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Optimizing of Railway Maintenance Activities Using Fuzzy Logic: An Intelligent Approach for Improved Reliability

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Abstract

Transport system efficiency is a fundamental and strategic issue for all transport companies. The ability to adapt transport networks reliably is crucial as demand fluctuates, specifications shift and traffic specificities cannot be neglected. Uncertainty, ubiquitous in rail transport networks, complicate this task even further. These uncertainties can manifest themselves in a variety of ways: unexpected fluctuations in journey times, rolling stock failures or the emergence of additional traffic tasks that could not have been anticipated in the initial scheduling process. Each type of uncertainty creates a potential risk related to system imbalance, which requires rapid and complex adjustments to guarantee rail traffic availability and stability. These maintenance scheduling issues in rail transport systems demand planning approaches that extend beyond traditional techniques. It is crucial to evolve maintenance scheduling tools able to manage scheduling under stable conditions, as well as to effectively respond to unexpected disruptions and quickly shifting traffic conditions. This paper addresses these challenges problem and proposes a reliable and robust maintenance policy taking account of tasks imprecision and human expertise. The maintenance model is designed to assist decision making systems to increase traffic safety significantly, while saving time and money. To resolve this problem, a fuzzy inference system is used to appropriately deal with uncertainties using Colored Petri nets and fuzzy logic. The findings indicate that the adaptive fuzzy model developed has an excellent ability to precisely learn and predict traffic constraints and lead to significant changes in decision making and the incorporation of feedback into the management and support system.

Keywords: Fuzzy logic, railway maintenance, reliability, predictive maintenance, Colored Petri Nets, frugal exploitation.

1 Introduction

Transport infrastructure is identified as playing a crucial role in the dynamics of economic development in Europe. It is vital to acknowledge the significance of these as a means of enhancing regional competitiveness, promoting regional cohesion and

improving economic attractiveness. This is achieved by facilitating the mobility of people and goods. In light of these considerations, Thevenin et al. underscore the pivotal role of transport networks in shaping urban structure, commencing with an examination of long-term accessibility. The study indicates that this approach may be applicable to other national contexts and networks, consistent with Vickerman's (1995) findings that infrastructure is crucial for analysing varied development across a European scale [15].

The importance of regional and secondary rail lines, which had previously been overlooked, is now widely acknowledged as a fundamental component of the region's infrastructure. The development of these technologies has become a matter of European concern, necessitating the implementation of appropriate and sustainable economic models.

The desert areas of the Mediterranean region, which are often located in close proximity to the sea, expose railway infrastructure to severe environmental conditions. In France, the Salin-de-Giraud line is a pertinent example, as are certain lines in Tunisia, which are located in close proximity to saline areas. These environments give rise to specific maintenance requirements, particularly due to the presence of salt, a corrosive agent.

In addition to that, it is important to note that the maintenance instructions supplied by Hyundai are based on generic standards, which are illsuited to these particular conditions. In Tunisia, measures have been implemented to adapt these recommendations to the local context. A parallel strategy could be adopted in Europe, where analogous circumstances prevail.

In summary, regions are facing climate-related challenges for their railway infrastructure.

The Sahel, however, faces a more severe and complex set of climate-related challenges, coupled with existing socio-economic vulnerabilities, making the development and maintenance of a resilient railway network a significant undertaking. It is used as a benchmark case study to demonstrate a regionally adapted maintenance strategy.

However, as these systems expand in scale and complexity, ensuring operational reliability, availability, and safety becomes progressively challenging. This is especially pertinent in light of the aging infrastructure and the increasing demand for services. Conventional maintenance strategies, including corrective maintenance and time-based preventive measures, often prove inadequate in dealing with the dynamic, unpredictable, and simultaneous nature of railway operations[1]. This results in resource inefficiencies, unanticipated system failures and heightened maintenance costs. The advent of Industry 4.0 technologies, including the Internet of Things (IoT), big data analytics, and cyber-physical systems, has introduced new prospects for the modernization of maintenance practices. The utilisation of artificial intelligence (AI) methodologies has emerged as a pivotal element in this transformation, promising to facilitate predictive and adaptive maintenance management. Among the various AI techniques, fuzzy logic has demonstrated its efficacy in managing imprecision and uncertainty, offering a flexible decision-making framework that is based on linguistic variables and expert knowledge. The allowance of evaluations of a more nuanced nature pertaining to maintenance factors, including but not limited to fault severity, time constraints, potential failure costs and machine load, is a characteristic of fuzzy systems. This property enhances the adaptability and realism of maintenance planning. In order to manage maintenance effectively, it is essential that modeling tools are capable of capturing the concurrency, synchronization, and variability involved in maintenance processes. Using Colored Petri Nets (CPNs) as a modelling tool for such systems open the door to powerful analyses. Coloured tokens, each encoding a detailed attribute, has been demonstrated to empowered the flexibility of CPNs as a structured yet adaptable methodology in the representation of dynamic workflows, the management of resource allocations, and the handling of concurrent events within complex maintenance operations.

Though fuzzy logic and coloured Petri nets have been used separately in several industrial sectors, the integration of both approaches for railway maintenance optimisation remains unexplored. The purpose of this study is to overcome this deficiency by including fuzzy inference mechanisms for hierarchical task scheduling in coloured Petri net modeling for dynamic maintenance process management. The aim of this approach is twofold: Firstly, to enable flexible decision-making in uncertain circumstances as well as, secondly, to improve railway maintenance operations. In addition, the approach aims to ensure coherent and efficient scheduling and task execution. A case study based on the Tunisian railway network validates the proposed methodological approach.

Although fuzzy logic and Petri nets have both been applied in isolation to industrial and transportation systems, the integration of these approaches within a unified decision-support model remains uncommon, particularly in the context of railway maintenance scheduling under uncertainty. The present paper introduces a hybrid Fuzzy–CPN framework that combines the reasoning flexibility of fuzzy inference with the dynamic modelling capacity of Colored Petri Nets. This integration facilitates the system's capacity to manage linguistic uncertainty during the modelling of concurrent and real-time maintenance operations. It is acknowledged that the application of such a hybridisation in this particular domain has not been previously documented.

In this study, the focus is on defect prioritization, dynamic task insertion and maintenance execution process optimization. The paper is organized as follows. Section 2 provides an overview of the most relevant contributions to intelligent maintenance management. Section 3 details the integrated framework proposed, with particular emphasis on the fuzzy inference mechanism and dynamic modeling of the maintenance process using colored Petri nets. Section 4 introduces the experimental set-up, followed by a comprehensive discussion of the simulation results generated from a Tunisian railway network case study. A detailed review of the main results is provided in Section 5, highlighting the approach's strengths and limitations. Moreover, the results' practical implications are explored, providing valuable insights for further research and application. Finally, the paper concludes with a discussion of potential directions for future research.

2 Related Work

In order to ensure the continuity of service, the safety of the system, and the reliability of the infrastructure, it is imperative to schedule maintenance in railway networks in an efficient manner. In light of the escalating intricacy of railway operations, the mounting constraints on resources, and the diminishing intervention windows, researchers are undertaking endeavours to explore intelligent maintenance strategies that are equipped to manage uncertainty and dynamic reallocation.

The potential of fuzzy logic to model human reasoning and to manage imprecise information has led to its widespread application across multiple sectors, including transportation, manufacturing, and automation. Decision-making processes within the domain of railway operations have witnessed the integration of fuzzy logic, a mathematical paradigm that deals with imprecise information, to facilitate a range of critical functions. These functions encompass customer classification, route selection, energy consumption forecasting and risk evaluation, particularly in contexts characterised by uncertainty. Its adaptability is especially useful in maintenance scenarios where the variables of failure severity, urgency, and resource availability are difficult to quantify accurately [2, 3].

Furthermore, the utilisation of Coloured Petri Nets (CPNs) in conjunction has been identified as a significant tool in the modelling of discrete, event-driven systems involving concurrency, resource sharing, and conditional transitions . The utilisation of Petri nets has been demonstrated as a successful methodology in simulated maintenance workflows, the optimisation of task sequences, and the evaluation of system performance under operational constraints in numerous studies. In the context of railway control models, train tracking and dynamic task reallocation systems, for instance, Petri nets can be employed, providing validation capabilities and enhanced process visibility [4, 5].

In the recent literature, there has been an exploration of hybrid models that combine the use of fuzzy analysis with Petri nets, or with learning-based algorithms for the purpose of predictive maintenance. The efficacy of adaptive neuro-fuzzy inference systems (ANFIS) in identifying nonlinear degradation patterns has been well documented; meanwhile, the success of fuzzy expert systems in balancing sustainability, cost, and operational constraints is equally noteworthy. In the field of rail infrastructure analysis, fuzzy clustering has emerged as a methodology for the categorisation of railway track conditions, facilitating the subsequent prioritisation of preventive measures [6].

Subsequent advancements are focused on the integration of fuzzy reasoning with digital twin concepts, machine learning, and stochastic simulation. The implementation of such strategies enables the modelling of factors such as uncertainty in sensing, human factors, and reliability of components in condition-based and predictive maintenance[9]. For instance, hybrid models incorporating fuzzy logic, stochastic Petri nets and optimization algorithms are being used to schedule emergency maintenance windows, assess the human element in signalling systems and develop energy-efficient train operation strategies [7, 8, 10].

Despite the considerable advances that have been made, there is still an absence of a unified framework that simultaneously addresses fuzzy decision-making and dynamic maintenance execution within railway systems. In particular, the potential of fuzzy logic for prioritisation and CPNs for real-time task insertion and execution is an area yet to be explored. The objective of the current study is to address this discrepancy by proposing a hybrid fuzzy-CPN model capable of real-time adjustment to maintenance planning, while considering task criticality, operational constraints and concurrent process behaviour.

This study aims to address the research gaps previously identified, leading to the development of a hybrid decision-support model for the effective management of railway maintenance operations. The methodology incorporates fuzzy logic alongside formal process modelling with a view to ensuring both interpretability and operational responsiveness. The subsequent section is dedicated to the presentation of the proposed approach's architecture and functionality.

3 Methodology

he utilisation of a fuzzy inference system facilitates the adaptive prioritisation of maintenance tasks, with this prioritisation being based upon operational parameters.

In addition, the Colored Petri Net ensures the coherent insertion and rescheduling of maintenance activities within a dynamic system context.

3.1 Description of Fuzzy Logic

The difficulties experienced in decision-making processes within real-world maintenance environments, particularly within railway systems, stem from the utilisation of information that is imprecise, incomplete, and uncertain. In the context of complex scenarios, classical binary logic models based on strict true/false evaluation have been demonstrated to be inadequate. The introduction of fuzzy logic by Zadeh [11] provides an effective mathematical framework for addressing these limitations, by allowing partial degrees of truth ranging between 0 and 1. Fuzzy set theory is predicated on the notion of membership, whereby elements are connected to a given set with a certain degree of membership, as opposed to being constrained by predefined boundaries. This characteristic makes it particularly efficient for modeling of language concepts such as low, medium, or high, which align naturally with how human experts interpret operational conditions such as fault severity or resource availability. The fuzzy logic approach is categorised as a soft computing method and has been shown to be beneficial in circumstances where knowledge is articulated in a qualitative or linguistic manner [12].

In railway maintenance, fuzzy logic provides a practical method for prioritizing tasks based on uncertain parameters like:

- The severity of the fault (for example, how serious the failure is)
- Time constraints (such as remaining time before the breakdown).
- The cost of failure (e.g., potential economic impact)
- Machine Load (e.g., current usage level of the equipment).

Membership functions are used to model the degree of association with qualitative terms by representing each input parameter with a linguistic variable. The simplicity and computational efficiency of triangular and trapezoidal membership functions make them popular for use [13].

The fuzzy inference process is composed of the following steps[14]:

1. Fuzzification is the transformation of crisp input values into fuzzy values based on defined membership functions.

2. Rule evaluation involves applying fuzzy rules defined by experts, typically in the form:

- IF Fault Severity is Critical AND Time Constraint is Low THEN Priority is Very High;

3. Aggregation: Combining the outputs of all rules to produce a single fuzzy output;

4. Defuzzification is the process of converting fuzzy output into a crisp value using methods such as the centroid technique.

By including fuzzy logic, the maintenance decision system proposed becomes more flexible, transparent, and resilient to information uncertainty. A method that prioritizes interventions in complex, safety-critical railway systems is offered that emulates expert reasoning and is both human-interpretable and computationally tractable.

3.2 Proposed Maintenance Model

The proposed model incorporates a fuzzy inference engine and a CPN for the dynamic execution of tasks. The objective of the proposed model is to facilitate the effective management of maintenance operations in complex railway systems. The hybrid architecture enables flexible decision-making in uncertain circumstances and facilitates real-time responsiveness to operational disruptions. The problem of scheduling railway maintenance (Figure 1) in a simplified manner. In this model, a sequence of tasks must be completed within specified time and resource constraints to ensure uninterrupted operations. In order to prevent delays and maintain system efficiency, the model strives to dynamically prioritise and allocate these tasks.

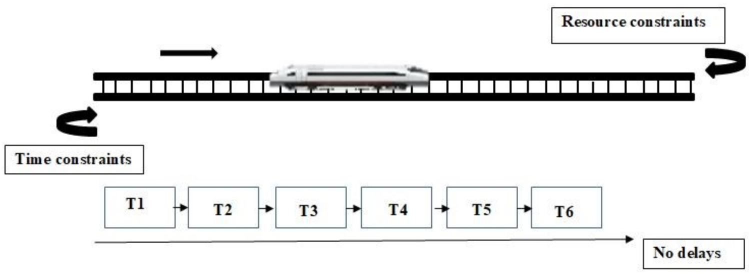


Figure 1: Railway maintenance line and some of its constraints

3.2.1 Model Architecture

The framework under consideration consists of two interconnected layers.

Uncertain input data is processed by means of a fuzzy decision system to determine maintenance priority levels.

The execution of tasks, as well as their coordination, is achieved through a CPN model, which is characterised by its ability to adapt to the dynamic environment of the project.

Recent research trends within this domain advocate a combined approach that integrates intelligent decision support with formal system modelling techniques for the purpose of predictive and adaptive maintenance [5]. This integration is a salient feature of contemporary research trends within this architecture, which is evident in the existing literature. Before proceeding, a few important terms are defined.

- Definition 1 (Teng, 1997): A fuzzy set F in a universe of discourse U is characterized by a membership function: μF: U$\rightarrow$[0,1]

- Definition 2 (Teng, 1997): A linguistic variable x in a universe of discourse U is characterized by:

$$V(x) = \left\{V_x^1, V_x^2, \ldots, V_x^{k_x}\right\} \quad \text{and} \quad N(x) = \left\{N_x^1, N_x^2, \ldots, N_x^{k_x}\right\}$$

where $V(x)$ is the term set of x, that is, the set of names of linguistic values of x, with each value V_x^i being a fuzzy number with membership function N_x^i on U.

3.2.2 Fuzzy Inference System (FIS)

A FIS is a mechanism that implements the Fuzzy Logic criteria in specific applications. By means of fuzzy input variables, the FIS enables the implementation of the logical dependency of these variables and the fuzzy output variables based on fuzzy rules. The FIS system consists of four main components: fuzzification, fuzzy rule set, inference method, and defuzzification:

- Fuzzification transforms a numerical input variable into a fuzzy subset,
- Inference identifies the fuzzy output subset by applying the dependency of the input-output variables via a fuzzy rule base,
- Defuzzification transforms the output fuzzy subset into a firm numerical variable.

Following the previous definitions, the input vector X that involves the input state linguistic variables xi's, and the output state vector Y that enables the output state linguistic variables yi's, may be defined as:

$$X = \left[x_i; \bigcup_i \left\{V_{xi}^1, V_{xi}^2, \ldots, V_{xi}^k\right\} \left\{N_{xi}^1, N_{xi}^2, \ldots, N_{xi}^k\right\}\right]_{i=1,\ldots,n}$$

$$Y = \left[y_j; \bigcup_j \left\{V_{yj}^1, V_{yj}^2, \ldots, V_{yj}^k\right\} \left\{N_{yj}^1, N_{yj}^2, \ldots, N_{yj}^k\right\}\right]_{j=1,\ldots,m}$$

3.2.3 Decision Variables and Fuzzification

The fuzzy subsystem is designed to consider four key operational parameters:

- The categorisation of fault severity is a critical aspect of any effective fault management strategy.
- The issue of time constraints is a pertinent one in this context.
- The financial implications of failure must be given full consideration.
- Machine Load

In order to model uncertainty and expert knowledge, each input is linked to linguistic terms (for example, Low, Medium, High) and membership functions that are typically triangular or trapezoidal.

The membership functions defined for each fuzzy input variable (time constraint, severity, failure cost, machine load and monitoring technique) are demonstrated in (Figure 2), alongside the output variable maintenance choice. The evaluation of maintenance conditions in the context of uncertainty can be conducted in a smooth and human-interpretable manner. To this end, the use of linguistic terms, such as 'Low', 'Moderate' and 'High', which are represented by triangular or trapezoidal functions, is recommended.

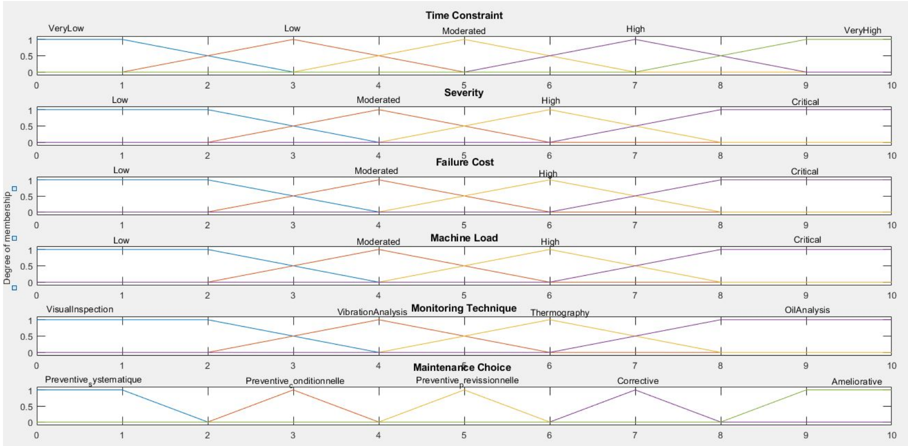


Figure 2: Fuzzification of the Input and Output Variables

3.2.4 Fuzzy Rule Base and Inference Mechanism

The fuzzy rule base created in this study is designed to generate maintenance decisions that are in line with operational priorities in the real world. Maintenance Choice comprises five distinct strategies: The following terms are employed in this text: 'Systematic preventive', 'Conditional Preventive', ' predictive preventive', 'corrective' and 'improved'. The decision-making process pertaining to maintenance is predicated on the consideration of five pivotal parameters: fault severity, time constraints, failure cost, machine load, and monitoring technique.

The linguistic description of inputs employs intuitive qualitative terms such as Low, Moderate, High, and Critical (for severity, cost, and load), and Very Low to Very High for the time constraint. The monitoring method is designated as a 'fuzzy input', and is divided into linguistic categories such as visual inspection, vibration analysis, thermography and oil analysis, which reflect the use of increasingly diagnostic-intensive techniques.

The rule base is the product of a reasoning process driven by experts. In situations where there is a severe paucity of time and a high machine load, predictive maintenance strategies are the preferred option for the system. Conversely, in circumstances where conditions are stable or the risk is minimal, systematic preventive maintenance is adequate. In instances where parameters fall within intermediate zones or where sensor-based techniques, such as vibration or thermography, indicate the necessity for closer observation, conditional maintenance should be considered.

The establishment of these regulations was guided by the principle of leveraging the domain's proficiency in railway and industrial systems. It is evident that scenarios where all parameters are mild naturally lead to Preventive Systematics, while mixed or evolving conditions trigger Conditional. In the event of escalating severity and failure cost, particularly when accompanied by advanced diagnostic inputs such as oil analysis, predictive preventive is regarded as the optimal response. The addition of corrective and preventive maintenance options is determined by system-specific needs or cost-benefit logic.

This model-based approach facilitates the interpretation, visualisation and simulation of a variety of real-time operating scenarios by maintenance engineers. In environments characterised by the abundance of data and complexity inherent in railway systems, the fuzzy system functions as a decision support instrument. This instrument is characterised by its capacity for explainability and customisation, thereby enhancing the reactivity and robustness of the system.

As illustrated in Table 1, this section showcases a curated selection of fuzzy inference rules that have been employed in the proposed model. The implementation of each rule involves the combination of multiple linguistic conditions on the input variables, with the objective being the derivation of the most appropriate maintenance strategy.

Expert knowledge and contextual observations from the Shelia coastal railway network were used to construct the IF-THEN rules in Table 1. The rules are based on typical operational situations, such as failure severity, machine workload, and time constraints. To identify relevant conditions that

Table 1: Examples of fuzzy IF–THEN rules for maintenance decision-making

Time Constraint	**Severity**	**Failure Cost**	**Machine Load**	**Monitoring Technique**	**Maintenance Type**
Very Low	Low	Low	Low	Visual Inspection	Systematic preventive
Low	Moderate	Moderate	Moderate	Visual Inspection	Systematic preventive
Moderate	Moderate	Moderate	Moderate	Vibration Analysis	Conditional Preventive
High	Critical	High	High	Oil Analysis	predictive preventive
Moderate	High	Moderate	Moderate	Thermography	predictive preventive
Very High	High	High	High	Oil Analysis	Corrective
High	Moderate	High	Moderate	Thermography	predictive preventive
Moderate	High	Moderate	Critical	Thermography	Corrective
High	High	Critical	Critical	Oil Analysis	Corrective
Moderate	Moderate	High	High	Oil Analysis	improved
High	Moderate	Moderate	Critical	Thermography	improved

commonly lead to maintenance interventions since direct access to industrial failure data was restricted. The rules were modified to reflect the local expertise and operational experience by adjusting the linguistic terms and variable ranges.

3.3 Modeling Maintenance Process with Colored Petri Nets

3.3.1 Motivation for Using Colored Petri Nets

In dynamic and complex maintenance environments, the accurate modelling of concurrency, resource constraints and task variability is imperative. Coloured Petri Nets (CPNs) provide a robust theoretical framework that incorporates graphical depiction, mathematical rigor, and modularity, rendering them particularly well-suited for the modelling of maintenance processes[Li et al., 2017; Wang et al., 2019].

In contrast to conventional Petri nets, CPNs permit the transmission of structured data, such as colours, via the tokens. This facilitates the differentiation of maintenance tasks into the categories of preventive, corrective and predictive, in addition to the delineation of severity levels and resource allocations. In addition, recent research emphasises the significance of Petri nets in facilitating smart maintenance systems and digital twin developments [Xu et al., 2021; Aivaliotis et al., 2020], thereby validating the appropriateness of CPNs for dynamic maintenance scheduling in uncertain conditions.

3.3.2 Structure of the Colored Petri Net Model

Coloured Petri nets are a substantial improvement on traditional Petri nets, facilitating complex system modelling in a more understandable manner, notably in industrial system prognostics and maintenance.

A distinctive feature of CPNs is their ability to embed colours in tokens. This enables a variety of resource or object classes to be distinguished, increasing the modelling flexibility. In comparison to traditional approaches the CPN reduces model size, whilst providing a more robust representation of dynamic processes and intricate interrelationships across a variety of environments.CPNs ability to manage a wider state and condition spectrum makes them especially suitable for modelling systems where monitoring resource and event evolution requires a high level of detail, including in preventive maintenance and failure prediction systems [4].

In this respect, a CPN is presented to illustrate a railway maintenance procedure. Maintenance decision-making in the railway system is governed by four fundamental criteria:

- The task's severity: an important factor that prioritises intervention based on its impact on the rail system's safety and performance.

- Mileage: this is crucial for planning maintenance based on component wear and preventive maintenance cycles.

- Machine load: is assessed on a rolling stock's usage intensity. If a unit is heavily loaded, it will require frequent servicing to prevent premature component wear.

- Monitoring techniques: this criterion covers the techniques used for monitoring the equip-ment's health. This encompasses such methods as vibration monitoring, temperature analysis, and the IoT sensors that allow to anticipate failures and optimise maintenance operations.

The Colored Petri net for maintenance is made up of four subnetworks (Figure 3). The first part 'P1' is the deterioration process subnetwork. The second section is dedicated to maintenance resources. The third subnet relates to maintenance policies. The last subnetwork is related to maintenance planning.

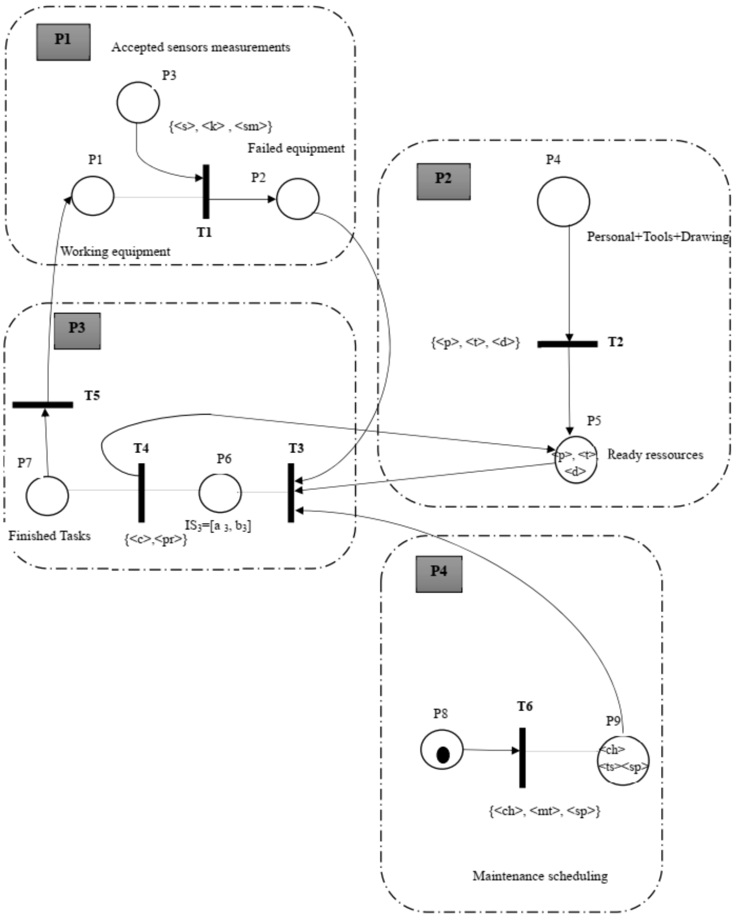


Figure 3: Colored Petri Nets for modeling railway maintenance process

A/ Deterioration Process (P1)

Generally equipment have two states, working or broken down. A subnetwork model (P1) depicting the deterioration process is shown in (Figure 3). Two places 'P1' and 'P2' respectively indicate the system's operational and failure states. The token indicates the system state. Triggering the 'T1' transition indicates the switch from the normal operating to the fault state. The place P3 simultaneously represents the task severity <s>, the kilometrage <k> as well as the sensor-delivered critical measurements <sm>, making this a crucial criterion for maintenance decision-making. The transition T1 is then triggered either by the appearance of one (or most) of the criteria, The colour set is denoted C= <s>, <k>, <sm>. If a particular task is ranked as severe, its token will be drawn, denoting its priority in the maintenance process. As far as the mileage is involved, the corresponding token will be fired only once it reaches the manufacturer-defined threshold necessitating a specific intervention An unmarked place denotes a refusal criteria and acceptable operating state. The measurements criteria constitute dynamic information obtained from the scheduling and monitoring departments.

B/ Maintenance Resources (P2)

According to the P2 block, when a breakdown happens and the drawings <d>, maintenance teams <p> and tools <t> are available, maintenance work can begin (place P5) . It is absolutely imperative that all three components are present and pulled together in order to cross the transition T2, and to ensure availability of all resources prior to maintenance action.

C/ Maintenance strategies (P3)

The purpose of this block is to preserve or restore an entity to a specific state. Maintenance policies can be divided into two categories: corrective and preventive. In both cases, the maintenance operation is triggered through a decision process involving the measured or estimated state of the resources in question. According to Figure 3 (sub-assemblies P3), transition 'T4' matches the maintenance process when the components are in the triggered state. If there are enough maintenance resources (sufficient mark at location P5), transition 'T3' will be triggered if there is preventive <pr> or corrective <cr> maintenance (place P6). The ''A3'' subnetwork linked to the maintenance process is based on the Colored Petri net. The time windows "IS3" assigned to places P6 indicate the maintenance activity durations. The time constraints represent the maintenance process uncertainty, which depends on the failure severity and the maintenance resources and spare parts availability.

D/ Maintenance scheduling (P4)

The 4th part is the subnetwork for maintenance scheduling. Scheduling involves allocating resources over time to tasks within time and capacity constraints. The maintenance scheduling of railway equipment's refers to the resource allocation to a task in one or several discrete connected time intervals and to a decision-making process aiming at optimizing one or several targets. Based on the diagnostic information, this subnetwork's (P4) role is to decide on the maintenance policy, to enable urgent procedures and finally to initiate recovery procedures. In this networks the place P8 represents machine load <ch>, the suitability of monitoring techniques <mt> and spare parts <sp> availability. These three parameters are crucial for maintenance scheduling. When the token moves to 'P9', this indicates that maintenance is required on this rolling stock.

3.3.3 Dynamic Behavior and Maintenance Workflow

The dynamic behaviour of the maintenance process can be observed by tracking token movements across locations. The fuzzy inference engine outputs determine the dynamic insertion of new maintenance requests, both planned and urgent, into the workflow. The model is enabled:

- The execution of multiple tasks concurrently.
- The real-time insertion of urgent maintenance tasks is a methodology employed to circumvent the disruption of ongoing activities.
- The process of assigning precedence to resources and subsequently redistributing them in accordance with the prevailing conditions of the system is of paramount importance.

The validation of maintenance strategies, the anticipation of bottlenecks, and the optimisation of resource utilisation can be achieved through the utilisation of simulation and analysis of the CPN.

3.4 Algorithmic Approach

The implementation of the proposed hybrid model—combining fuzzy inference and Colored Petri Nets (CPNs)—is structured into a modular, stepwise procedure designed to support dynamic maintenance scheduling under uncertainty. The algorithm ensures the prioritization, insertion, and execution of maintenance tasks in response to evolving operational contexts.

Step 1: Task Detection and Input Initialization Maintenance requests are generated from either scheduled planning or real-time system monitoring. For each task, five input parameters are collected:

- Fault severity
- Time constraint

Algorithm 1 Fuzzy-CPN-Based Dynamic Maintenance Scheduling

Input: Task T_i with parameters: Severity (S), Time Constraint (TC), Failure Cost (FC), Machine Load (ML), Monitoring Technique (MT)
Output: Recommended Maintenance Type and Execution Path
Normalize input values of S, TC, FC, ML, and MT
Fuzzify inputs using defined membership functions
Evaluate activated rules using Mamdani inference
Aggregate outputs and apply centroid defuzzification
Determine the maintenance type: Systematic, Conditional, Predictive, Corrective, or Improved
Generate a CPN token embedding task attributes (type, priority, duration)
Insert token into the initial place of the Colored Petri Net
Simulate CPN transitions: scheduling → execution → completion
if A high-priority task T^* is detected **then**
    Preempt lower-priority token(s)
    Re-evaluate T^* via fuzzy inference
end if
Log the decision and update system state

- Machine load
- Failure cost
- Monitoring technique

These inputs are normalized over a fixed domain and passed to the fuzzy logic layer.

Step 2: Input fuzzification The input values are converted to fuzzy sets via predefined membership functions. Each parameter is described by linguistic terms (e.g. low, moderate, high), and mapped to triangular or trapezoidal functions.

Step 3: Rules evaluation and inference The system assesses active fuzzy rules with Mamdani inference. For each corresponding rule, the activation degree is calculated and the associated fuzzy outputs are computed.

Step 4: Defuzzification The aggregate fuzzy output (maintenance choice) is defuzzified by the centroid method to generate a net maintenance score indicating the recommended maintenance mode (e.g. conditional preventive, corrective, etc.).

Step 5: RPC token generation Based on the Fuzzy Decision, a coloured token is generated. Each token carries task-specific attributes: priority level, type of maintenance, estimated time and resource requirements.

Step 6: Task insertion and execution The token is then inserted in the CPN model, simulating maintenance status:

Waiting → Scheduled → Running → Completed

Transitions are fired based on system conditions, such as resource availability, concurrency or preemption logic.

Step 7: Dynamic updating and feedback If a new, urgent task is identified (e.g., due to a sensor alert), the Fuzzy CPN loop reboots, evaluates the task and dynamically updates it. The resulting system adapts continuously to operational variations and resource conflicts.

The following section focuses on the practical application of the proposed fuzzy CPN-based maintenance optimization framework to a real case study of Tunisia's railway network. The purpose of this study is to assess the model's effectiveness in prioritizing repair interventions and managing maintenance workflows dynamically under operational uncertainty.

3.5 Case Study: Maintenance of Tunisian Railway Network

The Sahel railway line, subject of our study, presents particular interest since it serves the Sahline salt marshes, which are saline marshes located in eastern Tunisia, extending from Monastir to Sahline

(Figure 4a). This Tunisian example, with available concrete data, requires careful consideration to local conditions, particularly the presence of sand and salt from the marshes. However, this study does not deal specifically, with the effects of these factors; it is mainly, based on a set of generic recommendations, without any local context. In addition, the geographic configuration of this line bears strong similarities to some existing lines in France, making it easier to take comparative approach and potentially transpose proposed adaptations. In France, the Saint-Césaire to Le Grau-du-Roi line is a railway line that crosses areas where salt marshes are located, particularly near Aigues-Mortes, (Figure 4b).The key similarity is the fact that both railway lines run alongside salt marshes, highlights the interaction between transport infrastructure and these naturally occurring or exploited environments. The Grau de Roi road traverses the Aigues-Mortes salt marsh and is in proximity to the sea, (Figure 5b).

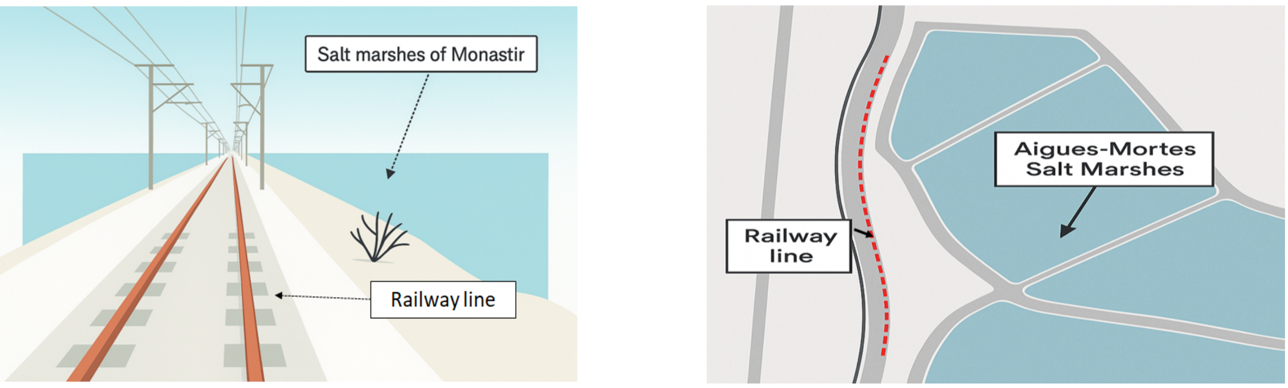
Maintaining rail transport networks in salt marsh areas requires a proactive approach and the adopts of specific technologies and methods to tackle the issues of corrosion and vegetation management, whilst respecting the sensitivity of these ecosystems. The proactive approach involves careful inspection planning, damage anticipation, and the implementing of preventive maintenance programs. The implementation of specific materials and techniques involves innovative solutions in protective coatings, corrosion-resistant alloys, and appropriate construction methods. While constant vigilance is provided through regular monitoring, sensors, and in-depth expertise in infrastructure behavior in this particular environment. Consequences from a maintenance point of view are:

- Extreme heat causing track degradation: indeed, high temperatures cause rail expansion and contraction, leading to track distortion, rail breaks and increased component fatigue.

- High Evaporation and Low Rainfall: The Camargue is characterized by intense evaporation and low rainfall, making it ideal for salt harvesting

- Flooding (due to heavy and irregular rainfall) causes track scouring: Intense, short-lived downpours can trigger flash floods that carry away ballast and track bed, causing major damage and disruption.

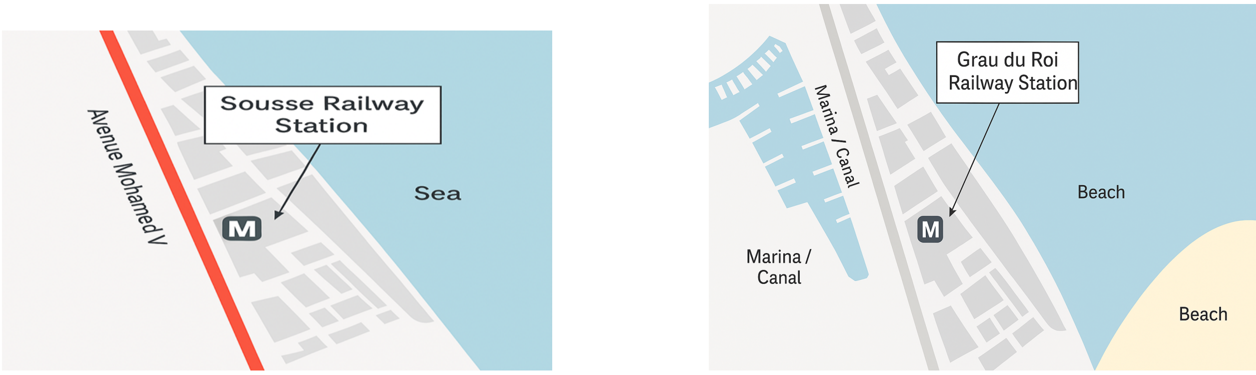
- Dust storms: frequent and intense dust storms can reduce visibility, which has an operational safety impact and risks damaging equipment by infiltrating and corrupting mechanical and electrical systems, which has an indirect impact on the safety and stability of rail operations and infrastructure investments.



(a) Monastir line, Tunisia (b) Nimes-Grau du Roi line, France

Figure 4: Monastir and Grau-du-Roi railway line

The Sahel Metro is an extensive railway network in the region, stretching 70 kilometres. It comprises 47 kilometres of double track between Sousse Bab Jedid and Moknine, as well as 23 kilometres of single track between Moknine and Mahdia. The network comprises 31 stations and stops, which are strategically positioned to serve urban, industrial, tourist and university centres (ibid). Notable destinations include Sousse Bab Jedid, Sousse Sud, Sousse city centre, the Sahline industrial zone, Habib Bourguiba International Airport and part of the Eddkhila tourist area. The network also extends to Monastir University and Monastir town, continuing on to Ksar Helal, Moknine, Khniss, Ksibet Mediouni, Bennane, Bouhjar, Lamta and Sayada. Furthermore, it extends to the Teboulba industrial



(a) Sousse-Monastir final station, Tunisia (b) Nimes-Grau du Roi final station, France

Figure 5: Sousse and Grau-du-Roi railway station

zone and the municipalities of Teboulba and Békalta, as well as the tourist area and the university campus of Mahdia. Consequently, the network plays a pivotal role in regional mobility, facilitating everyday travel and the economic development of the Sahel region. The Saline industrial zone as a particular interest from a maintenance point of view, because this name comes the presence of Salt marshes. In this area, the salt density is particularly high. This lead to specific corrosion phenomena that has not been considered by the systematic maintenance rules provided by the rolling stock builder. The Sahel metro operates with an average frequency of 40 minutes, providing 44 scheduled circulations per day from 05:00 to 22:00. It is estimated that it will transport more than 9 million passengers per year, with an average of 27,000 passengers per day.

(Figure 6) illustrates the stations on the Sahel Tunisia train line between Mahdia and Sousse. The metro's strategic focus is centred on the customer. This is demonstrated by its commitment to continuously improving service quality and facilitating dialogue with travellers. Such commitments are embodied by the organisation of panels and cultural events in station spaces. These measures foster the development of a framework of mutual trust between travellers and the metro.

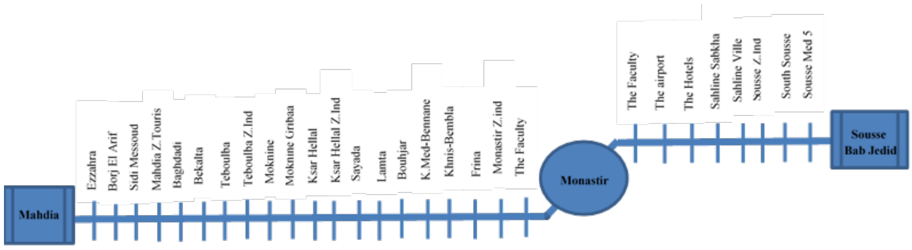


Figure 6: Topology of the rail network

3.6 Description of Simulations

To evaluate the potential impact of different operational parameters on recommended maintenance strategy, five numerical simulations were carried out. Each simulation methodically investigates the combined impact of two primary parameters on the maintenance decision. The findings are presented in the form of three-dimensional surfaces.

3.6.1 Simulation 1: Influence of time constraint and severity on conditional-preventive maintenance

The first simulation aims to analyze the impact of time and severity constraints on the level of conditional preventive maintenance. The 3D surface obtained is shown below.

As demonstrated in (Figure 7) , for low levels of time constraint and severity, the model demonstrates a propensity for a conditional approach, exhibiting moderate output levels.

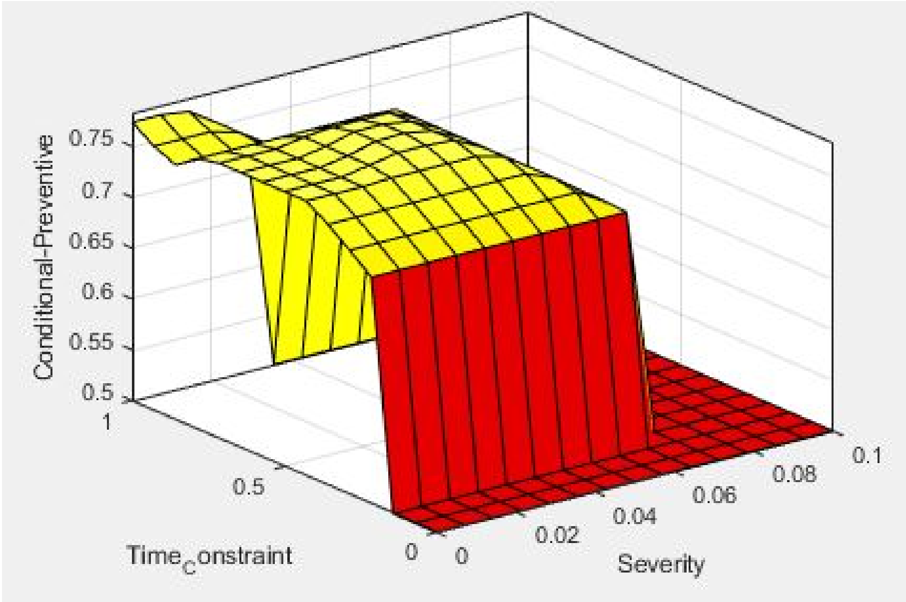


Figure 7: Three-dimensional trapezoidal membership function: Conditional Preventive Maintenance = f (time constraint, severity)

As time constraints increase, and even in the presence of moderate severity, the advice gradually evolves gradually towards increased conditional preventive maintenance. This can be interpreted as a necessary anticipation of reduced time available for action.

3.6.2 Simulation 2: Influence of the machine load and severity on improved maintenance

A second simulation was conducted to assess the simultaneous impact of machine load and severity on the strategy for improving maintenance. The results are presented as a three-dimensional surface. (Figure 8) illustrates that at moderate machine load and with low to moderate damage severity, the favoured approach is to perform improved maintenance. Clearly, low machine load and high damage severity reduce the relevance of this approach, indicating that improved maintenance is more suitable in progressive wear circumstances than in rapid degradation.

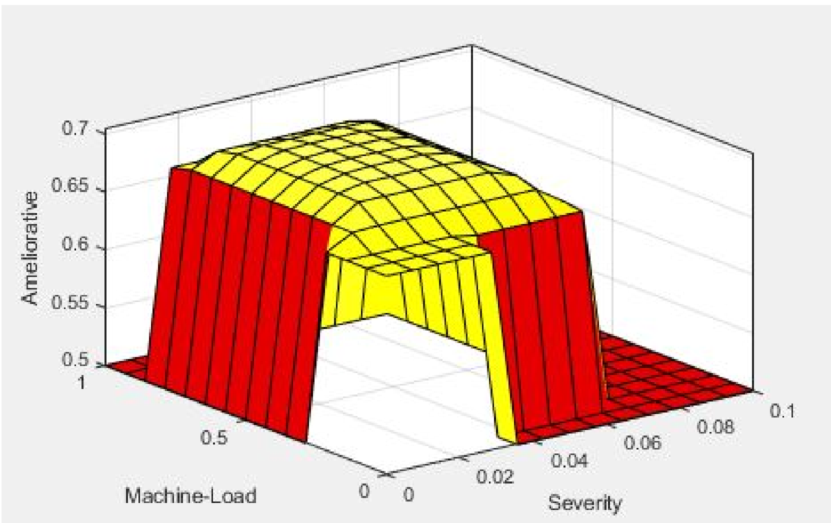


Figure 8: Three-dimensional trapezoidal membership function: improved maintenance = f (severity, machine load)

3.6.3 Simulation 3: Influence of machine load and severity on corrective maintenance

The third simulation examines the cross-impact of machine load and severity on the corrective maintenance recommendation. The subsequent figure illustrates the results obtained.

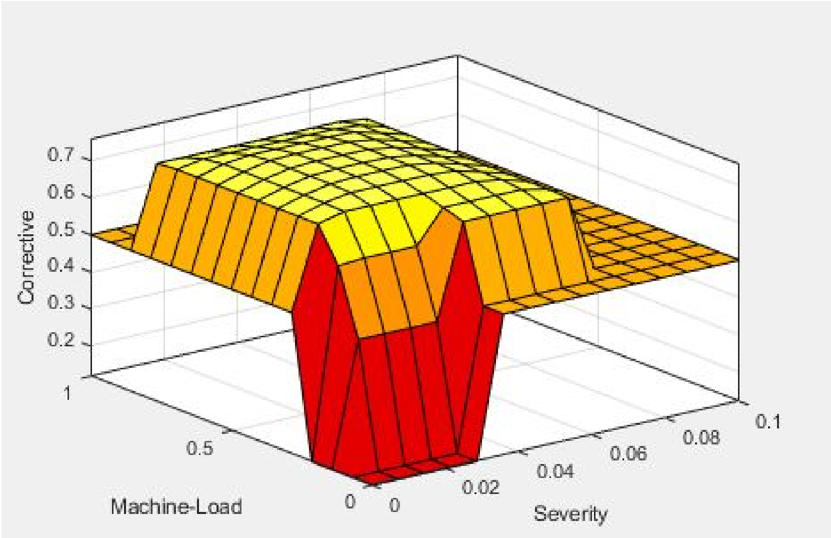


Figure 9: Three-dimensional trapezoidal membership function: corrective maintenance = f (severity, machine load)

(Figure 9) shows that corrective maintenance is mainly favoured in conditions of low machine load and low severity. When one of these parameters increases, the trend is towards a reduction in corrective actions, in favour of more preventive or predictive strategies.

3.6.4 Simulation 4: Influence of machine load and severity on predictive maintenance

In order to study the combined effect of machine load and severity on the implementation of predictive maintenance, a fourth simulation was carried out. The corresponding surface is shown below.

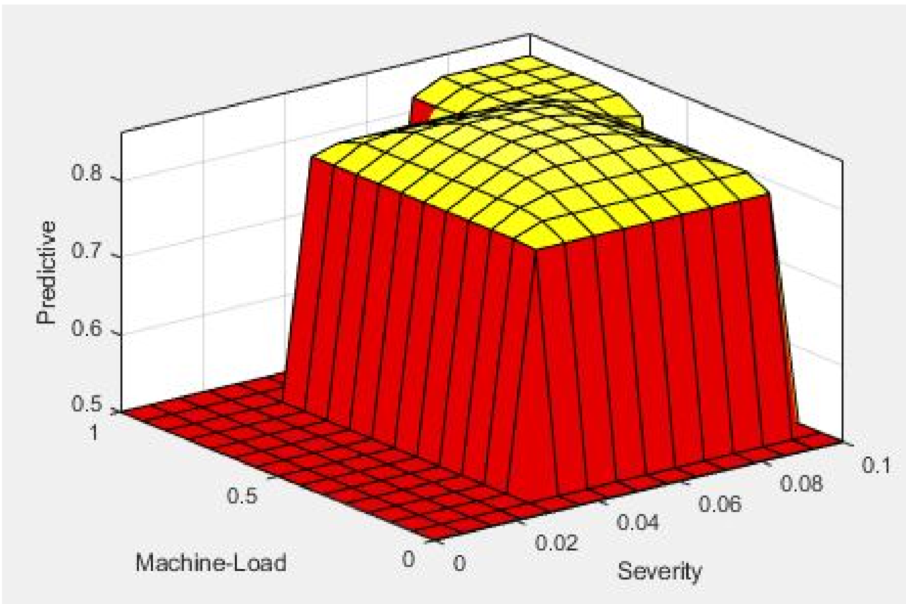


Figure 10: Three-dimensional trapezoidal membership function: predictive maintenance = f (severity, machine load)

As shown in (Figure10), in situations characterized by high machine load and severity levels, predictive maintenance appears to be the most popular approach. Inversely, in instances where load is minimal, and even where the severity of the problem increases, the interest in predictive maintenance is moderate. This finding underlines the importance of operational constraints in prioritizing interventions.

3.6.5 Simulation 5: Influence of failure cost and severity on systematic maintenance

Finally, a fifth simulation explores the relationship between failure cost and severity to guide the systematic-preventive maintenance strategy. The results are summarised in the figure below.

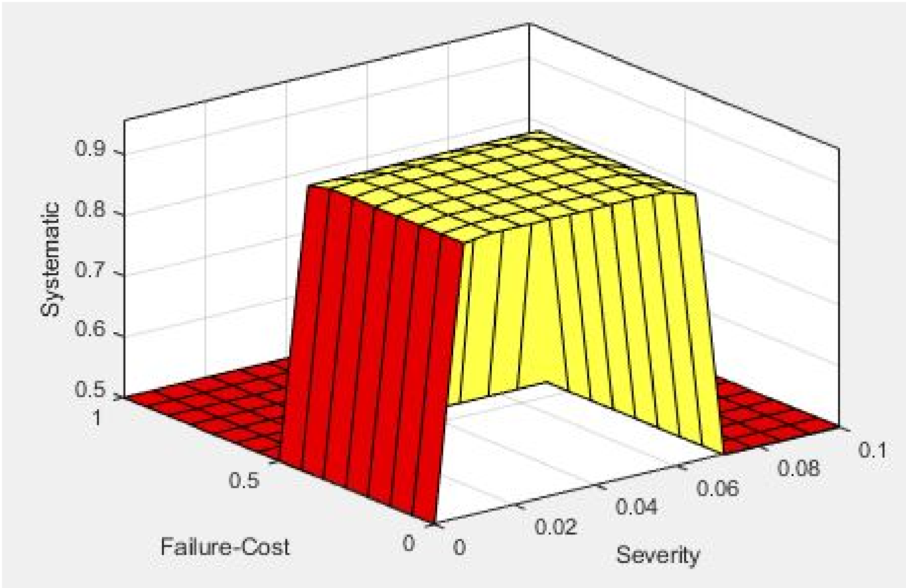


Figure 11: Three-dimensional trapezoidal membership function: systematic maintenance = f (severity, failure cost)

As illustrated in (Figure 11), an escalation in failure cost or severity gives rise to a predilection for a systematic maintenance strategy. However, in cases where the cost and severity are low, a less systematic approach is adopted.

This phenomenon elucidates the economic rationale underpinning the selection of preventive strategies.This phenomenon elucidates the economic rationale underpinning the selection of preventive strategies.

3.7 Analysis of Results

The simulation results evidently demonstrate the adaptive capability of the proposed system to dynamically tailor maintenance recommendations in response to variations in operational conditions. A detailed analysis of the five simulation scenarios highlights several key patterns:

- Effect of Severity: Severity emerges as a dominant factor, systematically triggering a shift towards more proactive maintenance strategies as its level increases.

- The Effect of Failure Cost: It is evident that an augmentation in the estimated failure cost will result in a substantial reinforcement of systematic maintenance policies. The implementation of such policies is aimed at mitigating the considerable economic risks associated with unexpected breakdowns.

- The Effect of Time Constraint: The contraction of available time windows has been demonstrated to engender an earlier prioritisation of preventive actions, even in circumstances where the severity level remains moderate, with a view to ensuring operational continuity.

- The Effect of Machine Load: In conditions of elevated machine loading, there is an encouragement of the strategic implementation of predictive maintenance methodologies, whilst concomitantly reducing the necessity for reactive (corrective) interventions.

In summary, the developed system demonstrates a high degree of flexibility and robustness, thus enabling optimised maintenance planning that balances reliability enhancement with cost efficiency under varying operational and environmental constraints.

4 Discussion

The simulation scenarios in Figures 7 to 11 illustrate the dynamic behavior of the Fuzzy–CPN model under various maintenance conditions, as demonstrated by the following discussion.

Simulation results clearly indicate the effectiveness of the proposed framework, based on fuzzy logic and colored Petri nets, in the dynamic optimization of railway maintenance strategies.

This paper seeks to explore the following research questions in this section:

First, what are the benefits of integrating these two modeling techniques? Secondly, what are the main challenges and limitations encountered? Lastly, what are the practical implications for real-world implementation within railway networks?

4.1 Advantages of Fuzzy Logic and Petri Nets

This study proposes a novel maintenance framework that integrates fuzzy logic and Colored Petri Nets (CPNs). It is hypothesised that this integration offers significant advantages for managing complex and uncertain operational environments:

- Adaptability to uncertainty:

Fuzzy logic enables the system to prioritize maintenance operations even when faced with imprecise or evolving data. This is made possible through the use of expert-inspired rule bases and flexible membership functions that reflect real-world decision-making nuances.

- Formal process modeling with CPNs:

Colored Petri Nets provide a rigorous structure for validating and simulating maintenance processes. They allow for the modeling of complex task interdependencies, dynamic resource allocation, and event-driven transitions, ensuring logical consistency and operational feasibility.

- Support for concurrency and dynamic evolution:

The hybrid Fuzzy–CPN approach enhances the system's ability to manage simultaneous and unpredictable events—common in real-world railway maintenance scenarios. It allows maintenance workflows to evolve dynamically while maintaining operational coherence.

4.2 Limitations and Challenges

Despite the benefits of the proposed approach, it is vital to acknowledge the limitations and challenges associated with it.

Firstly, the association of fuzzy inference and CPN results in an increased model complexity, which can lead to problems in model conception, tuning and interpretation. It is imperative to use careful fuzzy rule definitions, membership functions and Petri net structures to ensure system traceability and manageability.

Secondly, the computational costs of simulation can become considerable, particularly when extended to large, highly interconnected rail networks. It is imperative that fuzzy evaluations and CPN simulations are further optimized in terms of their computational requirements, if they are to be applied in real time.

Thirdly, integration with existing maintenance management systems presents a practical challenge. It is obvious that a significant proportion of operational systems are founded on legacy and inflexible platforms. Incorporating dynamic fuzzy CPN frameworks would necessitate implementing meticulous integration strategies, encompassing data standardization, middleware development and staff training.

Finally, it should be noted that due to confidentiality restrictions imposed by the infrastructure owner and the train manufacturer, real maintenance datasets could not be disclosed. Therefore, the proposed model was validated through expert-defined scenarios inspired by the operational context of the Sahel metro network. Despite the absence of quantitative performance metrics, these simulations depict realistic maintenance conditions, such as failures caused by saline corrosion and sand dust. The model's behavioral accuracy is supported through qualitative validation, while future work will involve numerical benchmarking upon availability of industrial data.

4.3 Practical Implications

The practical implications of this research are substantial, particularly for railway network managers seeking to modernise and optimise maintenance strategies.

The fuzzy-CPN framework provides a foundation for intelligent maintenance systems that can be integrated with IoT sensor networks, facilitating real-time monitoring of equipment states and feeding live operational data into the fuzzy decision engine.

Moreover, the integration of the framework with predictive analytics would empower managers to anticipate failures with greater precision and to schedule interventions dynamically based on evolving conditions, as opposed to static time-based schedules.

In addition, the using of Colored Petri Net for modelling facilitates the development of digital replicas of railway infrastructures. These digital twins can then be employed to conduct real-time simulations of maintenance workflows. This enables the evaluation of alternative strategies, the prediction of bottlenecks, and the optimisation of resource allocation. The integration of these digital twins with fuzzy-CPN intelligence has the potential to facilitate the transition of railway operators towards the development of autonomous, self-adaptive maintenance systems.

5 Conclusion

The present paper addresses the dynamic scheduling problem of maintenance activities within railway networks. In the field of railway maintenance, compliance with strict standards of operational reliability and safety is mandatory, and it is the responsibility of the relevant stakeholders to comply with them. The proposed framework integrates a fuzzy inference system with a colored Petri net model, thereby facilitating the maintenance management and operation optimization in contexts characterized by variations in operating conditions and associated uncertainties.

The fuzzy-decision system facilitates the prioritisation of maintenance tasks by appraising pivotal factors, including fault severity, time constraints, financial cost of failure and machine load, thereby ensuring interventions are congruent with the evolving criticalities of the system. Concurrently, the Colored Petri Net framework models the insertion, execution and rescheduling of maintenance tasks in real time, whilst managing resource constraints and handling disruptions.

The integrated approach is predicated on the minimisation of risk with regard to emergency situations resulting from delayed interventions. Such situations have the potential to impact both infrastructure integrity and traffic operations, ultimately resulting in a degradation of railway service quality. The proposed model ensures continuous service reliability, even in situations where traffic conditions and operational disruptions may fluctuate. This is achieved by enabling the flexible and coherent scheduling of preventive, predictive and corrective maintenance activities.

In most cases, the introduced maintenance integration strategy enables additional maintenance tasks to be included in the machine's availability. Traffic can thus continue in the worst-case scenario. Colored Petri nets are a valuable tool for the careful modeling and analysis of railway maintenance processes, as they capture the intricate interactions between tasks, resources and temporal constraints. Despite their effectiveness in describing parallelism and synchronism, complementary approaches are needed as systems become increasingly complex and lack integrated decision-making mechanisms. To achieve optimized scheduling of maintenance tasks, a methodology combining colored Petri nets and a dynamic insertion algorithm has been proposed. Further implementation and experimental evaluation of the proposed methodology, including simulations using real data, should allow the model to be refined and its potential impact on the operational effectiveness of maintenance systems to be assessed.

It will be important to broaden the applicability of the maintenance methodology detailed in this paper. Monitoring urban and maritime transport network as SEDs would provide a tangible assessment of the proposed approach. It would be worthwhile developing a specific approach to rolling stock predictive maintenance by incorporating digital twins.

The proposed Fuzzy–CPN model represents a novel hybrid reasoning-simulation framework, in contrast to conventional approaches such as ANFIS, standalone Petri Nets, or purely predictive maintenance systems. The combination of interpretability of fuzzy inference with the dynamic modelling capability of Petri Nets enables both uncertainty management and process-level adaptability. In contradistinction to black-box predictive methods, the present approach provides transparent, rule-based reasoning that dynamically responds to real-time conditions. This hybrid integration has been demonstrated to enhance decision accuracy, flexibility, and robustness, representing a significant step forward towards intelligent, self-adaptive maintenance systems.

This integration serves to highlight the practical efficiency and scientific relevance of the proposed tools for intelligent monitoring and maintenance within complex railway systems.

In the future, the Fuzzy–CPN framework could be enhanced by integrating digital twins for real-time system simulation and IoT-based sensors for live condition monitoring and adaptive scheduling. Moreover, machine learning could automate rule tuning and pattern recognition, decreasing the need for expert-defined logic. With these enhancements, we can expect more autonomous and intelligent maintenance systems that can continuously learn and self-optimize.

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