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A Data-Driven Chance-Constrained Receding-Horizon Framework for Railway Turnout Maintenance Optimization

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Abstract

This study presents a data-driven stochastic framework for degradation modeling and maintenance optimization of railway components parts under uncertainty. The proposed framework integrates data-driven degradation and repair-effectiveness models with an MDP-based regime-transition model, enabling the representation of realistic asset life-cycle behavior under changing conditions. Building on these stochastic degradation scenarios, a chance-constrained receding-horizon optimization framework is developed to support maintenance and renewal decision-making. Maintenance activities are evaluated using risk-adjusted cost, and reliability indicators, while chance constraints ensure compliance with predefined risk thresholds. The approach was validated using real datasets. The resulting framework enables adaptive maintenance planning that balances economic performance and system reliability under uncertain degradation conditions.

Keywords: predictive maintenance, railway turnouts, stochastic degradation modeling, chance-constrained optimization, receding-horizon optimization, lifecycle cost, Monte Carlo simulation.

1 Introduction

Railway turnout systems are complex multi-component assets whose performance depends on the condition of their individual elements [1]. During operation, these components are continuously subjected to mechanical loads, dynamic impacts, and environmental conditions that lead to progressive degradation. The growing demand for rail transportation and increasing train frequencies further accelerate wear and deterioration processes [2].

To maintain safe and reliable operation, turnout systems require regular maintenance and periodic replacement of degraded components. However, these interventions are resource-intensive and involve significant costs associated with labor, equipment, track possession periods, and traffic disruption management. Consequently, maintenance decisions must balance the benefits of preserving asset condition against the operational and economic burden of interventions.

Determining when and how to perform maintenance and replacement is therefore a critical challenge. Effective maintenance planning aims to maintain safety, reliability, and availability while minimizing life-cycle costs and avoiding both premature interventions and unexpected failures [2; 3]. However, determining optimal maintenance and replacement strategies remains challenging due to the significant uncertainties that affect both degradation and maintenance processes. The evolution of component condition is influenced by variable operating conditions, traffic loads, environmental factors, and heterogeneous maintenance effects, making future asset behavior uncertain.

Traditional deterministic approaches are often insufficient to represent these uncertainties because they typically assume fixed degradation patterns and simplified operating conditions [4]. Physical and mechanistic models, while valuable for understanding degradation mechanisms [5], also present important limitations in real railway applications. These models generally require strong assumptions regarding material properties, loading conditions, environmental influences, and component interactions. In practice, railway turnout systems operate under highly variable conditions that are difficult to fully characterize mathematically. Furthermore, physical models often require extensive calibration, expert knowledge, and large amounts of high-quality data, while still struggling to reproduce the variability observed in real degradation processes. Similarly, conventional probabilistic approaches commonly rely on predefined parametric distributions that may not accurately reflect the stochastic behavior of degradation and maintenance effects observed in railway infrastructure systems [6; 7].

To overcome these limitations, data-driven approaches have recently attracted increasing attention in railway infrastructure maintenance [8; 9; 10; 11]. In particular, non-parametric statistical methods provide greater flexibility by modeling uncertainty directly from historical observations without imposing restrictive assumptions on the underlying probability distributions.

To overcome these limitations, this work adopts a data-driven, non-parametric framework that models uncertainty directly from historical data. Realistic degradation scenarios are generated through simulation and integrated into an optimization framework to support cost-effective maintenance and renewal decisions under uncertainty.

The remainder of this chapter is organized as follows: Section 2 reviews the literature on railway maintenance joint renewal planning and discusses the extensions of state-of-the-art solution approaches proposed in this work. Section 3 presents the problem definition, context, and motivation. Section 4 introduces the proposed stochastic optimization model for joint maintenance and renewal planning, Following this, Section 5 provides computational experiments and results. Finally, Section 6 concludes the paper and outlines potential future research directions.

2 State of the art

This section surveys existing studies on maintenance planning under uncertainty within the operations research literature.

Maintenance optimization in railway systems has been widely studied, with early works focusing on minimizing maintenance costs. For instance, [12] developed a life-cycle cost model integrating track deterioration and tamping policies, while [13] and [14] proposed optimization models for maintenance scheduling and planning at tactical and strategic levels. Risk-aware maintenance planning has gained significant attention in railway systems. Existing studies have proposed risk-based inspection and maintenance policies using failure probabilities to quantify asset risk [15], while others have integrated degradation models and probabilistic risk measures into optimization frameworks for maintenance scheduling [16]. Stochastic life-cycle cost models based on Monte Carlo simulation have also been developed to identify optimal renewal intervals under uncertainty [17], and risk-constrained maintenance planning approaches have been used to adjust maintenance aggressiveness according to acceptable risk levels [18]. Alternative reliability modeling techniques, including Markov chains and Petri nets, have likewise been explored [19; 20].

To better account for uncertainty over time, researchers have proposed scenario-based optimization frameworks. Examples include two-stage selective maintenance models with recourse decisions [21], multistage stochastic programming approaches that explicitly model the impact of maintenance actions on future degradation and failures [22], and chance-constrained model predictive control frameworks that ensure infrastructure quality requirements are satisfied with high probability [23; 24]. These methods introduce a foresight component into maintenance planning by considering future uncertainties and adapting decisions over time. However, many rely on parametric degradation assumptions, predefined uncertainty bounds, or computationally intensive stochastic optimization models. In previous works [25; 26], planning maintenance for railway curves using integer programming models and chance constraints was considered for cost minimization. Monte Carlo and bootstrapping are used to generate degradation scenarios [10].

Receding horizon optimization (also known as Model Predictive Control, MPC) have gained a lot of attention in predictive maintenance applications. Su & al (2015)

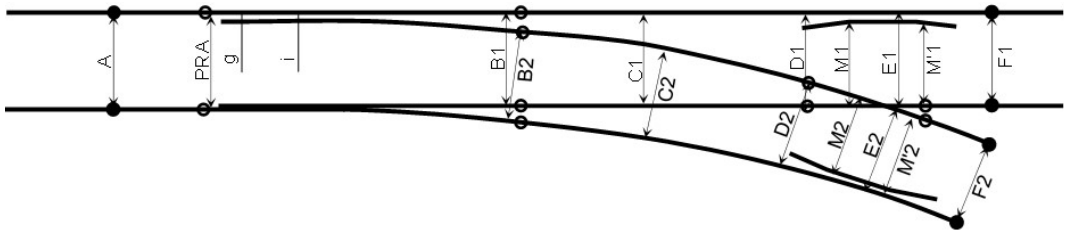

Figure 1: Monitored parts on the railway turnouts

formulate railway track maintenance as a hybrid MPC problem [27]. Another paper introduces a two-level Receding horizon optimization: the upper level uses predicted RUL to define maintenance windows, and the lower level solves a mixed-integer co-optimizing production and maintenance [28]. MPC was used for actuator health management [29]. Rokhforoz & Fink (2021) address joint maintenance and production scheduling via a distributed MPC+Benders approach [30]. The cited works demonstrate improved performance over reactive or periodic maintenance baselines by leveraging predictive degradation data and risk constraints

This work proposes a risk-aware framework for railway turnout maintenance optimization that combines non-parametric degradation modeling with receding-horizon decision-making. Historical data are used to generate realistic degradation scenarios, which are integrated into an adaptive optimization process for maintenance and renewal planning under uncertainty.

3 Problem statement

In this work, we focus on modeling the wear affecting turnout parts based on historical data collected from a railway network. To capture the spatial variability of degradation, the turnout is decomposed into multiple measurement points, as illustrated in the following figure 1.

In practice, these parts degrade over time under **heterogeneous operating conditions**. Furthermore, maintenance decisions are often made with **limited forward visibility**, since decision makers do not always have complete information regarding the future evolution of operating conditions. The degradation process is stochastic, and even within the same turnout, different degradation regimes may be observed as illustrated in 2 due to several influencing factors such as traffic load, wheel characteristics, and environmental conditions. Moreover, maintenance activities may themselves introduce variability into the degradation behavior depending on execution quality, and the current condition of the infrastructure.

This study develops a data-driven stochastic simulation framework to model degradation evolution at the compoenet level. The approach combines non parametric degradation and repair-effectiveness distributions, regime-transition dynamics to reproduce lifecycle behavior under uncertainty. Building on this framework, a risk-aware maintenance optimization strategy is proposed to identify maintenance decisions that minimize cost while satisfying reliability requirements. The methodology integrates approximate dynamic programming, chance-constrained optimiza-

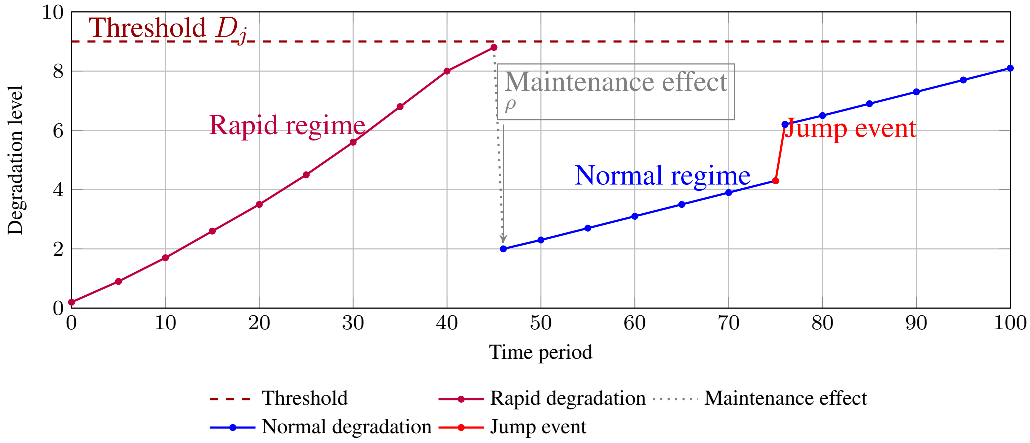

Figure 2: Regime-based degradation model with regime update after maintenance

tion, and receding-horizon decision making to account for degradation uncertainty and intervention effects.

4 Methodology

The proposed methodology is a data-driven stochastic framework that combines degradation modeling and maintenance optimization under uncertainty. This section presents the degradation model (Section 4.1) and the chance-constrained optimization framework (Section 4.2).

4.1 Regime-Based Degradation Modeling

To accurately represent the stochastic nature of the turnouts components deterioration, degradation is modeled through a set of operating regimes characterized by different degradation behaviors. Rather than assuming a predefined parametric distribution, the proposed approach relies on empirical distributions extracted from historical data as described in the next paragraphs.

4.1.1 Empirical Distributions for Regime-Based Degradation Modeling

The first step consists of extracting empirical distributions from historical data for degradation increments and jump events. The variable z^t is interpreted as the representation of three distinct degradation regimes. This decomposition improves the realism of the model by distinguishing progressive wear from abrupt degradation shocks. It also enhances decision support capabilities by enabling regime-aware maintenance and renewal policies.

- **Normal regime**: the normal regime corresponds to baseline aging under routine operating conditions. The degradation increments are typically moderate, with lower dispersion and small year-to-year variations. Formally,

$$\Delta_t \mid (z_t = \text{normal}, f) \sim \hat{F}_{\Delta}^{(f,\text{normal})},$$

where $\hat{F}_{\Delta}^{(f,\text{normal})}$ is estimated from empirically observed normal-state segments. The degradation rate is estimated from time series segments using linear regression.

- **Rapid regime**: the rapid regime represents accelerated deterioration, often associated with higher stress, adverse operating conditions, or temporary instability. Unlike normal behavior, this regime exhibits larger expected increments, resulting in faster maintenance threshold crossing. Formally,

$$\Delta_t \mid (z_t = \text{normal}, f) \sim \hat{F}_{\Delta}^{(f,\text{normal})},$$

where $\hat{F}_{\Delta}^{(f,\text{normal})}$ is estimated from empirically observed normal-state segments. A linear regression model is used to predict the slopes.

- **Jump regime**: The jump regime captures abrupt deterioration episodes (shock-like events) that are not well represented by continuous wear rates. These events produce large increments suddenly and therefore dominate upper-tail risk. For this regime no model is imposed. We use directly the empirical distribution of observed abrupt increments (delta-rate increments), after canonical merging of jump-like labels. Formally,

$$\Delta_t \mid (z_t = \text{jump}, f) \sim \hat{F}_{\text{jump}}^{(f)}$$

with $\hat{F}_{\text{jump}}^{(f)}$ calibrated from observed jump increments.

This hybrid strategy reflects the physics of the process: gradual regimes are well represented by slope-based dynamics, while abrupt regimes are better represented by direct increment distributions.

4.1.2 Transition matrix

The second step consists of modeling the transition dynamics between degradation regimes. Under the assumption that the asset is not replaced, the regime sequence z_t is modeled as a first-order, time-homogeneous Markov chain defined on the state space

$$\{Z\} = \{N, R, J\} = \{\text{normal}, \text{rapid}, \text{jump}\}.$$

The variable z_t represents the degradation regime of the asset at time t. The Markov assumption implies that the future regime depends only on the current regime and not on the entire past degradation trajectory. Formally,

$$\Pr(z_{t+1} = j \mid z_t = i, z_{t-1}, \ldots, z_0) = \Pr(z_{t+1} = j \mid z_t = i) = P_{ij},$$

where P_{ij} denotes the probability of transitioning from regime i to regime j in one time step.

To estimate the transition probabilities, observed transitions between regimes are counted from historical data. Let N_{ij} denote the number of observed transitions from state i to state j. The one-step transition probabilities are then estimated empirically as

$$\hat{P}_{ij} = \frac{N_{ij}}{\sum_{k \in \mathcal{Z}} N_{ik}}, \qquad i, j \in \mathcal{Z}$$

The resulting transition matrix is given by

$$P = \begin{bmatrix} P_{NN} & P_{NR} & P_{NJ} \\ P_{RN} & P_{RR} & P_{RJ} \\ P_{JN} & P_{JR} & P_{JJ} \end{bmatrix}$$

where the states N, R, and J correspond respectively to the normal, rapid, and jump degradation regimes.

4.1.3 Repair effectiveness

Repair effectiveness is modeled as a stochastic reduction mechanism that captures the fact that maintenance actions do not restore the asset to a perfectly new condition and do not have identical impact across interventions. Instead of assuming a fixed repair factor, we estimate an empirical effectiveness distribution from historical post-repair behavior. The repair factor is sampled as

$$\rho_t \sim \hat{F}_{\rho}^{(f)},$$

where $\hat{F}_{\rho}^{(f)}$ is calibrated from observed repair-effectiveness values.

4.2 Risk-Aware Receding-Horizon Maintenance Optimization

The degradation model developed in the previous sections provides a probabilistic description of the future condition of the turnouts parts. While such a model is essential for predicting degradation evolution, it does not explicitly indicate when and what to do. The next step is therefore to determine maintenance decisions that balance cost and system reliability throughout the lifecycle. This decision problem is inherently stochastic because future degradation trajectories are uncertain. To address this challenge, we adopt a **receding-horizon optimization framework** inspired by [23; 31].

Rather than optimizing decisions over the complete lifetime, maintenance actions are evaluated over a finite prediction horizon H. At each decision epoch t, future degradation trajectories are simulated over the horizon, candidate actions are evaluated, and the best action is selected, as illustrated in 3.. Only the first action is implemented. Once new condition information becomes available, the optimization problem is solved again using the updated system state. This process enables continuous adaptation of maintenance decisions to the latest asset condition and degradation forecasts.

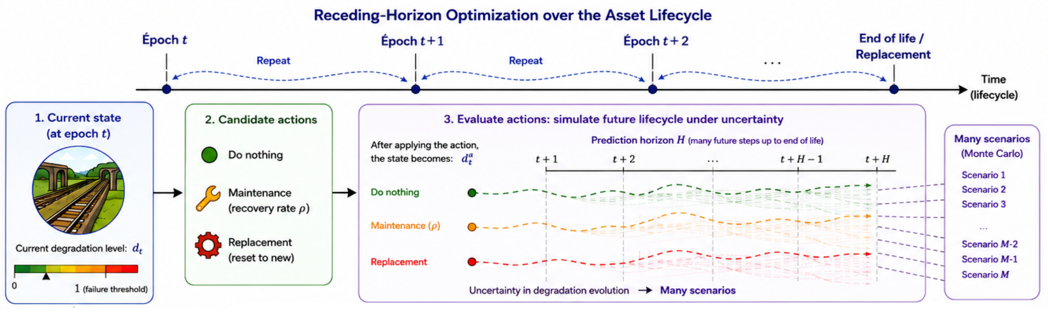

Figure 3: Receding-horizon optimization framework for maintenance and renewal planning

Let

$$s_t \in \mathcal{S}$$

denote the system state at decision epoch t, and let

$$a_t \in \mathcal{A}(s_t)$$

denote a feasible maintenance action belonging to the set of admissible actions.

The economic performance of a candidate action is evaluated through its expected discounted cumulative cost over the prediction horizon H:

$$J_H(s_t, a_t) = \mathbf{E}\left[\sum_{k=0}^{H-1} \frac{C(s_{t+k}, a_{t+k})}{(1+r)^k}\right],$$

where r denotes the discount rate and $C(s_{t+k}, a_{t+k})$ represents the operational cost incurred at future epoch $t+k$. This cost includes maintenance expenditures, replacement costs, downtime penalties, and penalties associated with excessive degradation levels or reliability violations.

Because different actions may generate costs distributed differently over time, direct comparison of cumulative discounted costs may be misleading. Therefore, the discounted cumulative cost is transformed into an equivalent annual cost (EAC),

$$\text{EAC}_H = \frac{J_H}{\sum_{k=0}^{H-1}(1+r)^{-k}},$$

which provides a normalised annualised measure of economic performance.

Although expected cost is an important performance indicator, it does not capture the uncertainty associated with future degradation trajectories. Two actions may exhibit similar expected costs while having significantly different levels of variability. From an operational perspective, decision-makers often prefer maintenance strategies that produce stable and predictable outcomes.

To account for this aspect, a risk-adjusted equivalent annual cost (RAEAC) is introduced. For each candidate action, M Monte Carlo rollouts are generated using the stochastic degradation model. Let $C_a^{(m)}$ denote the total discounted cost observed during rollout m. The expected cost is estimated as

$$\mathbf{E}[C_a] \approx \frac{1}{M} \sum_{m=1}^{M} C_a^{(m)},$$

while the corresponding cost variability is estimated through

$$\operatorname{Std}(C_a) \approx \sqrt{\frac{1}{M} \sum_{m=1}^{M} \left(C_a^{(m)} - \mathbf{E}[C_a] \right)^2}.$$

The risk-adjusted equivalent annual cost is then defined as

$$\operatorname{RAEAC}(a) = \frac{\mathbf{E}[C_a] + \lambda \operatorname{Std}(C_a)}{\sum_{k=0}^{H-1} (1+r)^{-k}},$$

where $\lambda \geq 0$ is a risk-aversion parameter. The standard deviation term penalizes actions associated with highly uncertain economic outcomes, thereby favoring maintenance strategies that remain robust under stochastic degradation conditions.

Additionally, the selected maintenance policy must also guarantee that reliability requirements are respected with a sufficiently high probability. To explicitly incorporate this requirement, we adopt a chance-constrained optimization framework.

Let

$$\alpha \in [0, 1]$$

denote the maximum accepted probability of violating a reliability or degradation threshold. For each candidate action, the violation probability is estimated through Monte Carlo simulation as

$$\hat{p}_{\text{deg}}(a) = \frac{1}{M} \sum_{m=1}^{M} \mathbf{1}\left(\text{degradation occurs in rollout } m\right),$$

where $\mathbf{1}(\cdot)$ denotes the indicator function.

Based on this estimate, the admissible action set is defined as

$$\mathcal{A}_\alpha(s_t) = \left\{ a \in \mathcal{A}(s_t) : \hat{p}_{\text{deg}}(a) \leq \alpha \right\}.$$

Only actions satisfying the prescribed reliability requirement are retained for optimization.

The maintenance decision at epoch t is obtained by solving the following chance-constrained optimization problem:

$$a_t^* = \arg \min_{a \in \mathcal{A}_\alpha(s_t)} \operatorname{RAEAC}(a).$$

The selected action therefore minimizes the risk-adjusted economic objective while ensuring that the estimated probability of reliability not respected remains below the accepted threshold.

The parameter α acts as a policy-level safety control governing the trade-off between economic performance and reliability. Smaller values of α lead to more conservative maintenance policies and earlier activities, whereas larger values allow greater risk exposure in exchange for lower short-term maintenance expenditures. The proposed framework relies on a simulation-based approximate dynamic programming (ADP) strategy embedded within a receding-horizon control architecture as illustrated in the algorithm 1.

.

Algorithm 1 Receding-Horizon Monte Carlo VIA ADP

Input: state s_t, horizon H, reliability threshold α, outer rollouts M_{outer}, inner rollouts M_{inner}, discount r

function $\hat{V}(s, h)$
    if $h = 0$ **then**
        return 0
    end if
    for each feasible action $a \in A(s)$ **do**
        $\hat{Q}(s, a, h)$ = mean over M_{inner} samples of $[\, c(s, a, s') + \frac{1}{1+r}\hat{V}(s', h-1)]$
        where s' is sampled from empirical transition model
    end for
    return $\min_a \hat{Q}(s, a, h)$
end function

Build feasible actions $A(s_t)$
for each $a \in A(s_t)$ **do**
    Run M_{outer} simulations and compute:
        risk_adjusted_annual_cost(a), $p_{\text{reliability}}(a)$)
        (using $\hat{V}(\cdot, H-1)$ for future cost)
end for
$A_\alpha = \{a : p_{\text{reliability}}(a) \le \alpha\}$
Select best action by lexicographic ranking:
    (risk_adjusted_annual_cost, $p_{\text{degradation}}$)
    on A_α if non-empty, else on $A(s_t)$
Execute only first action $a_t^\star$, update state, shift horizon, repeat
Stop when replacement is triggered

5 Results and discussion

This section presents the computational experiments conducted to evaluate the effectiveness of the proposed approaches for solving the stochastic maintenance and renewal formulation. The study focuses on a set of 200 turnouts from a real-world urban railway network, using historical inspection and maintenance data collected over the past ten years. It should be noted that the cost assessment in this study is limited to a set of turnout components for which data were collected, rather than the turnout as a whole. Owing to confidentiality agreements, the underlying data cannot be made publicly available. The table 1 below presents the values of the different parameters.

We compare the proposed approach with three proposed baselines, the difference between the baselines is in the way degradation increments from normal regime are chosen:

- **Max threshold (worst-case)**: it is the most pessimistic baseline. At each year, degradation is pushed with the maximum observed increment, so assets

Table 1: Model parameters.

Parameter	Value
B (max. repairs)	$[3, 5]$
δ (degradation rate)	$[0.2, 7]$
Threshold	$[21, 1016]$
Initial value	$[15, 1010]$
C_r (repair cost)	3.0
C_{rep} (replacement cost)	60.0
r (discount rate)	0.03
H (horizon)	6
M (simulations)	1000
Lifecycle	30 years

deteriorate fastest.

- **Q3 rate** : it uses the 75th percentile degradation increment. It is still pessimistic, but less extreme than the max case.
- **Mean rate**: it uses average degradation increment each step.

Figure 4 compares the performance of the different maintenance approaches with respect to the mean total cost, mean number of repairs, and mean replacement time. The results show that the proposed approach achieves the lowest mean total cost while requiring significantly fewer repair interventions than all baselines, which perform approximately repairs on average. Although the stochastic and mean-rate reactive strategies lead to longer replacement intervals, they incur higher costs due to the larger number of repair actions. Overall, the receding horizon approach provides a more balanced maintenance policy.

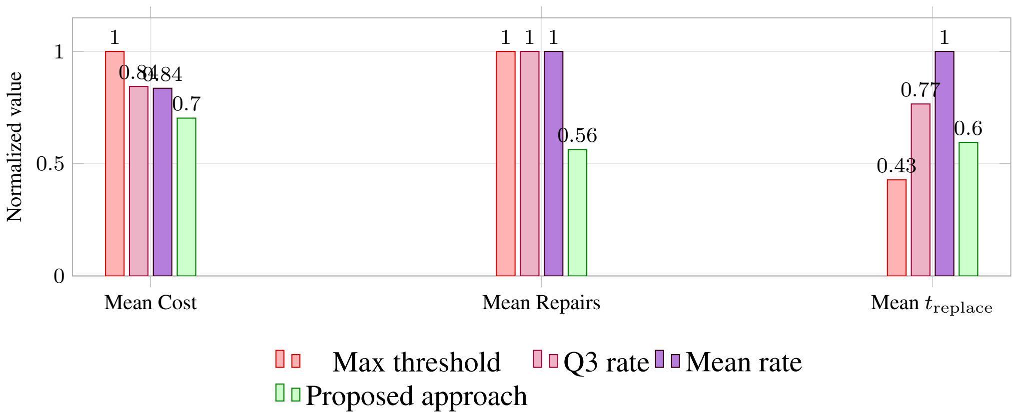

Figure 4: Comparison of maintenance policies. KPI values are normalized by the maximum value of each KPI.

Figure 5 illustrates the impact of the number of simulations on the execution time and the realized total cost. As expected, the execution time generally increases with n_{sims}, reflecting the higher computational effort required to evaluate more scenarios. In contrast, the realized total cost remains nearly constant, varying only between 79 and 81. This suggests that increasing the number of simulations beyond a moderate level has little effect on solution quality while significantly increasing computation time, highlighting a trade-off between computational efficiency and robustness.

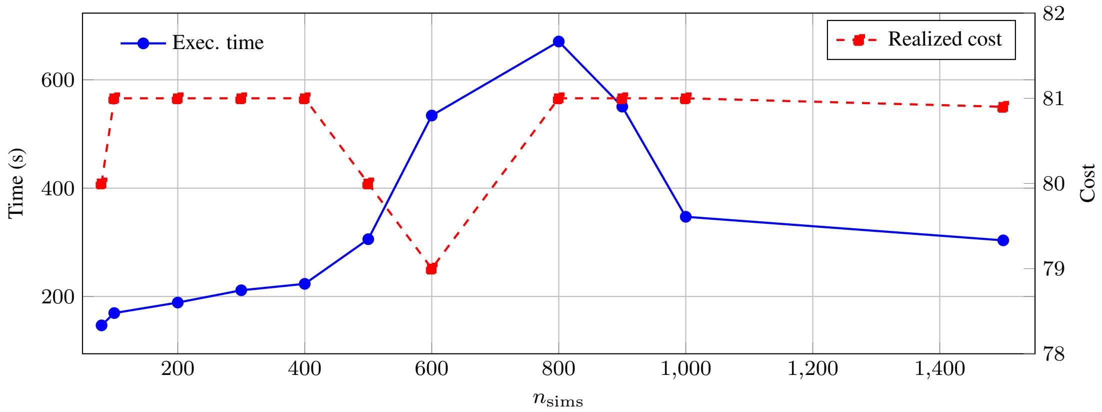

Figure 5: Execution time and realized total cost versus the number of simulations.

6 Conclusion

This paper presents a data-driven chance-constrained receding-horizon framework for optimizing maintenance decisions in railway turnout systems under uncertainty. The approach combines empirical degradation and repair-effectiveness models with a rolling-horizon optimization process to support cost-effective maintenance while satisfying reliability requirements.

Experimental results demonstrate that the proposed method outperforms benchmark strategies by reducing maintenance costs and the number of interventions while maintaining the desired reliability level.

Future work will focus on extending the framework to incorporate turnout-level decisions, resource and operational constraints, and long-term lifecycle considerations.

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