory and the centroid defuzzification procedure.

The purpose of the study of Zavareh et al. (2023) was to use Genetic Algorithms (GA) in railway companies for maintenance scheduling optimization with regard to emergency rescue wagons. In this study an integrated model is suggested for simultaneously performing scheduling, preventive maintenance and resource planning and providing prognostic information, on which basis the optimal system performance levels with respect to the operating costs and the repair time are determined.

The work of Catelani et al. (2020) was committed to the maintainability assignment procedure. In this study, four approaches are discussed (the failure rate-assignment method, the failure rate-performance trade-off-assignment method, the interval-analysis-based fuzzy maintainability assignment method and the time-based MA model). The conventional methods are marked by a number of drawbacks; consequently, the emphasis is on the temporal-feature-based method, proven to be better than the other methods and the most comprehensive one, as it does not feature the drawbacks of the other three methods.

The proposed article is a contribution to the current state of the art in railway maintenance scheduling and it deals with a time-limited ownership situation. Concretely, the interval when the rolling stock is available for performing the maintenance operation belongs to a time window.

Given the suggested maintenance strategy, this study provides an appropriate response for railway infrastructure managers in the context of an increased train path demand and extended operating time requirements, restricting the access time with regard to the maintenance infrastructure.

The study's contributions include the development of a new recovery strategy incorporating the rolling stock age and the journey cycle times, and, as regards the maintenance scheduling process, a newly devised fuzzy approach is proposed, enabling daily and weekly maintenance tasks to be incorporated into the machine availability schedule.

3. The Proposed Maintenance Approach

3.1 The Maintenance Principle

The maintenance principle, which is designed with the objective of ensuring the long-term functionality, dependability, and operability of technical and industrial systems, represents a fundamental tenet of system administration. It encompasses a collection of policies and procedures, grouped around three primary concepts: corrective, predictive, and preventive maintenance.

The overarching objective of the maintenance principle is to achieve a state of equilibrium between the reduction of operating costs and the enhancement of asset performance and availability. In an industrial context, a well-designed approach has the potential to significantly impact long-term productivity and competitiveness.

3.2 The Framework of the Proposed Maintenance Approach

A maintenance strategy can be split up into three main categories: predictive, preventive and corrective maintenance. Figure 1 depicts the maintenance policy classification.

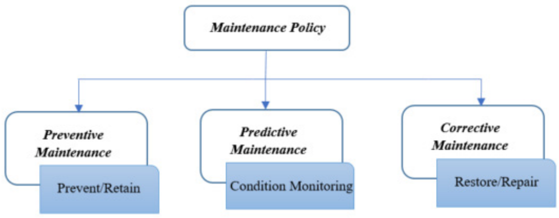

Figure 1. Maintenance Policy

Figure 2 (the scheduler) illustrates the maintenance scheduling principle or the supervisory approach to maintenance for a railway system, focusing on the potential occurrence of an emergency event.

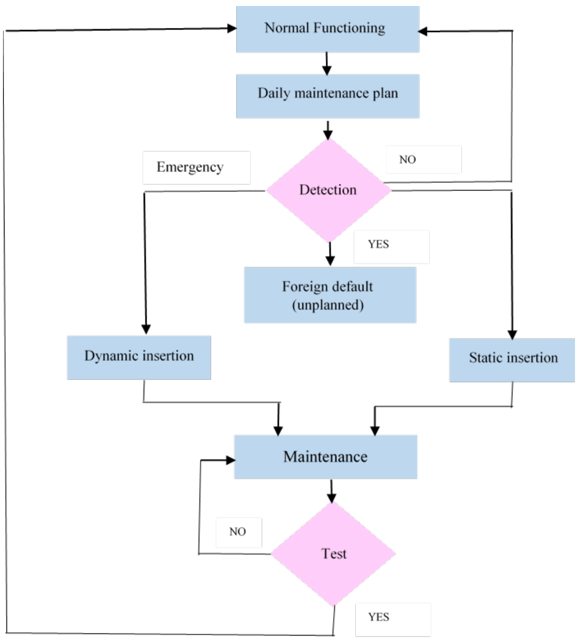

Figure 2. Maintenance scheduling principle

The developed algorithm dynamically updates the maintenance schedule to reflect new logbook data, ensuring all the required tasks below are performed in a timely and efficient way:

1. Moving the EMUs on the transport network;
2. For the appropriate EMU, performing all the maintenance activities according to the initial schedule;
3. Checking the logbook reports while the maintenance tasks are performed;
4. If a new alarm is detected while carrying out maintenance, dynamically inserting this job in the current EMU maintenance schedule;
5. Carrying out the new recovery task, while respecting the time constraints and task priority;
6. Repeating the remaining maintenance activities according to the initial schedule. The remaining maintenance tasks are TESTED, taking account of their severity and the time constraints;
7. This process is repeated for all EMUs in the network.

The flow chart in Figure 3 illustrates the maintenance process for each EMU, executing each task that was initially scheduled.When all tasks are accomplished or no new reports are generated, the maintenance process is terminated.

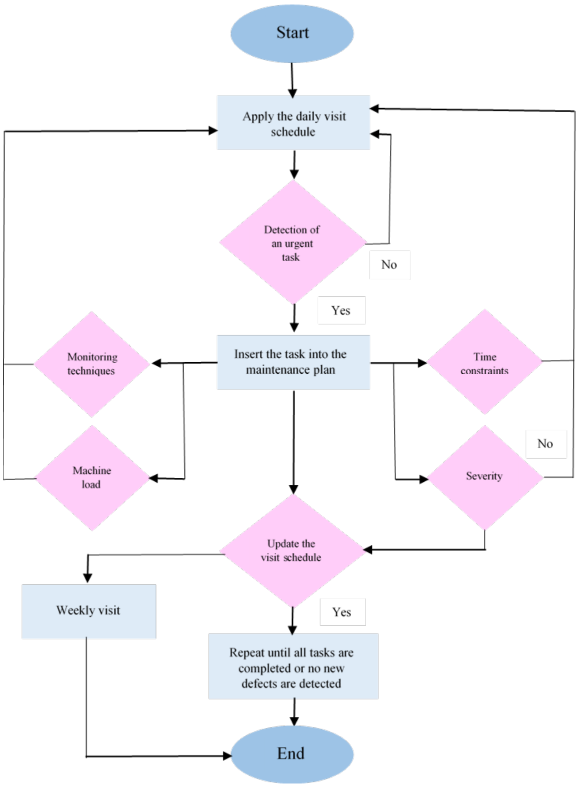

Figure 3. Dynamic insertion algorithm principle

Once a new and urgent task is identified, the process is implemented against four main criteria: the time constraint, the task severity, the monitoring techniques and the machine load.

3.2.1 Time Constraint

If an emergency task can be performed without affecting the initial schedule, it is integrated immediately.

If an urgent task needs more time to be carried out, despite disrupting the given schedule (delayed metro departures, traffic disruption etc.), it is given priority.

If an emergency duty is not accomplished, it may be deferred, for instance, to weekly visits.

3.2.2 Task Severity

If a task is only slightly severe, the initial schedule for the daily visit is preserved.

In moderate cases, where there are doubts regarding the task's impact, it may be treated as a delayed weekly visit.

In cases of critical severity, the work task should be carried out immediately, leading to disruptions in the daily visit program and traffic.

3.2.3 Monitoring Techniques

The monitoring methods are crucial for dynamic maintenance scheduling. They enable the detection, analysis and prediction of potential equipment defects, thus contributing to an improved intervention planning.

In doing so, these monitoring tools not only detect potential issues in advance of their becoming critical, but they also allow preventive and corrective maintenance operations to be scheduled more accurately. By incorporating these techniques into the dynamic planning flowchart, the maintenance planners can increase equipment reliability, reduce unplanned downtime and maximize resource efficiency.

3.2.4 Machine Load

Equipment loading is a fundamental issue in rail maintenance dynamic planning. The concept relates to equipment and infrastructure usage within the rail network, both in its current state and in relation to projected developments. An accurate equipment load assessment enables maintenance priorities to be optimized, according to its impact on the train operation and the rail system's overall efficiency. The result is a more efficient resource allocation whilst keeping service disruption to a strict minimum.

4. Fuzzy Sets and Maintenance

Fuzzy logic provides a flexible reasoning because:

- It enables the variables discourse to be swept up by the universal quantifier ∀ or the existential quantifier ∃;
- It enables a qualitative description of truth-value by incorporating the 'possibility' concept;
- It uses deductive rules that finally prove conventional logic.

4.1 Dynamic Insertion Algorithm for Maintenance Tasks

The integration process involves providing a new 'O_{ij}' operation sequence (operation i associated with job j) for a scheduling problem. This new integration must therefore resolve a new scheduling problem whilst reducing the integration's impact on the total time and traffic cost. The objective of dynamic insertion is to maximise rolling stock availability and to reduce the unexpected failure costs. The insertion of an 'O_{ij}' operation into the initial schedule meets the following conditions: There is no change in the scheduled operation distribution, No violation of the scheduled operation end dates.

In this paper, the integration approach will be applied to the scheduling and management of maintenance operations for a real railway line.

The following notations are used to describe the problem analysed throughout the paper:

- h: Index for rolling stock, $h = 1, \ldots, H$, here H is the number of subways;
- j: Index for job, $j = 1, \ldots, J$, where J is the number of jobs;
- i: Index for Maintenance Operation (MO), $i = 1, \ldots, I$, where I is the number of operations;
- ST_j :Starting time of job j on subway h;

- ET_j: Ending time of job j on subway h ;
- ST_{MO} : Starting time of the maintenance operation ;
- ET_{MO}: Ending time of the maintenance operation;
- A_h : Availability interval for rolling stock h.

$$P_{MOh} = \begin{pmatrix} 1\ Possibility\ of\ insertion\ of\ MO \\ for\ rolling\ stock\ h \\ \\ 0\ otherwise \end{pmatrix} \quad (1)$$

$$O = \begin{pmatrix} sup_h(\sum_{j=1}^{J}(ET_j - ST_j))\ if\ job\ j\ occupies\ the\ largest \\ time\ slot\ on\ subway\ h \\ 0\ otherwise \end{pmatrix} \quad (2)$$

In order to insert the projected jobs in periods of subways availability, without changing the initial scheduling solution, a recursive algorithm based on the priority of the machine with the Highest Operating Lead Time (HOLT), is proposed:

Algorithm. Dynamic Insertion Procedure

For (i = 1; i< I); P_{MOh}= 0; A_h=∅
For (h = 1; h< H)
If
{
$O = sup_h(\sum_{j=1}^{J}(ET_j - ST_j))$
$MO_h \subset A_h$ (The duration of operation insertion corresponds to the period of metro availability)
Time constraints are verified
then
$P_{MOh} = 1; MLTH = \sum_{i=1}^{I}(ET_{MO} - ST_{MO})$
(maintenance lead time for a metro h)
}
End
Insert a maintenance operation on the metro h(MOh)
End

Redo the same procedure for the entire rolling stock.

The dynamic insertion algorithm is employed in order to insert a new maintenance task, considering the emergency parameter as a criterion.

Considering that a set of maintenance tasks is performed during a given night, it makes sense to look for a better solution in the neighborhood of the solution provided by the proposed insertion algorithm, using a genetic algorithm or simulated annealing.

The algorithm presented in the current paper is at least a functional specification for integrating local knowledge in the existing maintenance rules provided by the train builder.

It is evident that this technique has considerable potential for application in dynamic control and supervision, with the ability to preserve human operators, incorporate their reasoning and enable a good traceability.

Fuzzy sets are an extended form of classical set theory that models uncertainty by attributing to each item a membership degree between 0 and 1. In maintenance, this approach is employed for managing condition uncertainties, thereby improving the accuracy of diagnostics and the effectiveness of maintenance strategies.

The fuzzy set theory provides a generalized approach to conventional two-valued sets, with a membership function to manage the partial truth concept. This aids the modeling of uncertainties in natural language, where vague linguistic terms, such as “very” or “probably” describe vague situations. Fuzzy sets and fuzzy reasoning systems provide computer systems with the ability to handle these imprecise terms. The approach is particularly valuable for modeling uncertain or ambiguous data, and for describing complex dynamic systems using fuzzy if-then rules.

In a fuzzy set A, each element x of the universe X is assigned a degree of membership to the set, as determined by a membership function $\mu_A(X)$ where $\mu_A(X)$ takes values in the interval [0, 1]:

$$\mu_A : X \to [0,1] \quad (3)$$

$$\mu_A(X) = 0 \quad (4)$$

This indicates that x is not a constituent of the fuzzy set A.

$$\mu_A(X) = 1 \quad (5)$$

This indicates that x is entirely associated with A.

$$0 < \mu_A(X) < 1 \quad (6)$$

This indicates that x is, at least in part, an element of A.

4.2 Fuzzy Inference System

The inference mechanism employs fuzzy logic, membership functions, logical operations and if-then rules to establish a connection between a given input and an output. The process of mapping combines fuzzy inputs derived from the Fuzzification process with a rule base, in order to produce a fuzzy output for each rule (Figure 4)

The FIS system comprises four constituent elements: fuzzification, the fuzzy rule set, the inference method, and defuzzification, where fuzzification converts a numeric input variable into a fuzzy subset, inference generates the fuzzy output subset by mapping the input-output variable dependency into a fuzzy rule base, and defuzzification turns the fuzzy output subset into a closed numeric variable.variable.

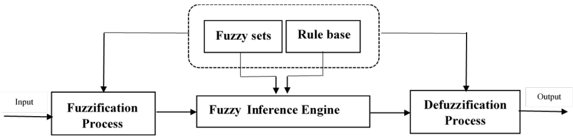

Figure 4. Fuzzy Logic Inference System

4.3 Fuzzification of the Input and Output Variables

Railway transport is subjected to many uncertainties associated with processes, customers or disturbances (strikes, weather conditions etc.). Rail traffic is seldom perfectly repetitive. All authors who tackle uncertainties have considered two major disruptions: equipment-related disruptions, and more specifically equipment breakdowns and operating time changes. Possibility functions have been developed to represent the uncertainty of the various parameters (severity, failure cost, machine load etc.). These functions reveal the certainty zones for an operating interval and enable the operator (or supervisor) to identify failures and to decide on reconfiguration/repair actions.

Figure 5 shows the sets of fuzzy logic membership functions, each one describing fuzzy variables related to a maintenance process. Every variable is described by membership functions with different grading levels.

Each graph represents a membership function for a specific variable. This enables a quantitative variable to be converted into a qualitative assessment. For instance, the variable 'time constraint' has several categories, such as 'very low' to 'very high', and each input value is allocated a fuzzy membership function.

These membership functions are frequently employed in fuzzy decision systems to define if-then rules.

4.4 Inference Mechanism

The dynamical behavior of a fuzzy system is generally characterized by a set of fuzzy linguistic rules. Fuzzy sets, fuzzy logic and fuzzy inference are involved in these rules by using linguistic if-then statements.

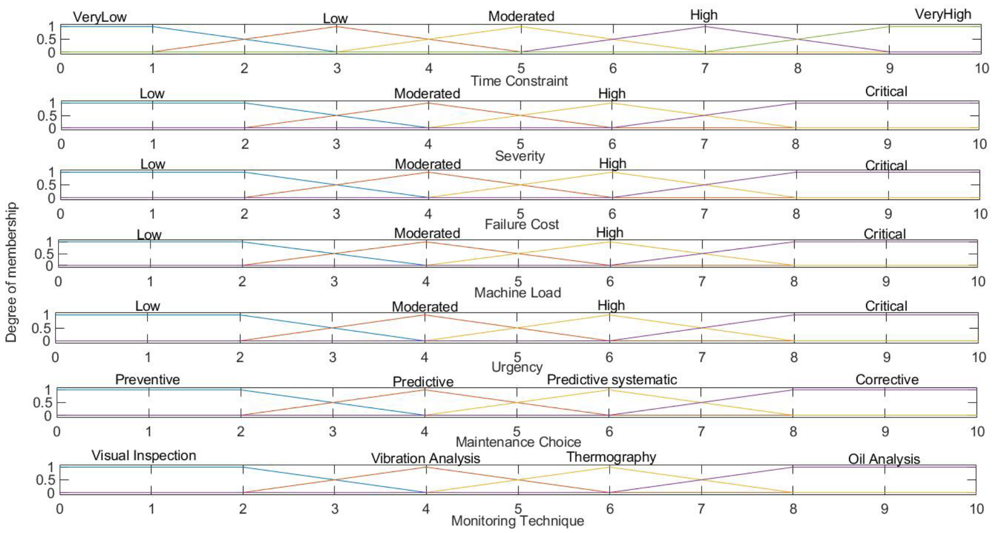

Figure 5. Fuzzification of the Input and Output Variables

These rules are founded on the human expert's knowledge and experience in the relevant domain. The fuzzy rule pattern is usually presented in a general form:

IF a is A AND ...AND B is b THEN y is Y,..., AND x is X

4.5 Defuzzification

The defuzzification process is a mathematical procedure that is employed for the purpose of converting a fuzzy set into a real number. In order to arrive at a single output number for a fuzzy system, the fuzzy sets generated by fuzzy inference in fuzzy rules must be mathematically combined. In the case of a fuzzy system with multiple output variables, defuzzification is calculated for each of them individually, albeit in a manner that is largely analogous.

There are several varieties of defuzzifiers. The most widely applied defuzzification techniques

are Mamdani's fuzzy inference method and the Centre of Gravity modelling technique.

In order to implement the Centre of Gravity Method, it is necessary to utilize a fuzzy controller to output y. Let's assume there are n membership values, $\mu_1,...,\mu_n$, for n singleton output fuzzy sets in the rules (one value per rule). It is assumed that these fuzzy sets are nonzero only at $\alpha_1,....,\alpha_n$. The following defuzzification output is produced by the defuzzifier:

$$y = \sum_{i=1}^{n} \frac{(\mu_i \alpha_i)}{\mu_i} \tag{7}$$

5. Illustrative Example

5.1 Presentation

The Sahel Railway Network is a crucial element of the Tunisian railway network, providing service to the Sahel region of the coast, which includes the cities of Sousse, Monastir, and Mahdia. This area is notable for its high population density and economic importance, and is famous for its tourism, agriculture, and industrial activities.

Establishing a connection between Sousse, Monastir, and Mahdia and their surrounding areas is essential. The Tunisian National Railway Company (SNCFT) has been responsible for overseeing the operations, maintenance, and future expansions of the Sahel Railway Network.

The Sahel Metro railway line spans 70 kilometres, with two sections that span 47 kilometres each between Sousse Bab Jedid and Moknine and a 23-kilometer segment from Moknine to Mahdia.

The Sahel Metro runs 44 daily trips with an average frequency of 40 minutes, starting at 05:00 and ending at 22:00. This service carries over 9 million passengers annually, with an average of around 27,000 passengers per day. The Sahel-Tunisia railway line between.Mahdia.and Sousse.stations is illustrated in.Figure 6 which also includes the stations between them and the related travel times.

By continuously striving to enhance service quality, the Sahel Metro aligns with its strategic goals and prioritizes customer satisfaction. This involves actively listening to travellers promoting dialogue, and establishing mutual trust. In addition, train station spaces are energized through cultural events, creating a more engaging and pleasant environment for passengers.

Figure 6. Sahel railway network (Mellouli et al., 2024)

5.2 Fuzzy Logic and Railway Transport

Railway transport can be impacted by numerous uncertainties that involve operational processes, passengers, and disruptions such as strikes or adverse weather conditions. Rail traffic tends to follow a non-repeating pattern. Two primary types of disturbances are frequently discussed in the study of these uncertainties: equipment-related disturbances, specifically breakdowns, and traffic-related disturbances, such as changes in operating times.

Fuzzy sets are an extension of classical set theory employed for modeling uncertainty and imprecision in complex systems. This approach is particularly useful in contexts where the boundaries between classes are not clearly defined, such as in maintenance problems.

In maintenance, the uncertainties inherent to degradation processes, failure diagnosis and system maintenance decision-making can be better controlled with fuzzy sets. Instead of classifying equipment as simply 'good' or 'bad', for example, a fuzzy set model is able to provide an evaluation of the equipment status throughout a continuum, allowing optimized decisions to be taken when scheduling interventions. This improves both the reliability and effectiveness of predictive and preventive maintenance strategies by integrating the uncertainty and variability of operating data.

In this study, predictive maintenance techniques are employed for improving the reliability of railway equipment and maintaining traffic operations under various conditions. This paper highlights the significance of predictive maintenance in ensuring the sustainability of rail traffic, including the degraded modes of operation, while maintaining satisfactory quality and safety levels.

5.3 Case Study

The effectiveness of the proposed fuzzy predictive maintenance approach is demonstrated through an example based on five fuzzy rules, namely:

1. If the time constraint is Very Low, the task severity is Low, failure cost is Low, and the machine load is Low, then the urgency is Low, the maintenance choice is Routine, and the monitoring technique is Visual Inspection;
2. If the time constraint is Low, the task severity is Moderated, the failure cost is Low, and the machine load is Low, then the urgency is Moderated, the maintenance choice is Preventive, and the monitoring technique is Vibration Analysis;
3. If the time constraint is Moderated, the task severity is High, the failure cost is Low, and the machine load is Low, then the urgency is High, the maintenance choice is Predictive, and the monitoring technique is Thermography;
4. If the time constraint is High, the task severity is Critical, the failure cost is critical, and the machine load is high, then the urgency is Critical, the maintenance choice is Corrective, and the monitoring technique is Oil Analysis;
5. If the time constraint is Very High, the task severity is Low, the failure cost is Low, and the machine load is moderated, then the urgency is Critical, the maintenance choice is Corrective, and the monitoring technique is Oil Analysis.

In this subsection, specific monitoring methods are presented which, although not of scientific interest, are helpful in explaining the use of fuzzy technology.

The membership functions for the various variables employed in the fuzzy logic system, which is employed for assessing the maintenance task emergencies, are illustrated in Figure 7.

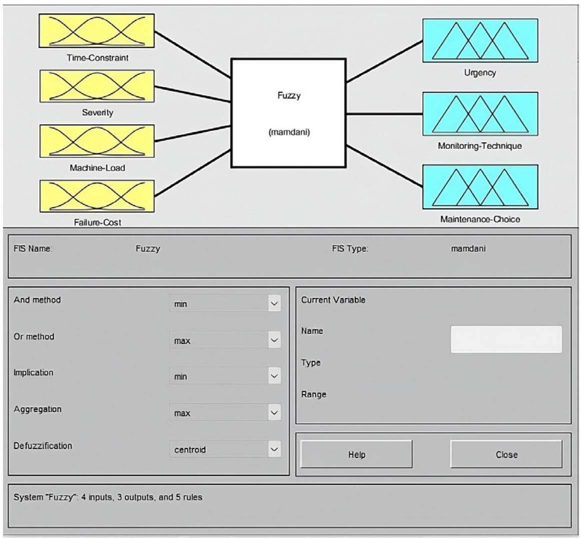

Figure 7. The Mamdani fuzzy inference method

The Mamdani's fuzzy logic system enables the dynamic management of the maintenance tasks, taking into account multiple factors with imprecise or uncertain values. The system is designed to provide responsive and effective recommendations based on vague rules and logical inferences, which enables it to accurately classify tasks, plan time and resources, and allocate them effectively.

Each rule uses the AND operator in the premise; hence, the MIN function is applied (the Mamdani inference method). The output variables, corresponding to the five previously-mentioned fuzzy rules, are illustrated in Figures 8, 9 and 10.

Figure 8 shows a 3D surface from a fuzzy logic model, most likely created using MATLAB's Surface Viewer tool as part of a Fuzzy Inference System (FIS).

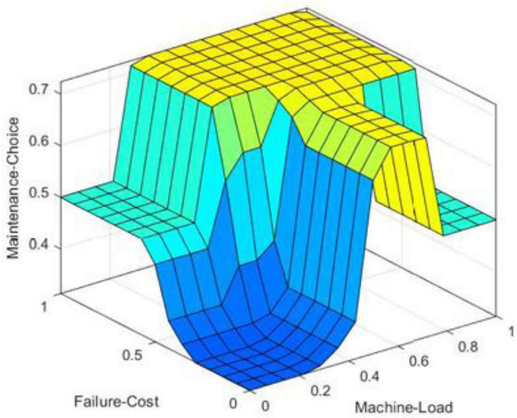

Figure 8. Three-dimensional trapezoidal membership function: Maintenance choice = f (failure cost, machine load)

It can be clearly established that for a low machine load or a low failure cost, the model suggests a low maintenance necessity (low Z-axis values).

However, for a higher machine load or failure cost values, the model output (maintenance choice) rises, potentially indicating a maintenance recommendation.

The simulation illustrated in Figure 9 reveals that the emergency procedures can be adjusted according to the machine's load and the task severity. This simulation provides a decision-making framework for optimizing machine maintenance and resource management in an industrial environment. The findings indicated that the combination of machine overload and serious problems significantly increased the intervention urgency. In particular, the urgency becomes higher as the load and task severity increase.

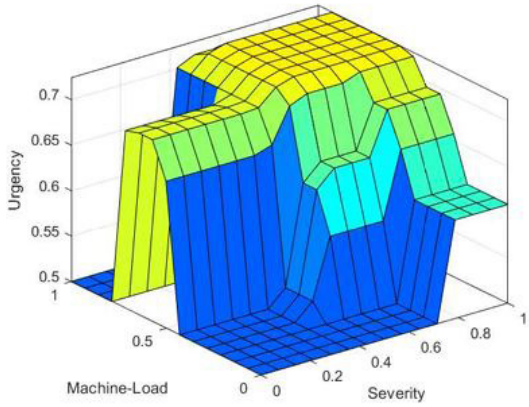

Figure 9. Three-dimensional trapezoidal membership function: Urgency = f (severity, machine load)

This simulated model in Figure 10 represents a useful application of fuzzy logic for monitoring level modulation. This framework provides a model that can be employed in order to enhance the effectiveness of predictive maintenance effectiveness, with specific reference to the monitoring techniques, to reduce downtime and extend the rolling stock service life.

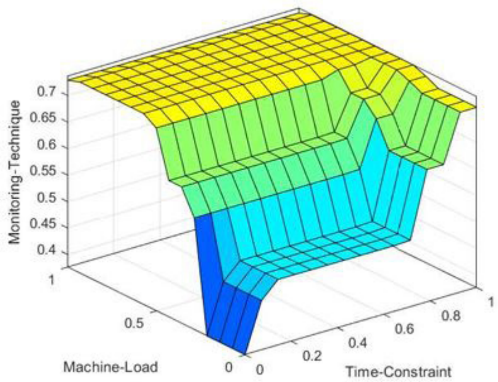

Figure 10. Three-dimensional trapezoidal membership function: Monitoring Technique = f (time contraint, machine load)

The model demonstrates the impact of time constraints and machine load on the monitoring techniques. In industrial contexts where machinery is subject to significant constraints, this type of fuzzy model contributes towards determining the maintenance priorities and allocating resources more efficiently.

6. Conclusion

The term "fuzzy" is used to describe the capacity to handle inputs that are imprecise or vague. In contrast to the use of intricate mathematical formulae, fuzzy logic control employs linguistic descriptions that establish a connection between input data and the resulting actions.

The fuzzy control method may be employed in instances where the control processes are too intricate to be evaluated through conventional quantitative methods, or when the available data is interpreted qualitatively, inexactly, or with uncertainty. In comparison with the alternative methodologies for addressing uncertainty, the fuzzy controller features a number of advantages, including the fact that it needs fewer computational resources to be implemented.

The aim of this paper is to explore the development and implementation of maintenance algorithms for modern railway systems, and of the effective strategies for performing urgent maintenance tasks. The simulations carried out and the obtained results highlight the effectiveness of the proposed approach in a maintenance task integration scenario.

To that, the Simulations have shown that the proposed algorithm and task insertion methodology is also viable: the dynamic fuzzy logic approach has a significant advantage in terms of responsiveness and flexibility.

In the future, the proposed maintenance approach could be employed in combination with other classical or deep learning approaches.For example, classification techniques, potentially combined with industrial vision technoogy. To that, a specific failure of a local railway line may be totally or partially covered by the maintenance rules provided by the train builder (Mihuleț et al., 2025). In this sense, the introduction of an Ai-based approach can complement the proposed Fuzzy Maintenance approach by providing high-quality input data to improve the accuracy and efficiency of the FIS. This blend of advanced sensing technology and fuzzy logic principles can potentially lead to a more robust and adaptive railway monitoring and control system.

The proposed fuzzy maintenance approach can definitely be extended to other networks. However, it fails to cover two issues. The first is the fault progression: the process of identifying, extracting or quantifying damage is not straightforward. The second aspect is the degradation process. It is impossible to anticipate the deterioration of a component which is beyond repair, as it may be unsafe to operate under such conditions.

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