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Intelligent Petri Nets Based Maintenance Decision-Making Model Considering RCF Degradation

A. Meghoe,[1] T. Tinga,[1] A. Saleh[2] and M. Chiachío[2]

[1] **University of Twente, University of Twente, Enschede, Netherlands**
[2] **Engineering School, University of Granada Spain**

Abstract

Railways play a vital role in sustainable transportation by offering exceptional energy efficiency and reduced greenhouse gas emissions compared to alternatives like road or air transport. However, the operational and maintenance expenses associated with railway infrastructure are substantial, exceeding 25 billion Euros annually in Europe, with track degradation costs being a significant portion. To address this challenge, an optimal maintenance strategy is essential to reduce costs while maintaining high-quality service standards. This study proposes a methodology that combines meta-models, Petri Nets, and advanced decision-making techniques to optimize maintenance decision-making in railway infrastructure. Specifically, meta-models are used to predict Rolling Contact Fatigue crack initiation, while Petri Nets are employed to model crack propagation and optimize maintenance decisions. The integration of these approaches aims to identify optimal maintenance strategies to mitigate crack progression, minimize operational costs, and ensure safety and reliability in railway systems. A case study demonstrates the effectiveness of the proposed methodology in identifying optimal maintenance strategies. The findings highlight the potential of integrating meta-models, Petri Nets, and advanced decision-making techniques for optimizing maintenance decision-making in railway infrastructure.

Keywords: maintenance strategies, railways, rolling contact fatigue, meta-models, reinforced learning

1 Introduction

Railways are a sustainable option for transport due to their exceptional energy efficiency as they consume less fuel than alternatives like road or air transport, resulting in reduced greenhouse gas emissions [1]. However, it is crucial to acknowledge that railways also involve substantial expenses for their operation and maintenance. Railway infrastructure and vehicle maintenance are estimated to cost over 25 billion Euros per year in Europe, with costs continuing to rise [2]. This underlines the need to develop an optimal maintenance strategy to reduce maintenance costs and maintain high-quality service standards. Degradation of track yields the highest costs. According to the EU funded SIA project [3] the track expenses vary between 40% to 70% of the total maintenance and operation expenses.

The track degradation can be related to many factors, such as weather, traffic loads, and vehicle speed. Maintenance actions should be performed before the condition reaches a point where the asset can no longer fulfil its intended function, which may, at best, result in system downtime and, at worst, in potential safety risks. The solution would be performing just-in-time maintenance. Various maintenance concepts have been developed over the last decades, categorized from reactive to proactive maintenance [4]. Reactive maintenance, such as corrective or run-to-fail maintenance, cannot meet the operational demand as it results in increased downtime and costs and may disrupt safety. Condition-based or predictive maintenance can be used to utilise the available resources efficiently and avoid unnecessary maintenance while increasing the availability of the system. This study aims to find the optimal maintenance strategy focusing on the costs and using the meta-models and Petri Nets. The goal is to create a maintenance decision-making model considering operation, degradation, and maintenance. This model will simulate a range of inputs regarding usage, load, speed and type of maintenance actions.

Various methods and techniques are employed in optimizing railway track maintenance planning, ranging from linear and integer programming methods [5] to the widely utilized Markov decision process (MDP) approach [6]. The MDP approach captures the stochastic nature of railway systems, integrating uncertainties into maintenance decision-making. Dynamic programming based on MDP, such as value and policy iteration, proves particularly effective in large-scale maintenance optimization, enabling adaptive strategies in response to changing conditions. Additionally, Reinforcement Learning (RL) has emerged as a promising alternative, surpassing linear and non-linear programming and MDP in railway maintenance [7]. RL demonstrates effective scalability for complex systems, dynamically adjusting to changing conditions and enhancing efficiency through integration with advanced techniques like deep deterministic policy gradients and digital twin technology. The integration of simulation models with optimization engines, notably discrete event simulation (DES) and Monte Carlo simulation, addresses complexities inherent in real-world maintenance problems [8]. Petri nets (PN), known for their effective representation of DES, excel in modelling parallel, synchronized, and concurrent events [9]. This capability proves vital for simultaneously representing multiple sections within a railway branch experiencing degradation under various operational conditions. The combination of PNs with Value-based Reinforcement Learning (RL) methods gives rise to the innovative intelligent Petri Nets (iPN) methodology [10].

This methodology operates on the premise of a prediction model capable of predicting the Remaining Useful Life and assessing the condition of the track in question, where decisions must be made. As previously noted, track degradation leads to significant maintenance expenses, particularly concerning the rails affected by the Rolling Contact Fatigue (RCF) mechanism [11]. Hence, an RCF model will be integrated with iPN, incorporating maintenance actions associated with RCF, such as conventional grinding, high-speed grinding, acoustic grinding, milling [12], and rail replacements. The RCF models employed will be based on meta-models developed in [13] and regression models as will be derived in this study from Eddy Current and Ultrasonic crack measurement data. These models are chosen in particular considering the required computational efficiency of the maintenance decision tool.

This paper is structured as follows: section 2 discusses the RCF models regarding crack initiation and propagation and the iPN method, followed by the maintenance decision framework. Section 3 discusses the preliminary results of the maintenance decision tool, and finally, in section 4, the concluding remarks are presented.

2 Methodology

Head checks are one of the most common rail surface defects due to RCF and can lead to rail fracture when not treated in time [14]. They are triggered by repeated wheel-rail contact with high velocity and high axle loads [15] and can be spotted on the outer rail (at the gauge side) of curved tracks with radii between 500 and 3000 meters as a cluster of very closely spaced fine cracks. It should be noted that each cluster of head checks will be further regarded as a single head check i, and the crack depth is then defined as the maximum value of all the head checks within that cluster. Early detection of head checks is important to mitigate induced maintenance costs as well as the consequences of unexpected rail failures. However, as mentioned before, rail surface defect detection at an early growth stage can be challenging. Therefore, it is important to have a suitable model to predict the crack growth to be used as input in the Petri Nets and to reach an optimal maintenance decision, e.g. grinding, milling or track replacement. The size of cracks, or head checks, will be predicted in two phases: first, the crack initiation phase is considered, and second, the crack propagation phase.

2.1 Crack initiation model

The crack initiation model that will be used is a meta-model based on the Whole Life Rail Model [16] developed from field observations and numerical modelling to determine the probability of RCF on rails for steel grade R220. The WLRM is based on the dissipated energy in the wheel-rail contact, and the resulting damage index D

depends on the wear number $T\gamma$, which can be calculated as:

$$T\gamma = T_x\gamma_x + T_y\gamma_y \tag{1}$$

where T_x and T_y represent the tangential or shear forces and γ_x, respectively, γ_y the longitudinal and lateral creepages obtained from multi-body dynamic simulations. The WLRM, see Figure 1, shows how many cycles (in this case, the number of wheel passages) are required until a crack is initiated given a specific loading condition.

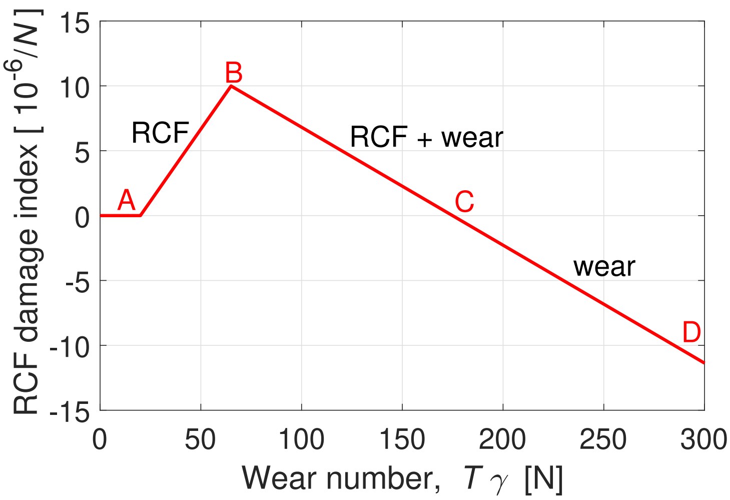


Figure 1: WLRM showing the RCF damage index as a function of the wear number for steel grade R260 and friction coefficient 0.3 [14].

The challenge with the WLRM lies in determining the wear number for every train wheel that passes through. This determination requires conducting a multi-body dynamics simulation that considers specific operational conditions and wheel geometry for each scenario. Typically, infrastructure managers do not have access to sophisticated software such as multi-body dynamic codes. To overcome this challenge, the current study utilizes a meta-model, as described in [13]. Meta-models are approximation models which are used to describe complex models of physical and engineering systems in an efficient way by means of input and output parameters. An extensive description of the meta-model development process and the specified range for the input parameters can be found in [17].

The meta-model is an alternative approach, predicting crack initiation and obviating the need for extensive multi-body dynamics simulations. The utilized meta-model in this study is in the form of a second-order polynomial that takes into account eight key input parameters, which are the operational condition parameters like the vehicle speed, the axle load, the longitudinal and lateral stiffness of the primary suspension of the vehicle's bogie, track geometry parameters like the rail cant, the vertical wear depth of the rail profile and the curve radius and the environmental condition represented by the coefficient of friction. The output (response value) of the meta-model is the wear number $T\gamma$ for the traversing wheel, i.e. the load parameter that governs the head check initiation.

$$T\gamma(\mathbf{x}) = \beta_0 + \sum_{i=1}^{k} \beta_i x_i + \sum_{i=1}^{k} \beta_{k+i} {x_i}^2 + \sum_{i=1}^{k-1} \sum_{j>i}^{k} \beta_{i,j} x_i x_j \tag{2}$$

where x is the vector of x_i, which are the various input parameters, and β_i are the fitted model parameters.

2.2 Crack propagation model

Once the wear number is determined for each passing wheel (by using the meta-model), the damage index can be calculated. Using the method proposed in the previous section, the initiation of head checks in a specific track section can be predicted. However, the severity of the head checks (in terms of the crack depth) will increase over time. This section describes how the defect evolution model is developed. The aim is to achieve a model that represents the crack depth of the head checks as a function of the traffic tonnage denoted by Mega Gross Tons (MGT).

The crack depth data used to obtain the evolution model is retrieved from Eddy Current (EC) and Ultrasonic (US) measurements, while the traffic tonnage information for the past ten years is provided by infrastructure manager ProRail. Eddy current measurements are only conducted for small cracks, i.e., those with a depth of less than 3mm, while ultrasonic measurements are undertaken for both surface and subsurface cracks, including larger ones. Observed crack depths are typically classified into a number of discrete depth classes. An extensive description of both testing methods (US and EC) can be found in [18].

The crack depth growth of each individual head check is defined as the difference between the crack depth values of two consecutive measurements. Thereafter, the MGT between these two consecutive measurements is obtained. Furthermore, it is assumed that newly initiated head checks can occur anywhere within the rail section with a certain probability. The location and number of newly initiated head checks within this study are selected through a stochastic model based on field observations.

A probabilistic approach is also adopted in developing the evolution model as depicted in Figure 2, whereby a distribution of degradation rates is determined for each range of crack depths based on the available crack propagation data obtained from the measurements. In this way, the operational use of the track is explicitly incorporated in the degradation modelling.

The first step was calculating degradation rates based only on propagations occurring between consecutive depth classes. This was done using the following equation:

$$DR = \frac{d2 - d1}{U2 - U1} \tag{3}$$

where DR represents the degradation rate, defined as the change in crack depth d over accumulated usage U between states 1 and 2. The obtained degradation rates and their weights are used to create a probability distribution for each depth class using the Gaussian Kernel Density Estimation (KDE) method. Propagations between consecutive depth classes are called one-level propagations, while those crossing more than one depth class are called n-level or multi-level propagations. The idea is to simulate multiple possible propagation scenarios by utilizing the prior distributions of degradation rates and then selecting the scenario that is closest to the actual overall propagation.

It was assumed that the degradation rate varies as the crack depth changes, necessitating the discretization of each multi-level propagation into one-level propagations to enable the calculation of a (PDF) for the degradation rates at each of the levels. A KDE is then fitted to model the degradation rates at this level, and the corresponding potential degradation rates are computed.

Understanding the initiation and degradation of cracks in a railway is inadequate for modelling the propagation of cracks. This is due to the fact that cracks do not exist at every single position along the rail; they occur in specific locations. Consequently, it becomes crucial to determine the number of cracks that have initiated or ascertain the proportion of the rail's total length that has been affected. To address this concern, a model has been developed to calculate the percentage of damaged length in a rail with cracks.

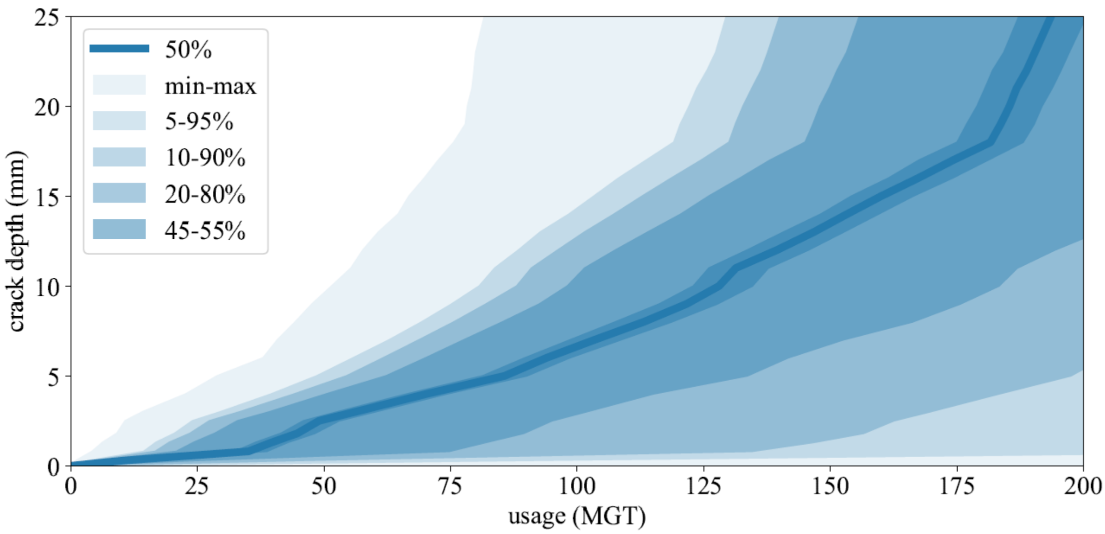


Figure 2: Crack propagation scenarios.

2.3 Petri Nets

Petri Nets (PN) are a graphical and mathematical modelling tool used for describing and analyzing systems involving discrete events and state transitions. They consist of two main components: places and transitions. Places represent states or conditions of the system, while transitions represent events or actions that cause a change in the system. These places and transitions are interconnected by directed arcs, which represent the flow of tokens, indicating the change of the PN state due to the occurrence of an event, see Figure 3.

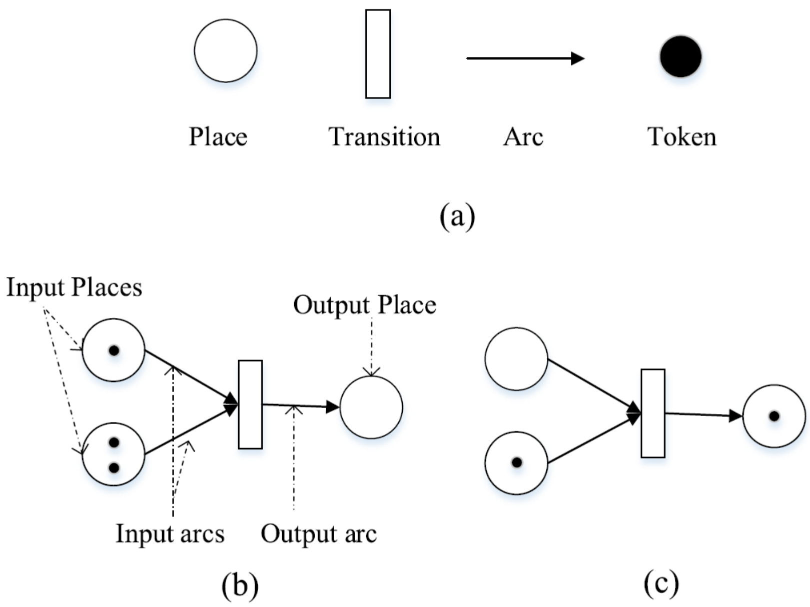


Figure 3: Petri net elements and transition firing. (a) elements of Petri net. (b) before transition firing. (c) after transition firing. [19].

PNs can be effectively used in maintenance decision-making tools by modelling the processes involved in maintenance activities and analyzing their behaviour. PNs can be used to model the various processes involved in maintenance activities, such as inspections, repairs, and replacements. Each maintenance task can be represented by one or more transitions, while the state of the system can be represented by the distribution of tokens over the places.

A PN is defined as a 5-tuple $\langle \mathbf{P}, \mathbf{T}, \mathbf{F}, \mathbf{M}_0, \mathbf{W} \rangle$ [20], where $\mathbf{P} = \{p_1, p_2, \ldots, p_{n_p}\}$ is the set of places, $\mathbf{T} = \{t_1, t_2, \ldots, t_{n_t}\}$ is the set of transitions, $\mathbf{F} \subseteq (\mathbf{P} \times \mathbf{T}) \cup (\mathbf{T} \times \mathbf{P})$ is the set of arcs, $\mathbf{W} : \mathbf{F} \longrightarrow \mathbb{N}_{>0}$ is the set of weights function, and $\mathbf{M}_0 : \mathbf{P} \longrightarrow \mathbb{N}_{>0}$ is the number of tokens in each place initially, which is the initial markings.

The architecture of the PN can be summarised in the incidence matrix, $\mathbf{A} \in \mathbb{N}^{n_p \times n_t}$, which is the subtraction of the *backward incidence matrix* $\mathbf{A}^- = \left[a^-_{ij}\right]$ from the *forward incidence matrix* $\mathbf{A}^+ = \left[a^+_{ij}\right]$, where a^-_{ij} coincide with $\mathbf{W}(p_i, t_j)$, which is the weight of the arc from place p_i to transition t_j, and a^+_{ij} coincide with $\mathbf{W}(t_j, p_i)$, which is the weight of the arc from transition t_j to place p_i. The dynamics of the PN are controlled by the state of each transition, which manages the flow of tokens. Each transition has a set of input places, ${}^\bullet\mathbf{P}_t$, referred to as the *pre-set places*, and output places, $\mathbf{P}^\bullet_t$, referred to as the *post-set places*. According to the *firing rule* in ordinary PNs, a transition, t_j, is said to be enabled once the markings of all its pre-set places are equal or greater than the weights of its pre-set arcs ($\mathbf{M}(p) \geq \mathbf{W}(t_j, p)\ \forall p \in {}^\bullet\mathbf{P}_{t_j}$). Every enabled transition can fire, and this consumes tokens from its pre-set places and produces tokens in its post-set places equal to the weights of the arcs connecting the places to the transition. This operation can be done for all transitions together in an efficient way using the *state equation* defined by:

$$\mathbf{M}_{k+1} = \mathbf{M}_k + \mathbf{A}^T \mathbf{u}_k \tag{4}$$

where k is the time step and $\mathbf{u} = [u_1, u_2, \ldots, u_{n_t}]^T$ is the firing vector. More rules can be added to deal with the complexity of dynamic systems. Timed transitions are one of the rules that assign a delay to transitions. A transition with a delay cannot fire unless a certain amount of time passes after it is enabled. This type of transition was used in the created PN model and is essential when modelling reliability engineering systems. Additionally, functions are defined and linked to the firing of transitions. Defining functions enables the modelling of continuous aspects in the PN model, which is inherently a discrete event model [9].

Addressing crack initiation in the railway system involves an examination of track geometrical characteristics. A proposed solution suggests managing branches with distinct geometries by dividing them into separate parts with unique properties. When cracks initiate, they impact specific regions within each part. To present a realistic portrayal, each part is subdivided into sections, ensuring that cracks are confined to specific areas upon crossing the initiation threshold. In the PN model, the railway branch is represented with subnets for each part, further divided into sections. This approach facilitates a comprehensive exploration of maintenance policies. The primary states and events of each part are described by places and transitions, respectively. States related to cracks and their distribution are modelled using functions. Transitions describe essential events within a branch, such as crack initiation and failure, which occur when a crack exceeds a specified threshold. Functions play a critical role in detailing the distribution of cracks across sections, the propagation scenario of each crack, the depth of individual cracks, and the effects of maintenance actions. Other transitions are used to describe system-level events, including inspection, corrective maintenance, and cyclic maintenance. The decision for corrective maintenance is based on the condition of each part post-inspection. Functions are intricately linked to these transitions to model the costs associated with various maintenance actions, allowing for the assessment of different maintenance strategies to identify the optimal one.

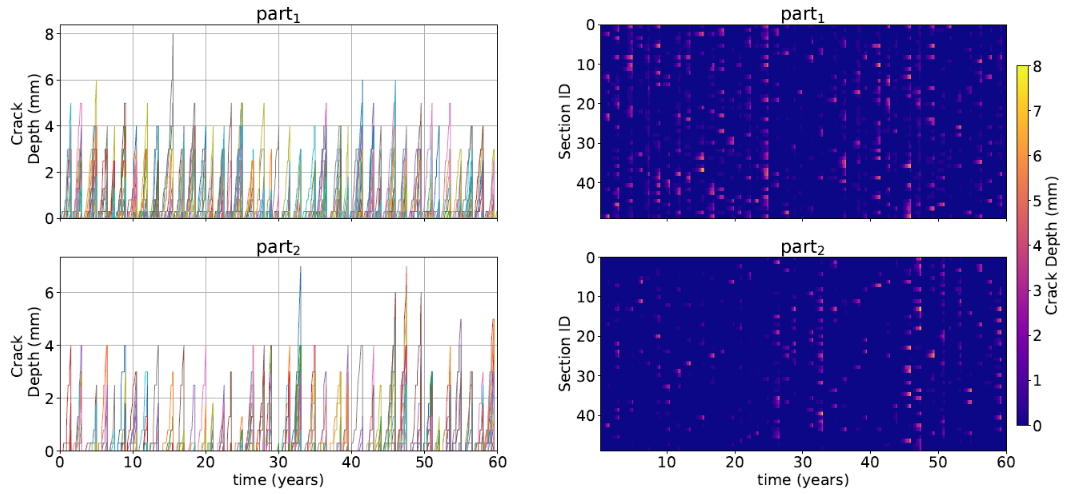
3 Results and Discussion

A case study of a rail branch, which consists of three parts that each contain 50 sections of 1000 meters in length and a rail cant of 100 mm, is considered. The first part has a radius of 1500 meters, the second part a radius of 2000 meters and the third part boasts a radius of 2500 meters. The Dutch rail network has developed a standardized classification method to gauge the severity of cracks based on their depths: light, medium, heavy, and severe for crack depths of less than 10mm, 10mm-20mm, 20mm-30mm, and above 30mm, respectively [21]. This study focuses on optimizing maintenance activities by reducing operational costs while keeping all cracks within the light and medium severity range (less than 20 mm).

The variables considered for optimization include the inspection frequency, the threshold for performing corrective maintenance, the threshold for performing replacements, the frequency of cyclic maintenance, and the number of grinding passes for cyclic maintenance. The aim is to fine-tune these factors to enhance maintenance efficiency while ensuring the safety of the rail. As the base case, the PN is simulated with the following input parameters: grinding interval every 15 MGT, number of grinding passes: 3 (0.035 mm of crack removal per pass), maintenance threshold at 3 mm of crack depth, replacement threshold at 15 mm of crack depth.

The results of the case study are depicted in Figure 4 and Figure 5. These visual representations provide a clear and comprehensive understanding of how cracks develop in the different parts of the branch, making it easier to interpret the findings. The results reveal that the third part of the rail branch remains crack-free throughout its lifetime, so this part is not plotted in these figures. However, the first and second part exhibit crack evolution, necessitating corrective maintenance. The disparity in crack occurrence is due to the differing radii of the rail sections, with the third part having a greater radius than the others, resulting in less curvature. Curved rails are more susceptible to cracks due to increased stress concentration at specific points along the curve, escalated wear from wheel-rail interaction, material fatigue induced by constant bending, and potential differential settlement. The findings emphasize that cyclic grinding every 15 MGT is insufficient to prevent cracks in all rails with radii less than 3000 m, underscoring the importance of regular inspections and proactive corrective maintenance measures.

The time distribution of the optimal maintenance actions across sections of the rail branch is depicted in Figure 5. The figure illustrates that milling was the preferred choice for most corrective actions. The decision between repair (milling or grinding) and replacement is influenced by the specified replacement threshold. The choice between milling and grinding, on the other hand, is based on cost considerations. Opting for milling in the majority of cases indicates that milling costs are lower than those of grinding for corrective actions in this case. This decision is justified by the milling's ability to remove greater depth from the rail, particularly considering that crack depths are relatively substantial (up to 7 mm) compared to the grinding's crack removal ability (0.035 mm per pass for a High-Speed Grinding (HSG) train). This demonstrates that grinding could be more effective for preventive maintenance, as it removes minimal depth from the rail while also preventing crack formation. However, it proves less effective when dealing with relatively large cracks. It should be noted that, in some cases, it is necessary to perform grinding immediately after milling to achieve a smooth rail surface and to reduce noise disturbances. However, this is not the scenario considered in this study.



(a) The variation of crack depths as a function of time. (b) Heatmap of crack depths and locations as a function of time.

Figure 4: Crack depths for 50 sections in two different parts with different curve radii of the considered case study.

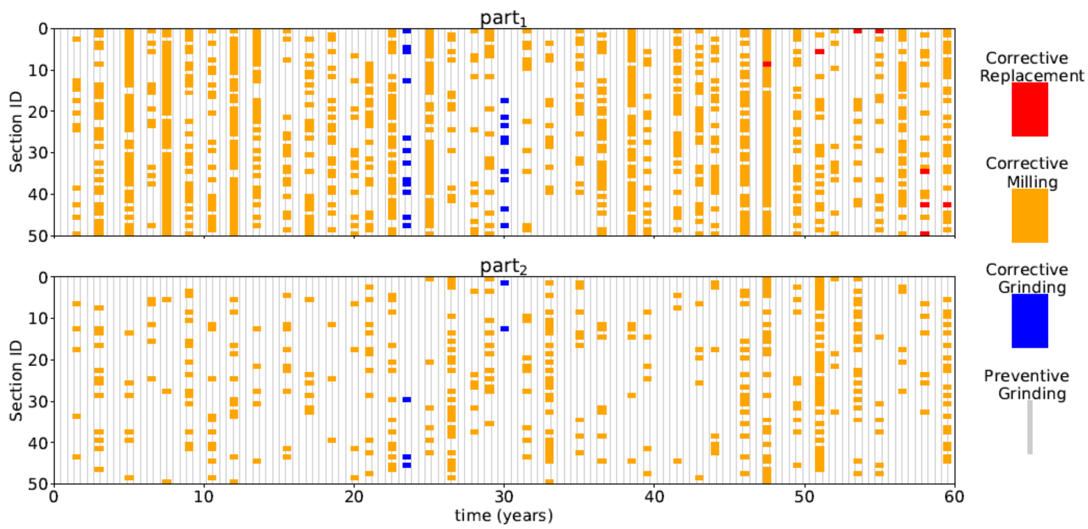


Figure 5: Distribution of optimal maintenance actions over time and sections for the considered case study.

4 Concluding remarks

In this paper, a meta-model approach is utilized to predict crack initiation, while Petri Nets (PNs) are employed to model crack propagation and optimize maintenance decisions. The results of the considered case study demonstrate the effectiveness of the proposed approach in identifying optimal maintenance strategies to mitigate the progression of cracks and minimize operational costs while ensuring safety and reliability in railway systems. Overall, the integration of meta-models, PNs, and advanced decision-making techniques offers a promising framework for optimizing maintenance decision-making in railway infrastructure.

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