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Abstract: This manuscript proposes a methodology to leverage digitalisation to efficiently generate an overview of required condition-based railway track interventions, possession windows, and expected costs for railway networks at the beginning of the intervention planning process. The consistent and efficient generation of such an overview not only helps track managers in their decision-making, but also facilitates the discussion among other decision-makers in later phases of the track intervention planning process, including line planners, capacity managers, and project managers. The methodology uses data of different levels of detail, discrete state modelling for uncertain deterioration of components, and component-level intervention strategies. It dynamically updates the condition estimates of components by capturing the interaction between deteriorating components using Bayesian filters. It also estimates the risks associated with different types of potential service losses that may occur due to sudden events using fault trees as a function of time and the condition of components. An implementation of the methodology is done for a 25 km regional railway network in Switzerland. The results suggest that the methodology has the potential to help track managers early in the intervention planning process. In addition, it is argued that the methodology will lead to improvements in the efficiency of the planning process, improvements in the scheduling of preventive interventions, and the reduction in corrective intervention costs upon the implementation in a digital environment.

Keywords: infrastructure management; railway systems; digitalisation; deterioration modelling; maintenance planning; intervention strategies

1. Introduction

Track managers currently estimate intervention requirements qualitatively in the initial phases of the intervention planning process based on the synthesis of visual inspection and measurement train results by a group of track engineers [1,2]. The current practice, however, is time-consuming, labour-intensive, and cognitively demanding for engineers. Moreover, the biases and subjectivity of experts' judgments may result in the sub-optimal scheduling of interventions. This could eventually result in higher intervention costs and more frequent service disruptions [3]. Consequently, a systematic approach that can generate a quantitative and comprehensive outlook of intervention requirements for all tracks over the future planning periods, considering all crucial factors and criteria, would be beneficial for track managers.

The current intervention planning process can be improved through the integration of a digital tool, leveraging recent technological advancement and the accumulation of extensive data on track component characteristics, their condition, the evolution of their condition over time, and the costs

associated with their maintenance and replacement. This tool can improve the ability of track managers to plan effectively [3,4].

This manuscript proposes a methodology to automatically generate a consistent overview of component-level interventions, costs, possession windows, and the evolution of failure risks for all track sections located in a railway network over future planning periods. This includes considering the interaction between deteriorating components using Bayesian filters, the impacts of the residual damages to the components due to imperfect execution of maintenance interventions using non-homogeneous transition probabilities, and the evolving risks associated with different types of potential service losses that may occur due to sudden and gradual deterioration events connected to the time and the condition of components using fault trees. The methodology uses data of different levels of detail, probabilistic discrete state modelling for uncertain deterioration of components, and component-level intervention strategies.

The methodology enables the use of both qualitative and quantitative data collected from several sources such as visual inspections, approximate and detailed estimates of failure risks, intervention costs and impacts on service. An application of this methodology is demonstrated by estimating a complete overview of component-level intervention requirements for track sections on a 25 km railway network in Switzerland.

The remainder of this manuscript is organised as follows. Section 2 provides a brief overview of the research on estimating the intervention requirements for railway assets. Section 3 includes a detailed description of the proposed methodology. Section 4 includes a detailed explanation of the example railway network along with a detailed description of results from the implementation of the proposed methodology. Section 5 explains how to enable the use of the methodology in infrastructure management firms. Section 6 includes the discussion of the results, strengths and limitations of the presented methodology. Finally, the manuscript is concluded in Section 7.

2. Literature Review

State-of-the-art methodologies aim to improve intervention planning for different infrastructure assets by addressing the concerns of different asset managers. A selection of these methodologies are summarised in Tables 1 and 2. These methodologies are based on either deterministic or probabilistic modelling approaches.

Deterministic models mainly assume the condition of a railway asset evolves over time as a (non-)linear function of the asset age. For example, Giunta et al. [5] developed maintenance strategies for the bitumen-stabilised ballast using a deterministic model as a function of the age of the ballasts. While these models ensure the ease of comprehension and implementation in the existing asset management systems, they do not account for the uncertain behaviour of railway assets throughout their life cycle [6].

Probabilistic models, on the other hand, consider the uncertainties associated with the evolution of railway assets' condition subject to several deterioration processes over time. For example, Fecarotti, Andrews, and Pesenti [7] determined the optimal track intervention strategies with the help of probabilistic modelling of deterioration processes to account for the uncertain evolution of track assets throughout their life cycle.

In addition, many state-of-the-practice methodologies use probabilistic modelling; for example, AASHTOWare in USA, Kuba and SwissTamp in Switzerland, and the Network Rail bridge-management system in the UK [8,9]. These systems estimate intervention requirements over future planning periods by classifying the damage indicator measurements, determined by the inspectors, into appropriate Condition States (CSs) and probabilistically modelling their evolution over time.

Table 1. Summary of a selection of literature related to railway intervention estimation.

Source	Theme	Detail level
Adey and Hajdin[15]	Methodology for determination of financial needs of gradually deteriorating bridges with only structure level data	Asset
Allah Bukhsh et al.[16]	Multi-year maintenance planning framework using multi-attribute utility theory and genetic algorithms	Asset
Bressi et al.[17]	Optimization of maintenance strategies for railway track-bed considering probabilistic degradation models and different reliability levels	Element
Chiachío et al.[18]	A knowledge-based prognostics framework for railway track geometry degradation	Asset
Consilvio et al.[19]	A data-driven prioritisation framework to mitigate maintenance impact on passengers during metro line operation	Asset
Consilvio et al. [20]	On Applying Machine Learning and Simulative Approaches to Railway Asset Management: The Earthworks and Track Circuits Case Studies	Asset
Fecarotti and Andrews[21]	A Petri net approach to assess the effects of railway maintenance on track availability	Component
Fecarotti and Andrews[12]	Producing effective maintenance strategies to control railway risk	Asset
Giunta et al.[5]	Life cycle cost assessment of bitumen stabilised ballast: A novel maintenance strategy for railway track-bed	Element
Hidirov and Guler[22]	Reliability, availability and maintainability analyses for railway infrastructure management	Component
Irfan et al.[23]	Framework for airfield pavements management—an approach based on cost-effectiveness analysis	Asset
Kaewunruen et al.[13]	Risk-Based Maintenance Planning for Rail Fastening Systems	Element
Kobayashi et al.[11]	A competing Markov model for cracking prediction on civil structures	Asset
Prescott and Andrews[24]	Investigating railway track asset management using a Markov analysis	Asset
Prescott and Andrews[25]	A track ballast maintenance and inspection model for a rail network	Component
Rúa et al.[26]	A top-down approach for a multi-scale identification of risk areas in infrastructures: particularization in a case study on road safety	Asset
Sadeghi et al.[27]	Improvement of railway ballast maintenance approach, incorporating ballast geometry and fouling conditions	Element
Sancho et al.[28]	Optimizing Maintenance Decision in Rails: A Markov Decision Process Approach	Asset
Sasidharan et al.[29]	A whole life cycle approach under uncertainty for economically justifiable ballasted railway track maintenance	Asset
Sharma et al.[30]	Data-driven optimization of railway maintenance for track geometry	Asset
Soleimanmeigouni et al.[31]	Prediction of railway track geometry defects: a case study	Asset
Sresakoolchai and Kaewunruen[32]	Railway infrastructure maintenance efficiency improvement using deep reinforcement learning integrated with digital twin based on track geometry and component defects	Component
Usman et al.[35]	Railway track subgrade failure mechanisms using a fault chart approach	Element
Usman et al.[36]	Using Probabilistic Fault Tree Analysis and Monte Carlo Simulation to Examine the Likelihood of Risks Associated with Ballasted Railway Drainage Failure	Asset
Vale and Simos[37]	Prediction of Railway Track Condition for Preventive Maintenance by Using a Data-Driven Approach	Asset
Vandoorne and Gräbe[38]	Stochastic rail life cycle cost maintenance modelling using Monte Carlo simulation	Element
Wenfi et al.[39]	Optimization Model of Life Cycle Repair Decisions for Track Network	Asset
Proposed methodology	Improving the intervention planning of railway tracks considering the interaction of components and uncertain evolution of failure risks	Component

Table 2. Summary of a selection of literature related to railway intervention estimation.

Source	Deterioration types		Deterioration modelling	Dynamic deterioration rates	Interaction between assets/components	Failure risks		Dynamic FR[1] calculation	IS[1] determination/utilization	Generating future interventions overview
	Gradual	Sudden				Structural	Service			
Adey and Hajdin[15]	✓	✓	Stochastic	×	×	✓	×	×	✓	×
Allah Bukhsh et al.[16]	✓	×	Mixed	✓	×	✓	×	×	✓	×
Bressi et al.[17]	✓	×	Stochastic	×	×	×	×	×	✓	×
Chiachío et al.[18]	✓	✓	Stochastic	×	×	✓	×	✓	×	×
Consilvio et al.[19]	×	×	-	×	×	×	✓	×	✓	×
Consilvio et al. [20]	✓	×	Stochastic	×	×	✓	×	✓	✓	×
Fecarotti and Andrews[21]	✓	✓	Stochastic	×	×	×	✓	×	✓	×
Fecarotti and Andrews[12]	✓	✓	Stochastic	×	×	✓	×	×	✓	×
Giunta et al.[5]	✓	×	Deterministic	×	×	×	×	×	✓	×
Hidirov and Guler[22]	✓	✓	Stochastic	×	×	✓	×	×	✓	×
Irfan et al.[23]	✓	×	Deterministic	×	×	×	×	×	✓	×
Kaewunruen et al.[13]	×	✓	Stochastic	×	×	✓	×	✓	×	×
Kobayashi et al.[11]	✓	×	Stochastic	×	✓	×	×	×	✓	×
Mehranfar et al.[1]	✓	✓	Stochastic	✓	×	×	✓	✓	✓	✓
Prescott and Andrews[24]	✓	×	Stochastic	×	×	×	×	×	✓	×
Prescott and Andrews[25]	✓	×	Stochastic	×	×	×	×	×	✓	×
Rúa et al.[26]	×	✓	-	×	×	✓	×	×	×	×
Sadeghi et al.[27]	✓	×	Deterministic	×	×	×	×	×	✓	×
Sancho et al.[28]	✓	×	Stochastic	×	×	×	×	×	✓	×
Sasidharan et al.[29]	✓	✓	Stochastic	×	×	✓	×	×	✓	×
Sharma et al.[30]	✓	✓	Stochastic	×	×	✓	×	×	✓	×
Soleimanmeigouni et al.[31]	✓	×	Deterministic	✓	×	✓	×	✓	×	×
Sresakoolchai and Kaewunruen[32]	✓	×	AI	✓	×	×	×	×	✓	×
Usman et al.[35]	×	✓	-	×	×	✓	×	×	×	×
Usman et al.[36]	×	✓	Stochastic	×	×	✓	×	✓	×	×
Vale and Simos[37]	✓	×	Stochastic	×	×	×	×	×	✓	×
Vandoorne and Gräbe[38]	✓	✓	Stochastic	×	×	✓	×	×	✓	×
Wenfi et al.[39]	✓	✓	Stochastic	✓	✓	×	×	×	✓	×
Proposed Methodology	✓	✓	Stochastic	✓	✓	✓	✓	✓	✓	✓

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[1]   FR: Failure Risks, IS: Intervention Strategies

Although these methodologies can be used to generate an overview of intervention requirements, they often lack the detail and considerations required by track managers such as service loss risks, and the granularity of intervention estimates. To address this limitation, some researchers suggested incorporating the sudden deterioration processes, such as the occurrence of natural hazards into the probabilistic methodologies. For example, Lethanh et al. [10] developed a Markov model for determining optimal intervention strategies taking into account both gradual and sudden deterioration processes using two sets of non-failure and failure CSs. Similarly, Kobayashi et al. [11] used Bayesian estimation and Markov Chain Monte Carlo method to estimate how assets evolve over time. These work, however, did not consider the interaction between deteriorating asset components. Therefore, some researchers proposed to consider such interaction in the construction of the models. For example, Fecarotti and Andrews [12] incorporated the risks associated with railway track failure into their probabilistic modelling to determine the optimal track intervention strategy. Although not explicitly, they considered the interaction between deteriorating railway assets. In addition, others suggested considering the dynamic changes in the deterioration modelling to account for the impact of the residual damages after the execution of maintenance interventions. For example, Mehranfar et al. [1] incorporated the dynamic changes in the deterioration rate of each asset component after each maintenance intervention into their probabilistic deterioration modelling to have more realistic estimates of intervention requirements using non-homogeneous transition probabilities. Some suggested conducting the deterioration modelling at the element level instead of the component level, meaning that the analysis is to be done for each element such as each bolt in a fastening system. For example, Kaewunruen et al. [13] proposed a risk-based intervention planning methodology for fastening systems. This level of detail, however, require a vast amount of high quality data and computing capacity.

Unfortunately, these cutting-edge methodologies are not often deemed desirable by track managers, despite their potential benefits. There are two major reasons for this. First, the implementation of these methodologies increases the efforts needed by track managers and the inspectors to generate an early-phase overview of track interventions. This is considered by many as a major barrier, e.g., collection and analysing element-level data on all track sections requires significant amount of time and effort since a detailed study must be conducted on all track sections in a network. Second, from the management point of view, it is more likely that an intervention is executed on all components of the same type in a track section, rather than targeting only a single element in that track section. Indeed, the likelihood might not be the same based on the specific characteristics of the components.

Ultimately, this manuscript presents a methodology to generate an efficient and complete overview of intervention requirements, their possession windows, and costs. It contributes to the state-of-the-art by:

- estimating intervention requirements and the failure risk at the component level, since this is considered to establish an appropriate trade-off between the required effort to implement the methodology and provided level of detail.
- using non-homogeneous deterioration rates coupled with Bayesian filters to provide an improved modelling of the components' deterioration, since the deterioration rate of the components changes over time due to both the imperfections in the execution of the maintenance intervention and the interaction between deteriorating components [14]. For example, a fresh ballast does not behave the same as a ballast that has been rehabilitated three times.
- incorporating the service loss in the estimation of intervention requirements in addition to the structural failure since the highest risks associated with railway tracks in a well-managed railway infrastructure is the service loss, and not total structural failure.

3. Methodology

3.1. Steps

The overview of the proposed methodology is shown in Figure 1. This methodology encompasses multiple steps that are described as follows:

0. **Set up the requirements and constraints**: the requirements and constraints for initialising and using the algorithm must be set up first.
1. **Select all track sections for which the estimates are to be made**: the track sections that are planned to perform a detailed investigation by engineering firms must be excluded.
2. **Estimate the condition of all components for all track sections at $t = 0$**: the initial condition of all track components should be consistently estimated.
3. **Estimate the condition of all components for all track sections at $t = 5$**: Intervention requirements must be estimated 15 years ahead of the execution due to budgeting and permission requirements [2,3]. The 15 years planning horizon consists of three blocks of five years, wherein, all interventions between $t = 0$ and $t = 5$ have already been planned and almost no major changes can be made [1]. This means that they have received their allocated budget, obtained the necessary permits, and are in the detailed execution planning stage [3]. Given this procedure, $t = 5$ is considered the initial point after which estimates can be made.
4. **Estimate the failure risk at $t = 5$**: the risks associated with the occurrence of the different service loss types need to be estimated.
5. **Estimate the probability that each component requires an intervention based on component-level intervention strategies**: these estimates are done for the periods between $t = 6$ and $t = 10$ and between $t = 11$ and $t = 15$.
6. **If no intervention is needed, set $t = t + 1$ and update the condition state of the components**: repeat steps 3 to 6 until the probabilities of components requiring intervention and the failure risks have been estimated for each of the five years within each planning period.
7. **Estimate the required interventions**: an intervention on a track section in the upcoming planning period is required if either the probability of requiring intervention on any of its components or the failure risk in that planning period exceeds a certain threshold value. The possible and most likely types of interventions, required possession windows, and intervention costs are estimated as a function of the intervention type and service impacts.
8. **Checking the termination condition**: if $t \neq$ max interval, i.e., end of the planning period, update the deterioration speed if the corresponding components, set $t = t + 1$ and update the condition state of the components, repeat steps 3 to 7 until the end of the planning period.
9. **Suggest intervention postponements**: prioritize interventions based on the failure risk value if the execution of all of them is not possible within the planning period. Then, the interventions associated with the lower risk track sections are postponed until the constraints are met.
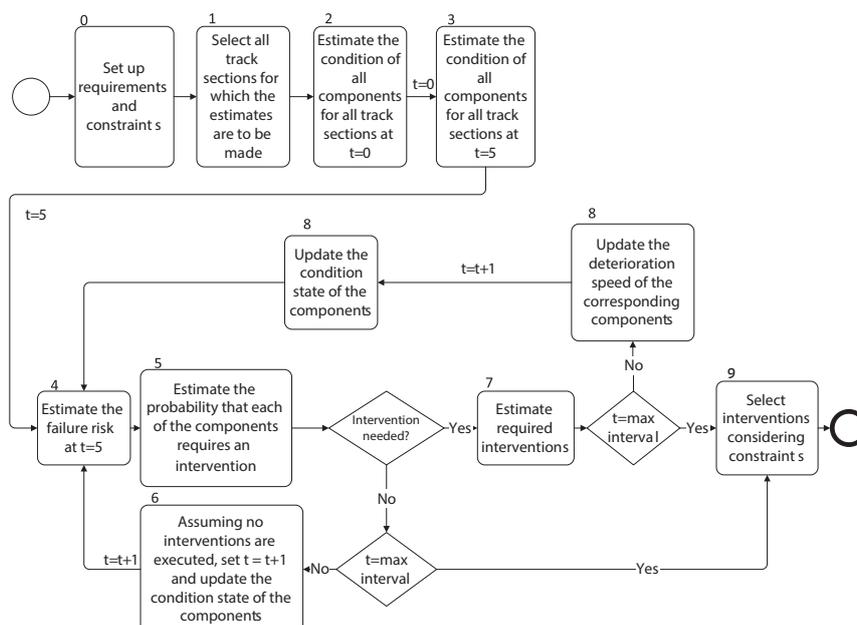
Figure 1. The steps of the proposed methodology to enable digitalised intervention planning process

3.2. Requirements and Constraints

The requirements and constraints for initialising and using the algorithm are:

- **Definition of track components**: the main track components are discerned through examination of the track drawings. Subdividing the tracks into components helps provide more insight into the content of future intervention requirements. For example, knowing that the switches of a track section will require a rehabilitation intervention in 10 years and that this will require the closing of the associated track for eight hours is more useful than just knowing that the track section will require a rehabilitation intervention and being unsure if the intervention can be executed with or without closing the rail line. In addition, this allows early estimations of the costs and the possibility of executing multiple interventions simultaneously on different components of the track section. A more detailed analysis would subdivide the track sections into their elements. For example, each switch associated with a track section consists of the switching machine, toes, switch rails, fastenings, ballasts, sleepers, heels, check rail, wing rail, crossing nose, stock rail, through rail, and subgrade [40]. This is, however, not currently proposed for two reasons. First, it would increase the work required by track managers and inspectors to obtain the initial overview of the track sections, which is a major barrier to implementation. Second, it is unlikely that interventions would target single elements, and it is more likely that multiple elements of a single component would need intervention. For instance, it is more plausible for an intervention to be executed on all fastenings in a track section simultaneously, rather than targeting a single fastening element. Therefore, estimating the required interventions on the component level provides a suitable balance between the accuracy and the required time and effort in estimating the information to make estimates for all track sections in a network.
- **Definition of possible condition states of track components**: the condition states are defined to reflect the physical condition of the components. Different classification schemes can be used for this purpose, such as a discrete scale from 1 to 5 that is used in this manuscript to classify the condition of components. In this classification scheme, the best condition is represented by Condition State 1 (CS1) and the worst condition is represented by Condition State 5 (CS5). These definitions have to comply with the organization's guidelines and preferences of track managers.
- **Estimation of the current condition state of components**: the current CS of components is estimated using existing data sources, e.g., proprietary asset condition database. If they are not explicitly estimated, the inspection reports can be used to determine the CS of the components by matching the damage indicators mentioned in the inspection reports with the definition of the CSs. In case the existing data are imperfect or if data on the condition of the components is not available, different methods such as Bayesian networks can be used to estimate the current condition of components [4].
- **Estimation of the likelihood of changing states over time, i.e., transition probabilities**: Estimating transition probabilities is necessary to predict the future state of components. In the absence of the condition monitoring data, these values can be estimated using expert opinion taking into account the interaction between deteriorating components and the impacts of the residual damages to the component due to imperfect execution of maintenance interventions. These values can be updated once enough information becomes available, for example, using data-driven approaches [33,34,41,42].
- **Definition of possible interventions for each track component in each CS and estimation of their costs and impacts on service**: the possible interventions associated with each CS for each component should include the activities to address the damage indicators mentioned in the definition of the CSs, along with the estimates of their costs and impacts on service. For example, a switch should be replaced if signs of plastic deformation are observed in the crossing nose of the switch, i.e., CS5. This intervention roughly costs 0.5 million Monetary Units (0.5Mum) and approximately takes 8 h to complete. These interventions and estimates can be defined using expert opinion or using existing references, e.g., [43].

- **Identification of the best component-level intervention strategies**: these strategies provide a guideline as to the actions to be taken when a component is in a specific CS. For example, the intervention strategy for the switches could indicate that no intervention needs to be executed on the switches if they are in CS 1-4, and a replacement is needed if they are in CS5.

- **Definition of fault trees for the track sections**: fault trees can assess how each component functions individually and how they work together to ensure the provision of sufficient service on the track section. These are used to approximate the probability of a track section not providing the expected service (failure) when the components are in different CSs. These fault trees can be developed initially with an acceptable level of detail and then be updated with more sophisticated ones based on the requirements of track managers.

- **Estimation of the occurrence probability of basic events**: the probability of occurrence for a basic event should be correlated to the time and the evolution of components' CS, which is likely to provide a realistic idea of how the failure risks evolve over time. For example, if a switch is in CS1, the failure probability of this switch due to the occurrence of a sever sudden event is very low ($10 \cdot e^{-}5$), whereas this probability is very high ($10 \cdot e^{-}3$) if the switch is in CS5. These estimations can initially be made using expert opinion and then be updated in the future using more advanced approaches such as Finite Element Analysis done by [44,45].

- **Estimation of the consequences of each failure type**: the consequences related to the occurrence of each failure type, i.e., the top events, must be estimated to enable calculation of the failure risks that are dependent on the time and condition of components. For example, the estimation of consequences must encompass owner and user costs, which include expenses related to materials and equipment, traffic management, and increased travel time due to the service reduction or loss. These estimations can be made using a combination of expert opinion and construction price indices, e.g., Swiss construction pricing index [46].

4. Case Study

The case study includes a network of eight stations spanning a distance of 25km located in Switzerland. A schematic overview of the case study is shown in Figure 2. This is a double-track network with an average daily passenger traffic of 45 trains on each track side. The geometry of tracks is measured using diagnostics trains twice a month for twist, cross-level, gauge, curvature, and alignment error [47]. In addition, other possible issues such as sleeper cracks or ballast loss are measured every year on the tracks with high demand using semi-automatic and manual inspections [2,49].
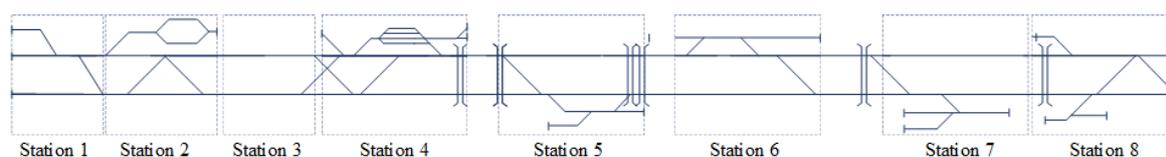

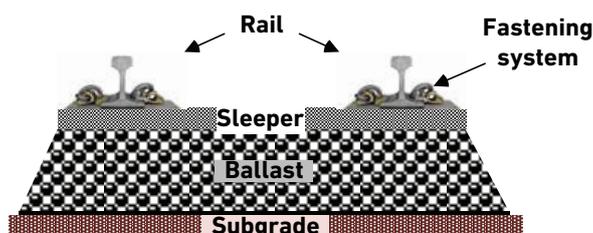**Figure 2.** The schematic overview of the case study

The case study is segmented into 154 tracks and 161 switches considering the length of 120-125 for each track section. The latest inspection reports regarding the condition of each track section are available in the internal track condition database, which were used as the basis for this case study. A summary of the condition of all track sections is provided in Figure 3. It is observed that while most switches are in a rather healthy condition, tracks are mostly in a damaged condition.
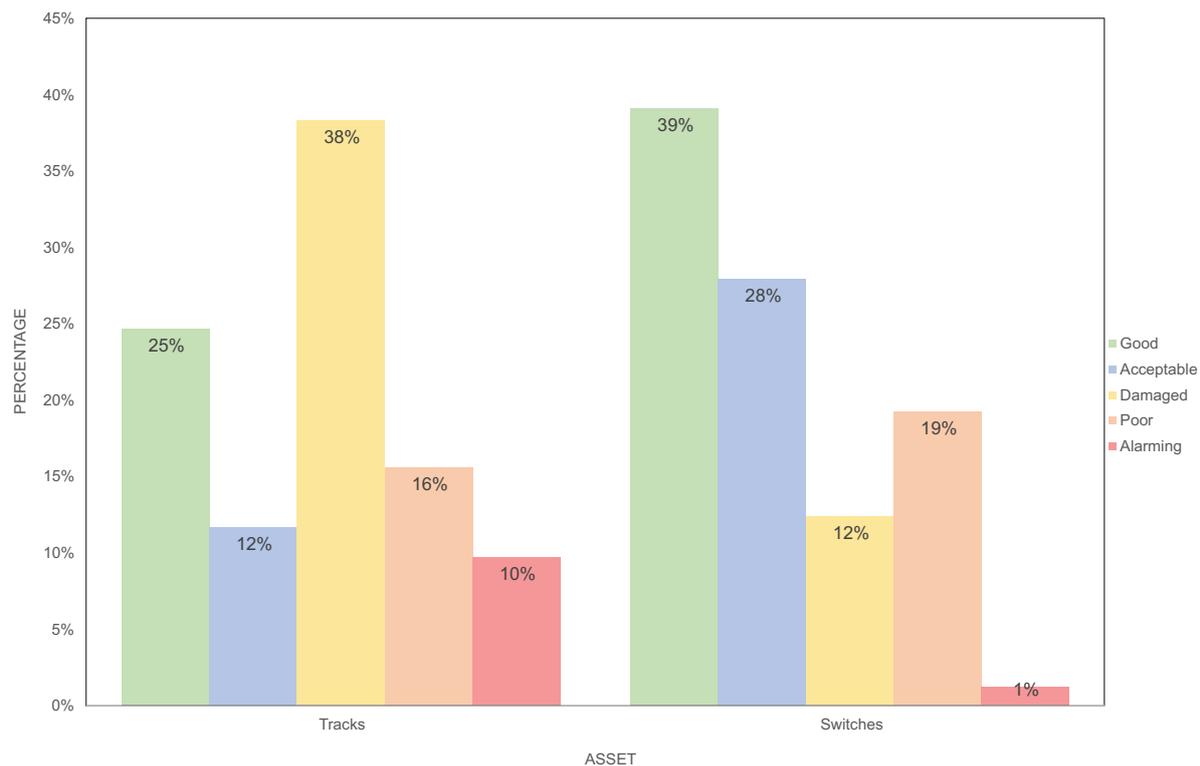
Figure 3. The latest condition distribution of the example tracks and switches

4.1. Components

Railway tracks are split into five main components, i.e., rails, fastenings, sleepers, ballasts/sub-ballasts, and subgrades, as illustrated in Figure 4. Ballasts and sub-ballasts are considered as one component since they deteriorate in a similar manner [43]. In addition, switches are considered as one component since their maintenance includes performing interventions on multiple elements [43,50]. Therefore, the case study consists of a total of 931 components.

Figure 4. A schematic overview of track components

4.2. CS of the Components at $t = 0$ and $t = 5$

The proposed methodology aligns with standard railway inspection protocols that operate at three distinct levels: visual inspection, diagnostic train assessment, and detailed investigation using destructive or non-destructive techniques such as ultrasound. The present research specifically addresses the first level, which is designed to support identify critical issues such as fractures and rail contact fatigue that subsequently trigger more detailed inspections and flag components for potential intervention consideration in future planning periods.

The condition of the components is represented through five discrete states, i,e., $CS = [1 \quad 2 \quad 3 \quad 4 \quad 5]$. In this scale, CS1 represents the best condition where there is no or minor damage and CS5 represents the worst condition where there exists severe damage that is unsafe. The states in between show increasing levels of damage. Table 3 shows an example definition for the CSs of the switches. Based on this table, switches are in CS1 if they have no issues and in CS5 if the settlement is too high or the cross nose is

deformed. Similar to switches, such CSs are defined for other components. The CSs are defined for all other track components similarly.

Such simplified definitions of condition states, while not capturing all causal deterioration mechanisms and detailed indicators, provide sufficient discriminatory power for strategic maintenance planning while maintaining computational feasibility. These criteria, nonetheless, require customization for each type of component based on inspection methodologies, regulatory frameworks, and operational contexts. The implementation of this methodology on a portfolio of railway track assets necessarily involves calibration in collaboration with maintenance execution specialists and compliance with existing regulations. Future research will explore methods to incorporate more complex deterioration processes without compromising the practical utility of the model for infrastructure managers.

**Table 3.** Example definition of the CSs for switches

CS	Condition description	Damage description	Damage indicator
1	New	None/insignificant	No significant damages, no sign of settlement.
2	Good	Minor	Slight wear on the mechanism, a slight sign of debris accumulation, a slight sign of settlement.
3	Sufficient	Significant	Insignificant signs of wear on the switchblade, Insignificant sign of wear on the crossing nose, small areas with slight corrosion, insignificant accumulation of debris, the amount of settlement reaches the alarm threshold.
4	Poor	Extensive	The frog shows some damage, switchblades damaged, switch actuator/motor can fail, significant accumulation of debris, the amount of settlement reaches the intervention threshold.
5	Insufficient	Safety is endangered	Plastic deformation of the crossing nose, loss of stability due to severe corrosion of the frog, extreme accumulation of debris actuator/motor have a high failure probability, the amount of settlement reaches the maximum tolerable threshold.

The CS of all track components at $t = 0$ is estimated based on information provided in the latest inspection reports, which is summarized in Figure 5(a). The CSs of each component were determined by matching the definition of CSs with the damage indicators mentioned in the inspection reports. The CS of components in each track section is then assumed to be the same as the overall CS for those sections where component-level information was consistently unavailable. This assumption allows for a consistent estimation of initial CSs across all components, ensuring a convenient approach in the absence of component-level information.

Probabilistic discrete state modelling is used to estimate how CSs evolve over time, which is similar to the modelling used in existing railway asset management systems [28,30]. Table 4 represents an example of non-homogeneous transition probabilities for switches over a one-year period, which corresponds to the mean interval between two inspections. Here, it is assumed deterioration rates increase as a function of the times maintenance interventions are executed on the component. This is because of imperfection in executing maintenance interventions, which do not always reinstate the physical and chemical characteristics of the components[15,64]. The impact of this on the deterioration rate can be determined using expert opinion. In case enough data are available other methods such as stochastic approaches can be used to determine this impact [51,52,52]. It is assumed there is a 2% increase in the deterioration rate following each successive maintenance intervention. This assumption is inspired by the works of Peng et al. and Li and Jia [53,54]. The maintenance count resets for each component upon the replacement of the component. This rationale is consistently applied across all components.
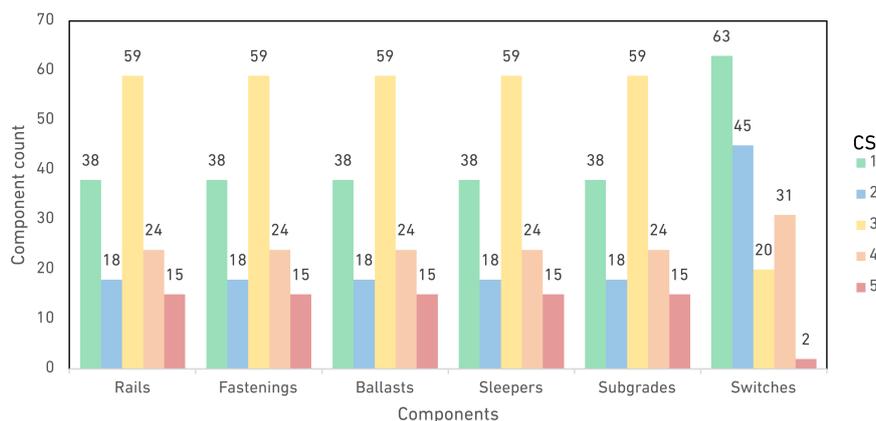
(**a**)
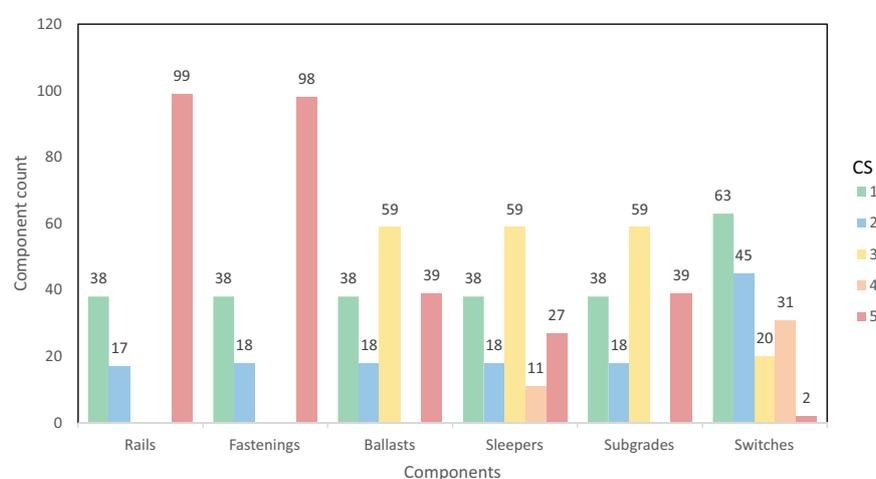
(**b**)

Figure 5. Overview of the CS of the track components at: (**a**) $t = 0$, and (**b**) $t = 5$. A caption on a single line should be centered.

Table 4. Example transition probabilities for switches

CS	1st maintenance					2nd maintenance				
	1	2	3	4	5	1	2	3	4	5
1	0.94	0.06	-	-	-	0.92	0.08	-	-	-
2	-	0.92	0.08	-	-	-	0.90	0.10	-	-
3	-	-	0.86	0.14	-	-	-	0.84	0.16	-
4	-	-	-	0.72	0.28	-	-	-	0.70	0.30
5	-	-	-	-	1	-	-	-	-	1

Moreover, the deterioration rates for each component are further refined to account for the interaction between deteriorating components. Bayesian filters are used for this purpose. These filters can be integrated into the existing infrastructure management system, without the need to make significant changes in the logic and the modelling structure [61,62]. This is likely to reduce the effort and the costs needed to implement the proposed methodology in a railway company. These filters are defined depending on the location of the components on the tracks. For example, while the condition of the rails is influenced by the condition of the fastenings, sleepers, ballasts, and subgrade, the condition of the subgrade and switches is independent of the condition of other components [21,43]. For example, Equation (1) represents the Bayesian filter associated with the interaction between rails

and other track components, which is indicated with Γ_{Rails}. In this equation, $\Gamma_{Rails} = I^1$ when other influencing components are in CS1 or CS2. The influence of the condition of other components, when they are in CS3, CS4, and CS5 on the CS of the rails is represented respectively by α, β, and η. The values associated with these filters can be estimated using expert opinion or using more advanced techniques, such as regression-based nonlinear optimisation or neural networks [55,56] in case enough information is available.

The calibration and validation of these parameters can be performed using empirical methods. For instance, regression methods or Bayesian updating can effectively compare predicted and observed deterioration rates [41,55]. Furthermore, sensitivity analysis can verify the reliability of the estimated parameters. For illustrative purposes in this study, it is assumed that $\alpha = 0.0001$, $\beta = 0.0005$, and $\eta = 0.001$, which are inspired by the works of Chen et al., Niroshan et al., and Kobayashi et al. [11,55,56].

$$\Gamma_{Rails} = \begin{cases} I & \text{if } CS^{Fastenings} = \{1,2\} \quad | \quad CS^{Sleepers} = \{1,2\} \\ & | \quad CS^{Ballasts} = \{1,2\} \quad | \quad CS^{Subgrades} = \{1,2\} \\[2ex] I_{ii} - \alpha \quad \forall i \in \{1,2,3,4\} & \text{if } CS^{Fastenings} = \{3\} \quad | \quad CS^{Sleepers} = \{3\} \\ I_{i(i+1)} + \alpha \quad \forall i \in \{1,2,3,4\} & | \quad CS^{Ballasts} = \{3\} \quad | \quad CS^{Subgrades} = \{3\} \\[2ex] I_{ii} - \beta \quad \forall i \in \{1,2,3,4\} & \text{if } CS^{Fastenings} = \{4\} \quad | \quad CS^{Sleepers} = \{4\} \\ I_{i(i+1)} + \beta \quad \forall i \in \{1,2,3,4\} & | \quad CS^{Ballasts} = \{4\} \quad | \quad CS^{Subgrades} = \{4\} \\[2ex] I_{ii} - \eta \quad \forall i \in \{1,2,3,4\} & \text{if } CS^{Fastenings} = \{5\} \quad | \quad CS^{Sleepers} = \{5\} \\ I_{i(i+1)} + \eta \quad \forall i \in \{1,2,3,4\} & | \quad CS^{Ballasts} = \{5\} \quad | \quad CS^{Subgrades} = \{5\} \end{cases} \tag{1}$$

An overview of the most likely CS of all components at $t = 5$ is shown in Figure 5(b). These are estimated using Equation (2) that multiplies the CS of components at $t = 0$ with the probability of them transitioning to the possible future states, shown with P, and with the Bayesian filter associated with each component, represented by Γ, within 5 years.

$$CS^{t+1} = CS^t \cdot P \cdot \Gamma \tag{2}$$

4.3. Component-Level Interventions and Intervention Strategies

Several interventions are required to maintain the expected serviceability of components throughout their life cycle. These interventions vary with respect to the component characteristics and damage severity. These interventions can be categorised using three generic terms, i.e., Rehabilitation, Renewal, and Replacement to represent different levels of execution complexity [15,43].

The intervention costs are calculated as the total of owner costs, C_O, and user costs, C_U, $C_{Total} = C_O + C_U$. C_O is calculated using a construction pricing index [46]. C_U is calculated by monetizing the average daily added travel time, i.e., 6'524 mu/day, using Equation (3). In this formula, the average number of passengers per day is represented by APD, average daily wage by ADW, and average daily added travel time per passenger by ATP.

$$C_U = APD \times ADW \times ATP \tag{3}$$

Table 5 shows example switch intervention costs, which increase with the complexity and labour demand of activities[12,21,43]. These costs are calculated similarly for other track components.

---

1. I is an identity matrix.

Table 5. Example switch intervention costs

Intervention type	$C_O (mu/quantity)$	Service disturbance duration (h)	$C_U (mu)$	$C_{Total} (mu)$
Rehabilitation	3'110	4	260'496	263'606
Renewal	3'930	4	260'496	264'426
Replacement	14'110	8	520'992	535'102

Component-level intervention strategies along with their effectiveness can be estimated using a combination of the internal documentation and expert opinion. In case these strategies do not exist in an organisation, they can be determined using different techniques such as Markov chains [1,15,34]. For example, Table 6 shows an example of multiple variants for switch intervention effectiveness, where the switch intervention strategy used is highlighted in violet, and the effectiveness is given in terms of probability of being in CS1 or CS2 after the execution of the intervention. This is derived using internal documents of railway assets. The switch intervention strategy indicates no intervention is needed in CS1 and CS2, while a replacement is needed in CS5. For CS3 and CS4, rehabilitation and renewal are applied, respectively. The effectiveness indicates the probability of a component being in CS1 or CS2 after executing an intervention, which can be estimated with different methods for example using Data Envelopment Analysis [57,59]. In this paper, these are inspired by the values mentioned in [57,59].

Table 6. Example intervention effectiveness for switches

	Intervention type	CS1	CS2	CS3	CS4	CS5
	Rehabilitation[1]	0.85	0.15	-	-	-
CS3	Renewal	0.95	0.05	-	-	-
	Replacement	1.00	-	-	-	-
	Rehabilitation	0.65	0.35	-	-	-
CS4	Renewal[2]	0.90	0.10	-	-	-
	Replacement	1.00	-	-	-	-
	Rehabilitation	0.50	0.50	-	-	-
CS5	Renewal	0.85	0.15	-	-	-
	Replacement[3]	1.00	-	-	-	-

0 1 2 3

4.4. Evolution of Failure Risks

There are different methods to assess the risks associated with the failure of components to provide a sufficient level of service such as Fault tree analysis or Failure Modes and Effects Analysis [40,48]. However, compared to other risk assessment methods, fault trees not only better help infrastructure managers visually map the logical relationships between basic component failures and the resulting system-level failure, i.e., top events, but also offer a great level of adaptability so that they can be continually updated as more data become available over time [36,58]. This iterative nature makes them well-suited for infrastructure intervention planning.

The evolution of failure risks is estimated using fault trees, connected to the components' failure severity. Top events are "restricted service" (due to rehabilitation at night) and "interrupted service" (due to replacement with total closure) defined for each track section, as shown in Figure 6(a) and Figure 6(b), respectively. The basic events are gradual or sudden deterioration of the individual components due to external loads, such as traffic or natural hazards.

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[0]   Note: The best switch intervention strategy is highlighted in violet.
[1]   Potential activities: Tightening of the fastenings, Tamping or ballast cleaning, lubrication of the switch blades, adjustment of switch settings.
[2]   Potential activities: Restoration of the rail surface by welding, manual grinding.
[3]   Potential activities: Replacing the damaged parts of the switch.
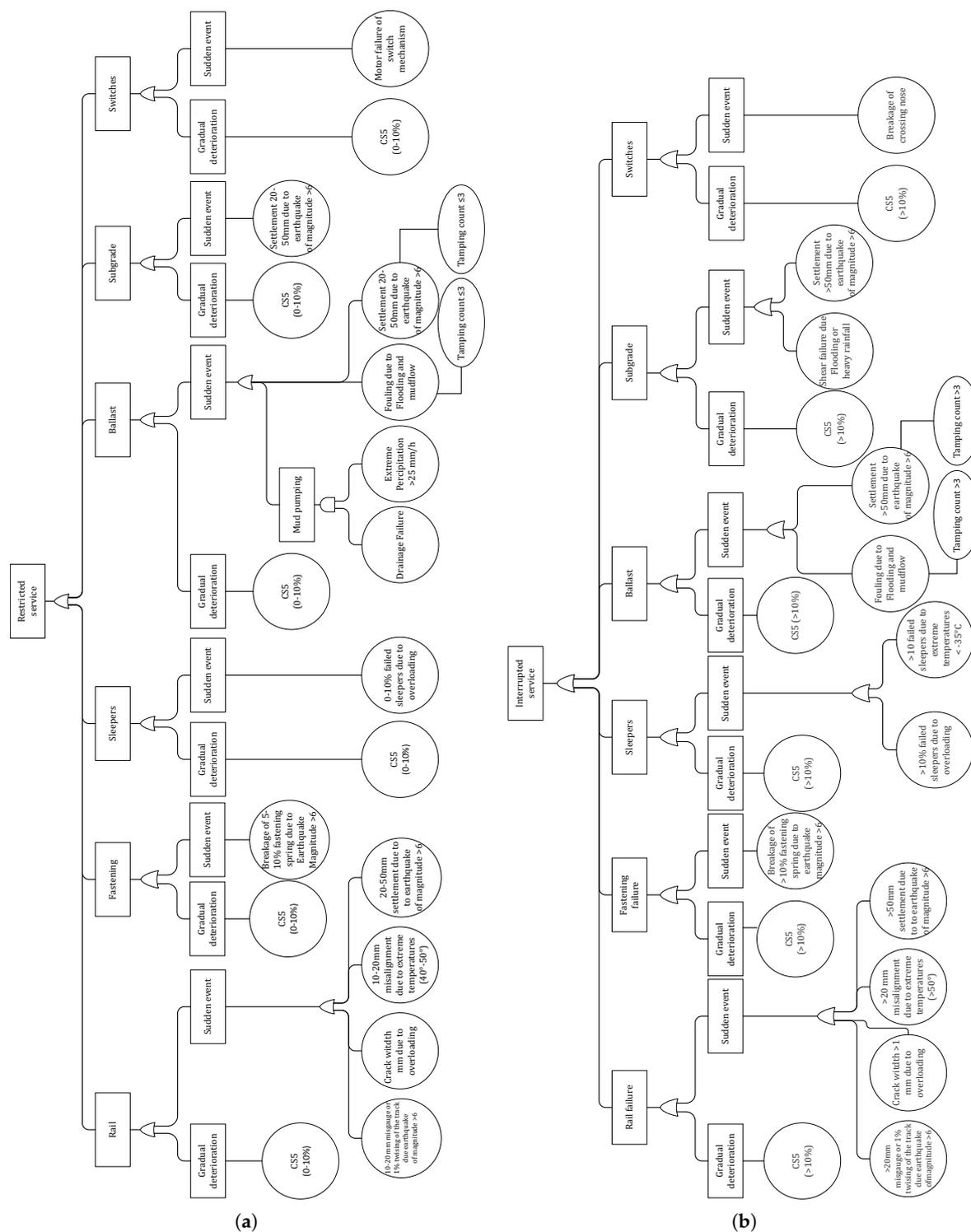
Figure 6. Examples of fault trees associated with: (**a**) restriction service, and (**b**) interrupted service. A caption on a single line should be centered.

Failure probabilities of components are estimated based on the occurrence probability of basic events. These events depend on the occurrence of external loads and the component resistance. The occurrence of external loads is independent of CSs of components and based on expert opinion, while the resistance of components varies with components' CS. This means the failure probabilities of components due to the occurrence of basic events vary for different CSs at different times, with a lower value for CS1 and a higher value for CS5.

Equation (4) indicates how failure probabilities are estimated, where PoF_{ij}^t represents the probability that component i fails at year t due to the occurrence of the sudden event j, PoS_j^t is the occurrence probability of the sudden events j until year t, Rf_i is the resistance factor of component i, and CS_i^t is the CS of the component i at year t, which is represented as a 1×5 vector. PoS_j^t is assumed to follow a Poisson process as suggested by Usman et al. [36]. This way of calculating the failure probabilities enables taking into account the changes in the occurrence probability of top events in each year within each planning period.

$$PoF_{ij}^t = PoS_j^t \cdot Rf_i \cdot CS_i^t \quad \forall i \in \text{Components} \quad \& \quad j \in \text{Sudden events} \tag{4}$$

For example PoF of a switch at year t due to the occurrence of the sudden event j with a return period of T years, i.e., $\lambda_j = \frac{1}{T}$ at year t and the resistance vector $Rf_{Switch} = \begin{bmatrix} Rf_{Switch}^{CS1} & Rf_{Switch}^{CS2} & Rf_{Switch}^{CS3} \\ Rf_{Switch}^{CS4} & Rf_{Switch}^{CS5} \end{bmatrix}$ can be calculated as:

$$PoF_{Switch,j}^t = \left(\frac{(\lambda_j \cdot t)^1 \cdot e^{-\lambda_j \cdot t}}{1!} \right) \times Rf_{Switch} \times CS_{Switch}^t$$

The consequences of each top event depend on how much work is needed to restore the level of service. These are estimated in terms of owner and user costs of executing immediate interventions using information from section 4.3. The failure risks associated with each track section are then estimated depending on the components' CS. These estimates enable obtaining a meaningful overview of interventions and avoiding intervening on different components every year. These also help plan interventions using a predefined failure risk threshold in case there are no component-level intervention strategies defined. This threshold is defined as the value of failure risks when all components are in CS4 since having any assets in CS5 is not desirable for the asset managers [1].

An overview of the evolution of failure risks for a selection of track sections is shown in Figure 7. In this figure, TS3 notably exhibits one of the highest failure risks, while TS11 exhibits one of the lowest. The primary reason for this difference is the initial CS of the components on these two track sections, which are in CS4 and CS1, respectively.
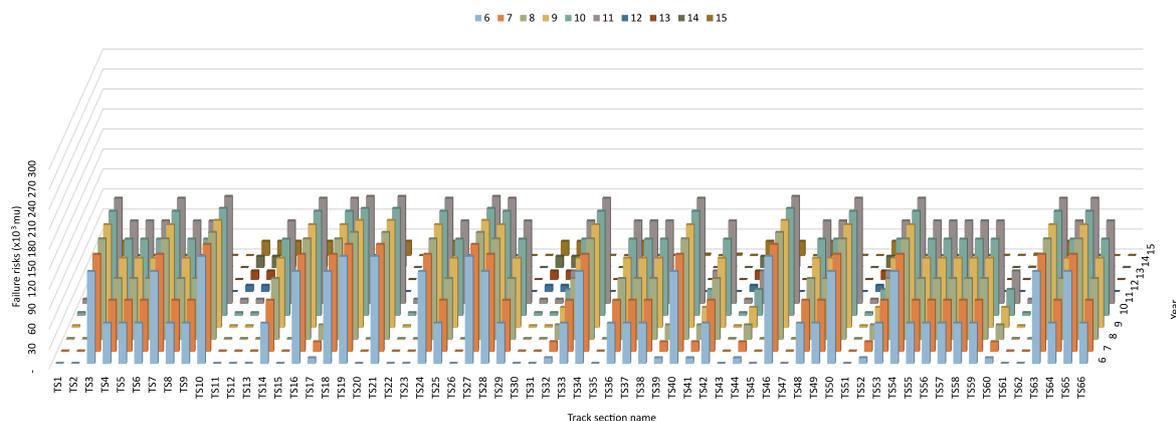
Figure 7. Overview of the failure risk evolution for a selection of track sections between $t = 6$ and $t = 15$

4.5. Overview of Component-Level Intervention Requirements

The interventions are estimated for the next planning periods, i.e., t=6 to t=10, and t=11 to t=15 considering deterioration rates and intervention strategies discussed in section 4. Interventions are scheduled to be executed on a component when the failure risks associated with each track section reach the pre-defined failure risk threshold in each planning period. After knowing which interventions are needed, detailed information regarding the most likely interventions such as the expected costs and possession windows are estimated. These estimates are not done for the period between $t = 0$ and $t = 5$ since any interventions between t=0 and t=5 have already entered a detailed planning phase based on the intervention planning process.

Table 7, for example, shows the chances of intervention requirements between t=6 and t=10, along with the estimates of possession windows requirements and the expected costs for only two switches. Based on this table, there is a 34% likelihood that S1 require an intervention. It is most likely that the type of this intervention will be rehabilitation, with 27% likelihood. If this is executed alone, the rehabilitation would be expected to take six hours, of which one would require no disruption to service, one hour would require restrictions to be implemented and four hours would require the associated track section to be closed. This would be expected to cost 263'000 mu.

Table 7. Possible and most likely switch interventions required between t = 6 and t = 10, with associated possessions and intervention costs

| Switch name | Chance of an intervention(%) | Details[1] | Expected duration (h) | Expected required possessions (h) if done alone | | | Expected intervention costs ($\times 10^3$ mu) |
				None	Traffic restrictions	Closure	
S1	34	**27**/6/1	**6**/7/11	**1**/1/1	**1**/2/2	**4**/4/8	**263**/264/535
S2	100	-/47/**53**	6/7/**11**	1/1/**1**	1/2/**2**	4/4/**8**	263/264/**535**

0 1

4.6. Prioritization of Interventions as a Function of the Failure Risk Estimates

Track managers must decide which interventions to postpone in a situation when detailed investigations on all track sections requiring interventions cannot be initiated, or if all interventions cannot be executed due to organizational restrictions. A benchmark is needed to enable managers to do so. Such a benchmark should capture different characteristics of the components as well as the concerns of track managers. For example, track managers consider CS4 as the last point before the initiation of emergency intervention [1,2]. This means that the ratio of failure risks associated with the track sections when their components are in their current or predicted CSs, and failure risks associated with the track sections when their components are in CS4 can be used to prioritize interventions[2]. This failure risk ratio reflects an indication of the failure risk level for each track section, which exists even without any damage. Track managers need to keep this level within a reasonable margin for each track section. At the same time, track managers do not aim to achieve the same failure risk level across all track sections. An example is shown in Figure 8. This would mean that if a detailed investigation of one of the track sections needed to be postponed, it would be the one for TS35, as the failure risks associated with this track section are the farthest away in terms of percentage from the failure risks associated with the track section if all of its components were in CS4.
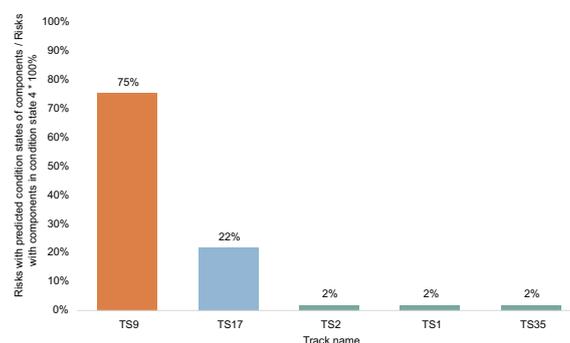
Figure 8. Failure risks with predicted CSs of components/failure risks with components in CS4 $\times 100\%$ between $t = 6$ and $t = 10$

0   Note: The values associated with the most likely interventions are indicated in **bold**.
1   The chance of the intervention being rehabilitation /renewal /replacement (%)
2   The calculation of the failure risks for each track section when all components are in CS4 are done by setting $CS_i^t = 4$ in Equation (4) and then calculating the failure risks with respect to the associated logic of the described fault trees.
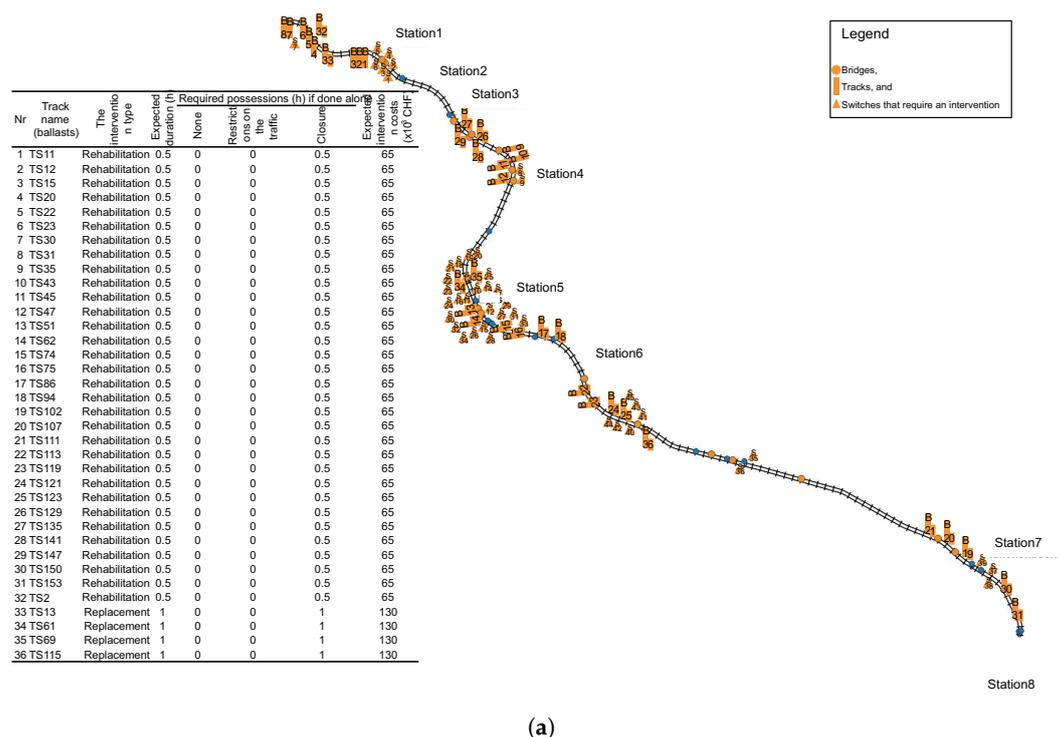
5. Enabling the Use

Enabling the use of the proposed methodology in the intervention planning process requires some effort from infrastructure managers to initialise the methodology. A schematic overview of the setup and implementation process is also shown in Figure 9. This methodology is designed to be implemented with minimum requirements, e.g., using a computer equipped with spreadsheet software. However, it is recommended to use a programming language such as R [60] to analyse the entire railway network of a country. The estimation of the required information can be achieved using various sources with different levels of detail, from expert opinion to detailed track management databases. After the proper implementation of the proposed methodology, the output can be used to develop intervention programmes that consider all asset-level and network-level constraints such as the interdependencies between the interventions. Moreover, the use of BIM[3] or GIS[4] allows for automatic storage and visualisation of the methodology's output as new information becomes available, which is crucial in a digitalised intervention planning process. For example, the output can be visualised for a selection of track sections that will require interventions on the case study railway network using a GIS platform to provide an overview of the most likely intervention requirement, along with the early estimates of related costs and possession windows over the future planning periods, as shown in Figure 10 for the periods between $t = 11$ and $t = 15$.
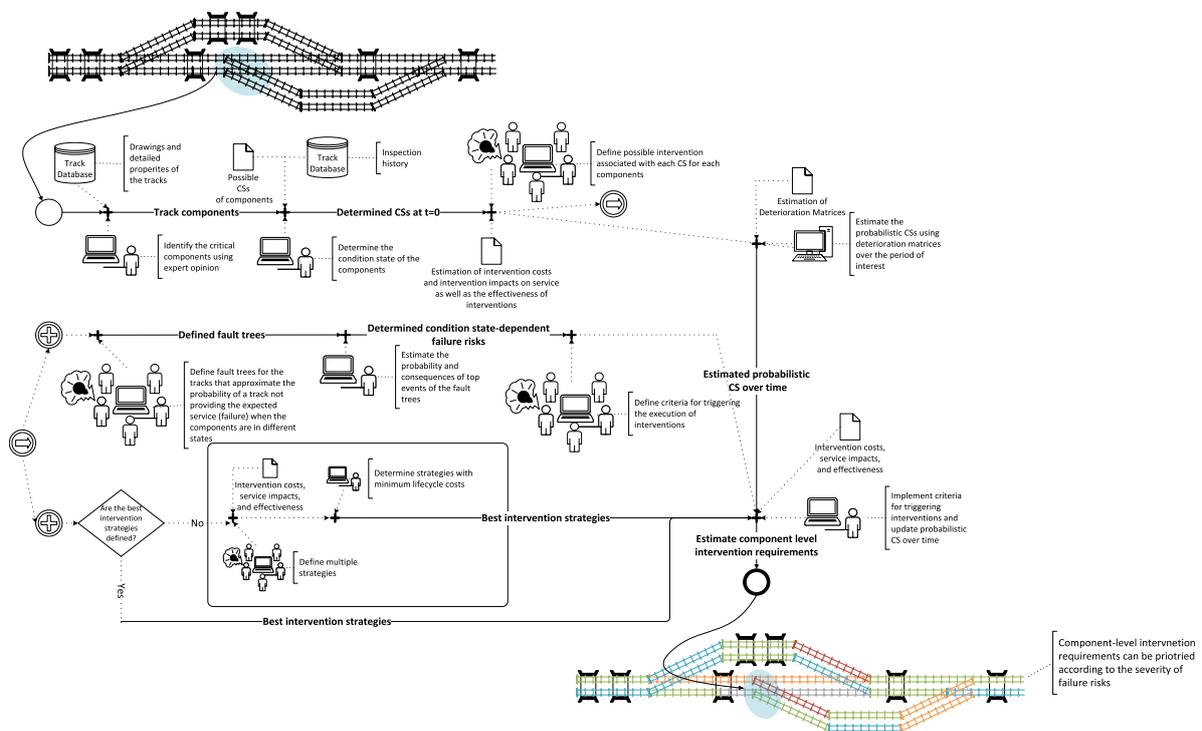
Figure 9. Schematic overview of the setup and implementation workflow within a digitalized infrastructure management process

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[3]   Building Information Modelling
[4]   Geographic Information System

| Nr | Track name (ballasts) | The intervention type | Expected duration (h) | Required possessions (h) if done alone | | | Expected intervention costs (×10³ CHF) |
				None	Restrictions on the traffic	Closure	
1	TS11	Rehabilitation	0.5	0	0	0.5	65
2	TS12	Rehabilitation	0.5	0	0	0.5	65
3	TS15	Rehabilitation	0.5	0	0	0.5	65
4	TS20	Rehabilitation	0.5	0	0	0.5	65
5	TS22	Rehabilitation	0.5	0	0	0.5	65
6	TS23	Rehabilitation	0.5	0	0	0.5	65
7	TS30	Rehabilitation	0.5	0	0	0.5	65
8	TS31	Rehabilitation	0.5	0	0	0.5	65
9	TS35	Rehabilitation	0.5	0	0	0.5	65
10	TS43	Rehabilitation	0.5	0	0	0.5	65
11	TS45	Rehabilitation	0.5	0	0	0.5	65
12	TS47	Rehabilitation	0.5	0	0	0.5	65
13	TS51	Rehabilitation	0.5	0	0	0.5	65
14	TS62	Rehabilitation	0.5	0	0	0.5	65
15	TS74	Rehabilitation	0.5	0	0	0.5	65
16	TS75	Rehabilitation	0.5	0	0	0.5	65
17	TS86	Rehabilitation	0.5	0	0	0.5	65
18	TS94	Rehabilitation	0.5	0	0	0.5	65
19	TS102	Rehabilitation	0.5	0	0	0.5	65
20	TS107	Rehabilitation	0.5	0	0	0.5	65
21	TS111	Rehabilitation	0.5	0	0	0.5	65
22	TS113	Rehabilitation	0.5	0	0	0.5	65
23	TS119	Rehabilitation	0.5	0	0	0.5	65
24	TS121	Rehabilitation	0.5	0	0	0.5	65
25	TS123	Rehabilitation	0.5	0	0	0.5	65
26	TS129	Rehabilitation	0.5	0	0	0.5	65
27	TS135	Rehabilitation	0.5	0	0	0.5	65
28	TS141	Rehabilitation	0.5	0	0	0.5	65
29	TS147	Rehabilitation	0.5	0	0	0.5	65
30	TS150	Rehabilitation	0.5	0	0	0.5	65
31	TS153	Rehabilitation	0.5	0	0	0.5	65
32	TS2	Rehabilitation	0.5	0	0	0.5	65
33	TS13	Replacement	1	0	0	1	130
34	TS61	Replacement	1	0	0	1	130
35	TS69	Replacement	1	0	0	1	130
36	TS115	Replacement	1	0	0	1	130

(**a**)

Figure 10. Most likely intervention requirements on the GIS model of the case study between $t = 11$ and $t = 15$

6. Discussion

The proposed methodology provides railway asset managers with an efficient overview of the component-level interventions, related costs, possession windows, and associated failure risks over future planning periods. The methodology considers components' condition, deterioration rates, the interaction between them, component-level intervention strategies, and a tolerable failure risk threshold. Additionally, the methodology enables prioritisation of component-level interventions based on the level of failure risks associated with each track section to decide which one should be selected to initiate the preliminary study phase.

One limitation of the methodology is that even though it is designed to be implemented with minimum effort, the initial estimates of all input information are still required to be made by infrastructure managers, e.g., initial components' condition, deterioration rates and the impact of their interaction on deterioration rates, possible interventions and their impacts on service and the associated costs as described in the manuscript. This limitation would be the same with all such methodologies. In some parts such as estimating the components' condition, generating the input information can be made easier using stochastic and data-driven methods.

Additionally, the development of fault trees is deemed demanding, but adequate consideration of failure risk is necessary to support decision-making. From a planer's perspective, it is useful to have a comprehensive overview of failure risk, i.e., the likelihood and consequences of having to close parts of the railway network for emergency maintenance interventions. From an engineer's perspective, it is difficult to estimate the probabilities of occurrence of base events and the consequences exactly, which is made harder when there are critiscms of the exactness. This in many cases is likely to mean that the estimates are not made, which unfortunately means risk is not explicitly considered. From a planer perspective, it is preferable to have general, albeit approximate, estimates rather than none at all.

A further challenge is to accurately estimate the potential effects on service, required possession windows, and if required the cost estimates. This challenge arises primarily for two reasons. Firstly, the methodology is to be used at an early planning stage, where there is limited knowledge regarding the specific activities encompassed in the interventions. Even if approximate though, this estimation is essential for acquiring an early yet comprehensive understanding of all track interventions in a railway

network. Secondly, even if estimates at the component level were known for individual interventions, the impacts on service and the intervention costs would fluctuate as individual component-level interventions become clustered into cohesive intervention programs. This is because clusterisation results in some interventions being executed earlier or later than they would be executed if the assets were considered alone, and that the combination of some interventions in time with others will likely result in a net reduction of both costs and service disruptions.

7. Conclusion

This manuscript proposes a methodology to estimate interventions, possession times, costs, and failure risks for track sections. It is exemplified through application on a 25km railway network in Switzerland. The novelty of the method includes the focus on components and their interaction overtime, and the use of fault trees to estimate condition-dependent failure risks. The methodology accounts for the factors that are of concern to track managers. It uses a five-state probabilistic model to estimate the current and future CSs and intervention requirements. It uses fault trees to estimate the failure probabilities and consequences for two top events related to different service loss scenarios. The consequences include owner and user costs. To comprehensively assess the advantages of this methodology, future studies should conduct testing on both real-world and simulated networks using different methods such as business processes simulation or structural equations modelling.

The proposed methodology provides a consistent and complete early estimation of component-level interventions, their costs, and associated possession windows as well as failure risks in the upcoming planning periods. The methodology considers the condition of the components, their non-homogeneous deterioration rates as a function of the maintenance count, the interaction between the deteriorating components, and the component-level intervention strategies. Interventions are triggered through the coupling of failure risks with the CS evolution. If deemed necessary, the decisions on postponing interventions or their prioritization can be made using the ratio between predicted failure risks and the failure risk threshold.

The methodology presented herein represents an advancement over the current state-of-the-art practices. It comprehensively encompasses crucial aspects essential in the track managers' decision-making process. This methodology effectively estimates the failure risks associated with the condition of asset components. Notably, the dynamic adaptation of fault tree calculations for the estimation of condition-dependent failure risks, coupled with a comprehensive overview of intervention requirements, distinguishes this methodology. To the authors' knowledge, such an application is unprecedented in existing railway asset management systems[43,63].

The systematic overview provided by this methodology in terms of the interventions required, the associated possession windows and the cost estimates streamlines the communication among various stakeholders in the intervention planning process, such as asset managers, line planners, and network developers. Having such a comprehensive overview is crucial for the development of stable train schedules, ensuring that multiple interventions are synergistically integrated within limited time frames.

The design of the proposed methodology was aimed at ensuring the ease of implementation. It allows for the estimation of required input information from several sources, ranging from expert judgment to existing databases, with varying levels of granularity. The accuracy of this input data can be refined further upon the availability of more detailed information. Additionally, other parts of the methodology, such as the definition of CSs can be improved to incorporate indications generated from advanced measuring tools. For example, these can cover cross-section loss of the rail head in percentage if such measurement is consistently available. Moreover, more detailed fault trees can be developed upon the needs of the infrastructure managers. The methodology accounts for the further

refinement of component-level intervention strategies. For example, the estimates of the initial CSs can be improved using DBN[5] to impute the missing values in the database [4].

Implementing the methodology presented in this manuscript within a suitable platform will enable track managers to efficiently take advantage of digitalisation. This will facilitate the generation of a detailed overview of the intervention requirements, their initial costs and impacts on the service, as well as the level of failure risks in future planning periods for all track sections in a systematic manner. The adoption and application of the proposed methodology are expected to significantly improve the efficiency and effectiveness of the intervention planning process. Future studies should focus on improving different aspects of the presented methodology, with a particular emphasis on applying the proposed methodology to generate the component-level intervention programmes for all assets within a railway network. For example, the consistent estimation of initial CSs for all infrastructure components using advanced models, such as physics-informed CS estimation [65], should be integrated into the current methodology.

Additionally, future studies should enhance the visualization capabilities of the presented methodology. The outcomes could be displayed on a GIS-based Building Information Modeling (BIM) platform for the entire railway network, including detailed BIM for each track section, to improve interpretation of intervention requirements, preliminary costs, and required possession windows for upcoming planning periods.

Finally, future research should quantitatively evaluate the efficiency improvements achieved through this methodology. Metrics such as planning time, number of iterations, decision-maker involvement, and maintenance budget approval success rates should be measured before and after implementation to provide empirical evidence of the methodology's effectiveness.

Appendix A. Bayesian Filters

The Bayesian filters associated with the interaction between fastenings and other track components, sleepers and other track components, and ballasts and other components are respectively shown in Equations (A1), (A2), and (A3). The same values as the ones discussed in Section 4.2 are used for these filters. Please note that the deterioration rate of subgrades is assumed to be independent of the CSs of other track components.

---

[5]   Dynamic Bayesian Network

$$
\Gamma_{Fastenings} =
\begin{cases}
I & \text{if } CS^{Sleepers} = \{1,2\} \quad | \quad CS^{Ballasts} = \{1,2\} \\
& \quad | \quad CS^{Subgrades} = \{1,2\} \\[2em]
I_{ii} - \alpha \quad \forall i \in \{1,2,3,4\} & \text{if } CS^{Sleepers} = \{3\} \quad | \quad CS^{Ballasts} = \{3\} \\
I_{i(i+1)} + \alpha \quad \forall i \in \{1,2,3,4\} \quad | \quad CS^{Subgrades} = \{3\} \\[2em]
I_{ii} - \beta \quad \forall i \in \{1,2,3,4\} & \text{if } CS^{Sleepers} = \{4\} \quad | \quad CS^{Ballasts} = \{4\} \\
I_{i(i+1)} + \beta \quad \forall i \in \{1,2,3,4\} \quad | \quad CS^{Subgrades} = \{4\} \\[2em]
I_{ii} - \eta \quad \forall i \in \{1,2,3,4\} & \text{if } CS^{Sleepers} = \{5\} \quad | \quad CS^{Ballasts} = \{5\} \\
I_{i(i+1)} + \eta \quad \forall i \in \{1,2,3,4\} \quad | \quad CS^{Subgrades} = \{5\}
\end{cases}
\tag{A1}
$$

$$
\Gamma_{Sleepers} =
\begin{cases}
I & \text{if } CS^{Ballasts} = \{1,2\} \quad | \quad CS^{Subgrades} = \{1,2\} \\[2em]
I_{ii} - \alpha \quad \forall i \in \{1,2,3,4\} & \text{if } CS^{Ballasts} = \{3\} \quad | \quad CS^{Subgrades} = \{3\} \\
I_{i(i+1)} + \alpha \quad \forall i \in \{1,2,3,4\} \\[2em]
I_{ii} - \beta \quad \forall i \in \{1,2,3,4\} & \text{if } CS^{Ballasts} = \{4\} \quad | \quad CS^{Subgrades} = \{4\} \\
I_{i(i+1)} + \beta \quad \forall i \in \{1,2,3,4\} \\[2em]
I_{ii} - \eta \quad \forall i \in \{1,2,3,4\} & \text{if } CS^{Ballasts} = \{5\} \quad | \quad CS^{Subgrades} = \{5\} \\
I_{i(i+1)} + \eta \quad \forall i \in \{1,2,3,4\}
\end{cases}
\tag{A2}
$$

$$
\Gamma_{Ballasts} =
\begin{cases}
I & \text{if } CS^{Subgrades} = \{1,2\} \\
I_{ii} - \alpha \quad \forall i \in \{1,2,3,4\} & \text{if } CS^{Subgrades} = \{3\} \\
I_{i(i+1)} + \alpha \quad \forall i \in \{1,2,3,4\} \\[2em]
I_{ii} - \beta \quad \forall i \in \{1,2,3,4\} & \text{if } CS^{Subgrades} = \{4\} \\
I_{i(i+1)} + \beta \quad \forall i \in \{1,2,3,4\} \\[2em]
I_{ii} - \eta \quad \forall i \in \{1,3\} & \text{if } CS^{Subgrades} = \{5\} \\
= \gamma_{i(i+1)} + \eta \quad \forall i \in \{1,2,3,4\}
\end{cases}
\tag{A3}
$$

Appendix B. Estimating the Condition State of the Components over Time

The Algorithm A1 shows the pseudocode associated with CS estimation taking into account the interactions between components and the impacts of the imperfect execution of maintenance interventions. The CS of the components was estimated each year taking into account the transition probability associated with each component, the acceleration factor, the number of years throughout the planning periods, the effectiveness of the interventions, the Bayesian filters and the initial condition of the components. CSs at $t = 5$, as mentioned in Section 3.1, are first estimated by multiplying the initial CSs by the transition probabilities for all components (lines 2 to 5). The year count is then updated on line 6. The main loop of the algorithm starts by estimating the CS of all components in year t by multiplying the CS of the components in year $t-1$ by the associated transition probabilities (line 9). The line 11 captures the interaction between the components by updating the deterioration rates of the components by multiplying their current transition probabilities by the Bayesian filter associated with each component. For example, if all components are in CS in year t then, as discussed in Section 4.2 and Appendix A, it would be $TP \times I = TP$. This means that if all components are in CS2, their transition probabilities would remain unchanged. In the next step, the algorithm checks if

the conditions for triggering interventions are met. If positive, the CS of the components in need of interventions is updated by multiplying their estimated CS by the intervention effectiveness vector, as seen in line 13. The impact of maintenance interventions on deterioration rates is captured in lines 14 and 15. In these lines, the algorithm checks if the intervention type was not "Replacement". In case this statement is positive, the algorithm updates the transition probabilities by multiplying the current transition probabilities by a given acceleration factor, as discussed in Section 4.2. The algorithm continues until the CSs for the last year of the last planning period are estimated.

Algorithm A1 Estimating CS of the components over time

1: **Input:** Transition Probabilities (TP), TP acceleration factor (AF), Planning Periods (PlP), Intervention Strategies (IS), Intervention Effectiveness (IE), Bayesian Filters (Γ), Initial Condition State (CS_0)
2: $t \leftarrow 1$
3: **for** $t = 1$ to 5 **do**
4:     $CS_t \leftarrow CS_{t-1} \times TP$
5: **end for**
6: $t \leftarrow t + 1$
7: **while** $t < PlP$ **do**
8:     **// For all components in parallel:**
9:     $CS_t \leftarrow CS_{t-1} \times TP$
10:     **// Check condition states of all dependable components and update TP with Bayesian Filters**
11:     $TP \leftarrow TP \times \Gamma$
12:     **if** CS_t indicates an intervention is needed (per corresponding IS) **then**
13:       $CS_t \leftarrow CS_t \times IE$
14:       **if** Intervention type $\neq$ Replacement (per corresponding IS) **then**
15:         $TP \leftarrow TP \times AF$
16:       **end if**
17:     **end if**
18: **end while**

Appendix C. Estimating Failure Risks

The Algorithm A2 shows the pseudocode related to the estimation of failure risks over time. The failure risks were estimated taking into account the length of the planning periods, the evolution of CSs over time, and the probability of occurrence of basic events depending on the condition of components. Based on this algorithm, the failure probability of the components due to the basic event j in year t, i.e., PoF_j^t, is calculated taking into account the probability of occurrence of that event in that year, i.e., PoS_t^j, the condition of the components in that year, i.e., CS_j^t, and a factor to represent the resistance of each component i in each CS against the impacts of the occurred of basic events (Rf_i). In the final step, the failure risks (FR^t) in each year are calculated taking into account the structure of the fault trees. The algorithm then checks whether the level of failure risk exceeds the acceptable failure risk threshold and if positive, flags for intervention. The loop continues until the end of the planning period. More detailed information regarding the definition and the use of fault trees connected to the condition of components are found in [1].

Algorithm A2 Estimating evolution of failure risks

1: **Input:** Acceptable Failure Risk Level (AFR), Condition States (CS_t), Planning Periods (PlP), Probability of Occurrence (PoS), Consequences (Con)

2: $t \leftarrow 5$

3: **while** $t < PlP$ **do**

4:     **for each** component i **do**

5:         **for each** failure mode j **do**

6:             $PoF_{ij}^t \leftarrow PoS_j^t \times Rf_i \times CS_i^t$

7:         **end for**

8:     **end for**

9:     $FR^t \leftarrow f(PoF_{ij}^t) \times Con$

10:     **if** $FR_{ij}^t > AFR$ **then**

11:         Flag for intervention

12:     **end if**

13:     $t \leftarrow t + 1$

14: **end while**

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