A Holistic Approach to Railway Infrastructure Asset Management

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Abstract: In the railway industry asset management decisions are focused on the maintenance, enhancement and renewal of assets in order to ensure a required level of dependability and improvement in services at the lowest whole life costs. To achieve these objectives system lifecycle models, rather than individual asset models, offer a greater advantage. The paper presents a modelling approach developed for constructing multi-asset system models to support well-informed railway infrastructure asset management decisions. The models are built using the Petri Net formalism and are analysed by a means of Monte Carlo simulations. A specific example of the railway superstructure model is presented. Its simulation results demonstrate the superiority of the system-wide model against individual asset models in terms of its accuracy in predicting the superstructure (system) performance and information available to support asset management decisions. Furthermore, by using the multi-asset system model interdependencies among maintenance regimes of different assets and different parts of the infrastructure can be modelled.

Keywords*: Railway infrastructure, asset management, system-wide models, Petri Nets.*

1. Introduction

Railway infrastructure asset management is a decision making exercise mainly focusing on asset selection and intervention strategies with the aim to deliver reliable and safe infrastructure at low costs. The largest costs incurred over the operation life of assets are intervention costs. Assets need be inspected, maintained, repaired, enhanced and renewed in order to deliver a reliable and safe infrastructure with sufficient capacity to run train services. It is therefore very important to determine intervention policies that would achieve the performance targets required at the minimum costs.

Mathematical models are widely used to support asset management decisions. As understanding of the asset operation and degradation are essential for tailoring maintenance activities and their schedules that prolong lives of assets, significant efforts have been made to develop tools to model performance and degradation processes of individual assets [1-3]. Another group of models proposed to aid the decision making processes in asset management focuses on modelling intervention activities and their impact on performance of the assets [4-6]. In terms of optimising the whole infrastructure performance, the models that consider joint dependability implications and costs of asset management decisions are the most valuable. Having an ability to assess how an intervention on a single asset group impacts other parts of the railway system cross-asset and cross-sub-system trade-offs can be made delivering cost savings without comprising safety.

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To aid the decision-making process in the management of the railway infrastructure, a new modelling framework has been developed and is presented in the paper. The modelling framework is used to construct and analyse multi-asset system models that predict the state of the railway infrastructure at various levels of granularity over a specified time horizon accounting for possible inspection, testing, maintenance, repair, renewal and upgrade options. Using the models short-term maintenance programme alternatives can be analysed investigating their effect on long-term performance of the infrastructure. The Petri Net (PN) technique is used to build the models. Due to the stochastic nature of the processes modelled, *e.g.,* a demand for intervention, and due to the size and complexity of the models a simulation method is used for the analysis of PNs.

The paper is organised as follows: in section 2 the proposed asset management modelling framework is discussed in detail, in section 3 a case study of the application of the modelling framework and its results are presented, finally, section 4 presents conclusions and summary of the paper.

2. Asset Management Modelling Approach

2.1 Modelling Technique

The asset management decisions rely on the knowledge and understanding of the asset performance and intervention processes. To be able to model these processes requires a modelling technique which is capable of modelling both stochastic and deterministic events, as well as their interactions. PNs [7] can capture such behavioural specifications of the processes and offer several advantages over other commonly used methods such as Markov methods, which assume only exponential rates between states, or Communicating State Machines, which are a special case of PN and cannot directly represent concurrency [8].

A standard PN consists of a set of places, a set of transitions and a set of directed arcs which connect places to transitions and vice versa. Transitions, drawn as bars, depict actions, events or processes that represent a change in the system state (*e.g.*, component degradation, failure) or performed activities (*e.g.,* component repair). Places, drawn as circles, represent preconditions and post conditions of the actions and processes. This could be a particular system state (*e.g.*, operational, failed) or activity being modelled (*e.g.*, maintenance completion). Transitions are linked to places and vice versa by directed arcs. Tokens move between places through transitions according to transition firing rules and mimic the dynamic behaviour of the system. A transition is enabled for firing if each of its input places contains at least as many tokens as the multiplicity of the input places. An enabled transition fires by removing as many tokens as the multiplicity of the input arcs from each input place, and adding as many tokens as the multiplicity of the output arcs to each output place.

In order to make the model representation more compact and to enhance the modelling power of the PN technique, the standard PN formalism has been extended. One of the extensions introduced that is often encountered in the literature is an inhibit arc [7]. Some more complex extensions relying on logical interactions between objects of PN that were initially proposed in [9] have been used in this work with further enhancements. Additionally, two new extensions to the standard formalism of transitions have been introduced. The first special construct is a periodical transition. The firing delay time of such a transition is determined by two parameters: 1) T, the time since the start of the model execution until the moment the transition becomes enabled and 2) p, the length of the time interval between periodical events, *e.g.*, periodical inspections. The firing delay time of the transitions is then equal to the reminder after the division *T*/*p* and signifies the remaining time until the next periodical event. If modelling periodical asset inspections, the firing delay time of the periodical transition would be equal to a remainder after the division of the lifetime of the asset by the length of the time interval between inspections.

The second of the PN extensions mentioned earlier introduces a multi-functional transition that combines time-related and place marking-related transition features. For example, a decision-making transition, whose firing delay time depends on the marking of specified places, combines features of the decision-making and place conditional transitions.

For large and complex PNs (as in the case of the model presented here) a discrete-event simulation is commonly used to check the system properties. The simulation process models the system over its lifetime. At the end of the simulation two types of outputs that facilitate the assessment of the system behaviour are produced: 1) the number of tokens received by places of interest and 2) the duration the places remained marked over the modelled time horizon. Thus, by counting tokens received by particular places during the simulation, discrete system parameters can be evaluated such as numbers of failures or maintenance activities performed over the lifetime. Similarly, by accumulating time periods when the places remains marked, time related parameters such as availability or downtime can be estimated.

In a case of a PN containing transitions with stochastic firing times, each simulation will produce performance parameters of the modelled system which will be stochastic in their nature. For this reason a Monte Carlo (MC) simulation technique, where the modelled system lifetime constitutes a single simulation experiment, is used to obtain expected values of the parameters. During the experiment delay times of stochastic transitions are randomly sampled from appropriate distributions and performance parameters of interest are obtained. The experiments are repeated until the convergence of the parameters of interest is confirmed, *i.e.*, when the coefficient of variation of a specified performance parameter is less than the prescribed tolerance value. Parameters chosen should not have heavy-tailed distributions in order to avoid using too few samples to obtain MC estimates [10].

The software used in the study for the execution of the PN is implemented in C++. Due to the enhanced features introduced to the PN technique, commercial software could not be used in this case.

2.2 Modelling Framework

This section introduces the concepts of the modelling framework emphasizing its main features. The detailed description of the framework will be presented in a case study in Section 3.1 where the application example will be discussed.

2.2.1 Railway Infrastructure Representation

The concept of the modelling framework architecture is based on a hierarchical representation of the infrastructure network. Using a top down approach the whole rail network is first broken down into operational routes, representing railway network parts in different regions of the country. Each route comprises of several lines which represent portions of a route between two major locations, *e.g.*, stations. The entire line is divided into sections based on a chosen criterion, *e.g.* dividing it into track sections separated by switches. Finally each section is further divided into segments.

In the presented hierarchical topology of the railway network individual asset (two types of assets will be considered in this study namely sleepers and rails) are modelled at a segment level. In this context, a segment of the track is equivalent to the smallest unit of the network for which degradation and intervention processes of its constituent elements can be determined. When representing each section in terms of segments, each section would have as many sets of segments as there are different assets in the section.

2.2.2 Asset State PN Model

Each asset segment has its PN that models the operational life of the asset by depicting asset's degradation process and interventions carried out. Even though an individual PN model is built for a specific asset, all asset PNs share some common features. Each asset segment PN consists of three interlinked sub-modules: degradation-failure, inspection and intervention. The modules are interlinked through commonly shared places.

Most railway assets do not fail suddenly but deteriorate gradually reaching an unacceptable or failed condition state. Behaviour of such assets is modelled by dividing the deterioration process into a finite number of discrete degradation states. Parameters for the degradation-failure model including the number of states and degradation rates are determined based on the observed asset behaviour using failure, maintenance and utilisation data.

The asset intervention model includes options to account for specific inspection, testing, servicing, repair, renewal and upgrade alternatives. The choice of the activities and their timing can be based on various criteria including risk, asset condition, asset reliability or simply a predefined time regime. Criterion for choosing a particular activity is determined based on the management strategy specified for the asset.

2.2.3 Infrastructure State Model Construction

The asset state models are used as subnets for building an infrastructure state PN model at a chosen hierarchical level. The PN model can be constructed to model either a single-asset or a multi-asset system. For example, in order to build a section state model for a single asset type, individual asset segment models are joined together. The section model, however, cannot be viewed simply as a collection of discreet segment models assembled together. Additional PN subnets are used to implement the model integration strategy addressing the asset management principles at a section level and taking into account existing interdependencies among asset management activities. An integration strategy will differ from asset to asset and from one intervention strategy to another. Similarly, by following an appropriate integration strategy and joining segment models representing individual sections, a line, route and finally whole network PN state model is constructed. In the same manner, a multi-asset state model can be constructed. In this case, the integration process involves the use of PN subnets that model the existing and potential interdependencies among intervention activities of different assets, common inspection routines or concurrent and opportunistic maintenance activities.

The conceptual structure of the proposed modelling framework is shown in Figure 1.

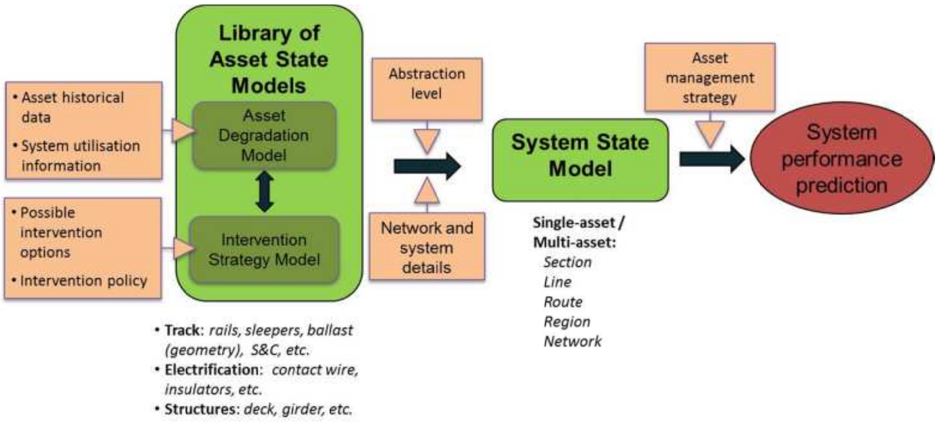

Figure 1: Modelling Framework Structure

3. Case Study

3.1 Superstructure PN Model

A model of the track superstructure, which comprises of sleepers and rails on a part of a single track railway line, is presented in the case study. The line in question is divided into 5 sections each one comprising 80 1/8th mile homogeneous segments. To increase the complexity of the modelled system, it is assumed that assets in the first three sections (denoted as location #1) and the last two sections (denoted as location #2) are subject to different environmental conditions which affect their degradation process and in turn the asset maintenance regimes. Thus, to construct the line system model sleepers and rails segment PN models are used as building blocks.

In the graphical representation of PNs built each node (a place, a transition) has its own unique identification code that can also specify the node's position within the hierarchical structure, specifically segment and section number. Specific attributes of nodes are presented by using particular form, style or colour of the object itself. For example, arcs drawn with a dashed line link conditional input places to place conditional transitions. An arc with arrows on both sides is used to represent two arcs of opposite directions between the same transition and place. Some of the values of transition attributes are also displayed textually. Transitions with different attributes are presented in Figure 2.

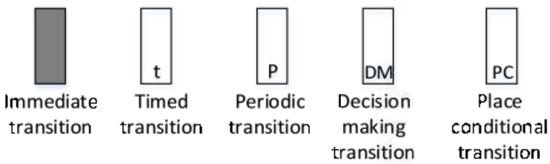

Figure 2: Transition Attributes

The degradation process of both asset types is gradual. Four degradation states are used to determine the condition of sleepers in a single segment (good, defective, several ineffective sleepers, critical number of ineffective sleepers reached) and five degradation states (good, minor defects, major defects, minor damage, major damage) are used to describe the condition of rails. For simplicity, the degradation processes of sleepers and rails are assumed to be independent. Furthermore, condition degradation of assets in one segment is not affected by the state of other segments. As an example, the PN sub-net modelling the degradation process of sleepers in a single track segment is illustrated in Figure 3.

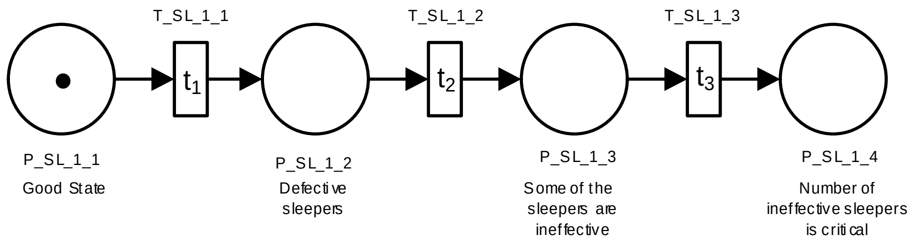

Figure 3: Sleepers Degradation Sub-net

The times to reach each degradation state in the degradation models are stochastic and their values are sampled from appropriate distributions. In the case study it is assumed that the degradation processes of both assets follow exponential distributions. Statistical analysis of records obtained from the asset maintenance database and the rail defect management system was performed to estimate values of the exponential distribution parameters which are provided in Table 1 and Table 2 respectively.

Table 1: Mean Number of Days to Reach Consecutive Condition Degradation States of Sleepers in a Single Segment

Change in condition	**Location #1**	**Location #2**
Good → defective sleepers	6313	1601
Defective sleepers → individual ineffective sleepers	1766	450
Individual ineffective sleepers → critical number of ineffective sleepers	10306	4085

Table 2: Mean Number of Days to Reach Consecutive Condition Degradation States of Rails in a Single Segment

Change in condition	**Location #1**	**Location #2**
Good → minor defects	3152	2937
Minor defects → major defects	615	889
Major defects → minor damage	3772	2405
Minor damage → major damage	132544	30729

To detect any signs of asset degradation and faults, the superstructure is inspected on a regular basis as part of the permanent way inspection regime which is specified based on the track category [11]. Sleepers are inspected visually and an ultrasonic test unit (UTU) is used for rail inspection. For the track category considered in the case study inspections are carried out every 2 and 4 weeks for sleepers and rails respectively. A typical PN sub-net modelling the inspection of sleepers in a single segment is presented in Figure 4 and Figure 5. Specifically, the PN presented in Figure 4 models the schedules of visual inspection activities in the segment. Only inspections when changes in asset condition are detectable are modelled. For example, once the condition of the sleepers, which were known to be in the "new" state, starts deteriorating and sleepers develop defects place P_SL_1_2 becomes marked and transition T_SL_2_1 becomes enabled. The firing delay time of the enabled transition determines the time till the next scheduled inspection when the condition will be detected. This transition along with transitions T_SL_2_2 and T_SL_2_3 are periodic transitions and their firing delay time is equal to the remainder after the division of the system lifetime by the inspection period (in this case 14 days). Note that places named P_SL_1_2 – P_SL_1_4 appear in both the degradation and inspection sub-modules as these places link the two sub-modules.

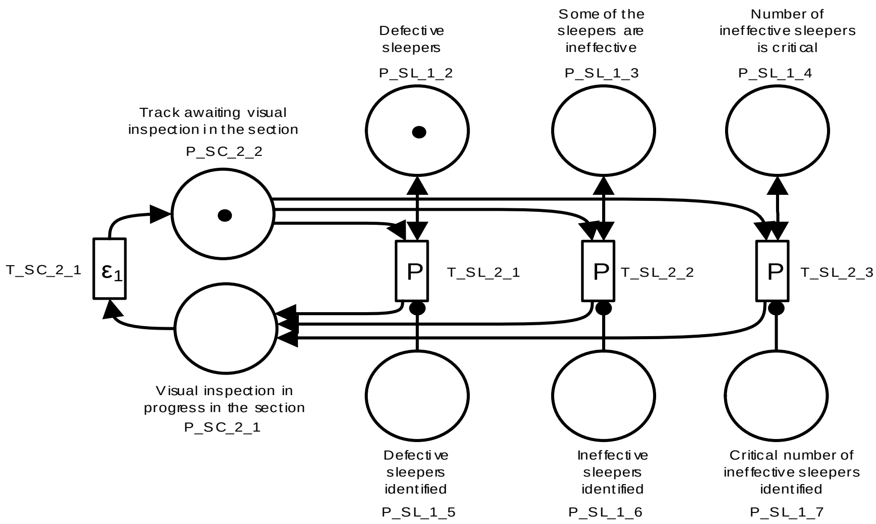

Figure 4: Sub-net Modelling Scheduling of Visual Inspection Activities

The PN in Figure 5 models an actual detection of a new degraded state reached. For example, the given marking of the PN sub-net indicates that minor defects of sleepers have been detected during the inspection and therefore a request for maintenance has been placed. Two transitions in the PN in Figure 5 are decision making transitions. Conditional marking rules introduced with these transitions ensure that only a single (the most severe) sleepers condition state is identified in a segment. For example, when transition T_SL_1_5 fires, based on conditional marking rules a single token is removed from places P_SL_1_5 and P_SL_1_8 at the same time. According conditional marking rules exist for transition P_SL_1_6. Note that when the latter transition fires places P_SC_1_1 and P_L_1_1 receive one token each. The number of tokens residing in these places indicate how many segments have emergency speed restrictions (ESRs) imposed in the specified section and the whole line respectively.

It is assumed that inspection schedules are prepared for individual sections. Thus, when building a scaled up infrastructure PN each segment will have a set of places and transitions modelling the detection of defects and faults in that segment (as shown in Figure 4 and Figure 5) and these will be linked to an appropriate inspection subnet associated with the section containing the segments in question.

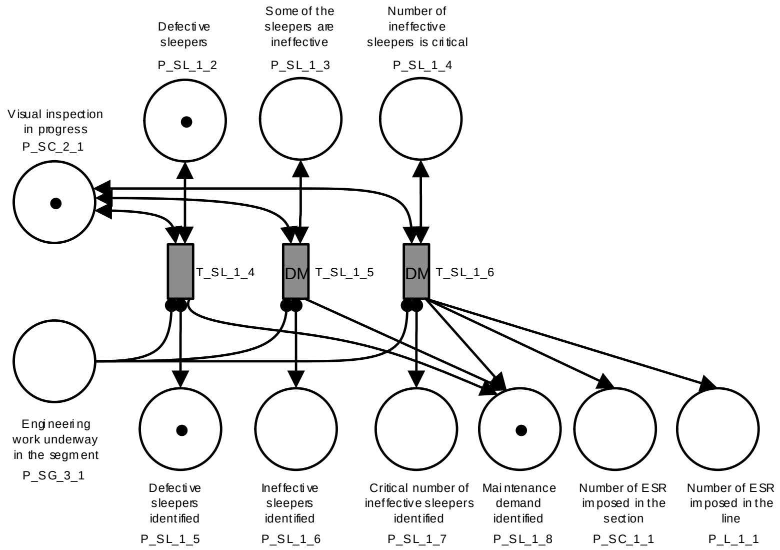

Figure 5: Sub-net Modelling Identification of Asset Condition During Inspection

Two types of maintenance activities are modelled in the case study: preventive and reactive. Preventive maintenance is only carried out for sleepers and is assumed to be performed regularly at fixed time intervals. Reactive maintenance of sleepers involves either repairs of defective sleepers or replacement of any ineffective sleepers. Reactive interventions of rails involve either rail grinding, welding or rail replacement. In the model the preferred choices for the techniques are modelled by determining the likelihood with which each technique will be selected to repair different rail defects and damages.

The sleepers' maintenance PN sub-net is shown in Figure 6 as an example. The given marking of places in the PN indicates that repairs of defective sleepers have been scheduled after a specified period of time. Since only minor defects of the sleepers have been found, the repairs will be carried out as part of routine track preventive intervention activities (not shown in Figure 6), *i.e.*, transition T_SL_3_2 will be eventually enabled. The latter transition is a periodic transition whose firing delay time is determined based on preventive intervention schedules. Otherwise, if the sleepers were found to be ineffective the work would be started as initially scheduled, *i.e.*, transition T_SL_3_3 would be enabled and fire immediately.

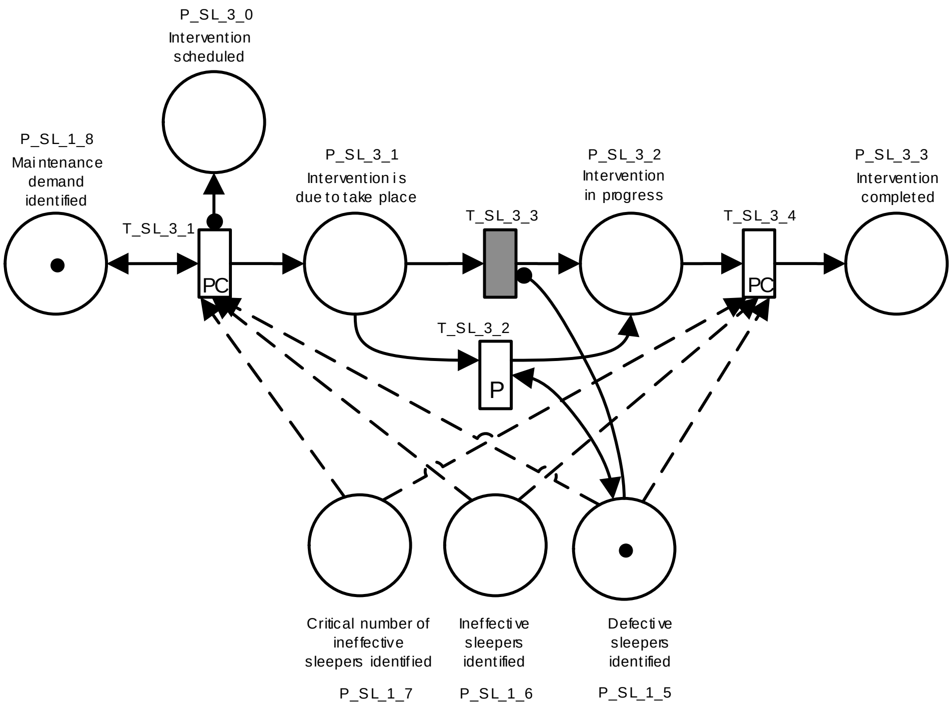

Figure 6: Sleepers Intervention PN Sub-net

In general, the delays in carrying out repairs and repair duration times depend on the severity of an asset defect or fault. In the model it is assumed that these times follow lognormal distributions whose parameters are determined based on guidance and requirements provided for the maintenance of track assets [12]. The input parameters used to model maintenance of sleepers and rails are provided in Table 3 and Table 4 respectively.

Table 3: Intervention Response and Duration Parameters for Sleepers

	Intervention response time distribution parameters		**Intervention duration distribution parameters**	
Condition State/Level	**Mean (days)**	**Standard Deviation (days)**	**Mean (hours)**	**Standard Deviation (hours)**
Defective sleepers	630	30	0.90	0.01
Individual ineffective sleepers	90	7	1.50	0.10
Critical number of ineffective sleepers	9	1	3.00	0.10

When building the superstructure section PN, asset state sub-nets will be replicated 80 times. Sleeper segment PN models will be linked to the section visual inspection sub-net, while rail segment PNs will be linked to the corresponding rail inspection sub-net. In addition, several new places will be added which will be linked to every segment PN to be able to monitor performance of the superstructure within the section. For example, to observe ESRs introduced in the section the place labelled P_SC_1_1 as shown in Figure 5 will be linked to each asset segment degradation sub-net in that section. The superstructure line PN model will be constructed by replicating the section PN 5 times. Similar to the section PN, additional places will be introduced in the line model to monitor the performance of the superstructure at the line level.

Table 4: Intervention Response and Duration Parameters for Rails

	Intervention response time distribution parameters		Intervention duration distribution parameters		
Condition State/Level	**Mean (days)**	**Standard Deviation (days)**	**Intervention Type**	**Mean (hours)**	**Standard Deviation (hours)**
Minor defects	360	30	Grinding	0.01	0.0033
			Welding	1.00	0.2500
			Rail replacement	2.00	0.5000
Major defects	135	7	Grinding	0.01	0.0033
			Welding	1.25	0.2500
			Rail replacement	2.00	0.5000
Minor damage	47	7	Grinding	0.01	0.0033
			Welding	1.50	0.2500
			Rail replacement	2.00	0.5000
Major damage	7	1	Grinding	0.01	0.0033
			Welding	1.75	0.2500
			Rail replacement	2.00	0.5000

Having constructed multi-asset section PNs allows the inclusion of opportunistic and concurrent maintenance strategies. The purpose of the opportunistic maintenance strategy modelled here is to take an advantage of the section possession time scheduled for the replacement of ineffective sleepers in a specified segment and to carry out maintenance of sleepers in adjacent segments within one half of a mile distance in the same section, given sleepers in the segments require corrective intervention. To implement opportunistic maintenance scenarios the transition labelled T_SL_3_3 in the sleepers intervention PN sub-net, as that shown in Figure 6, has the functionality of a decision making transition activated. The firing of the transition will mark places in the PNs of specified adjacent segments representing the initiation of maintenance ahead of the planned schedule. The resulting marking of these places will change the firing times of the place conditional transitions labelled T_SL_3_1 in the corresponding segments to instantaneous ones.

To model concurrent maintenance of assets, *i.e.* simultaneous replacement of rails and ineffective sleepers, the decision making transition labelled T_SL_3_3 in the sleepers intervention PN sub-net and its equivalent in the rails intervention PN sub-net have specific place marking rules introduced for this purpose. Given that the sleepers and rails in the same segment are scheduled to be replaced, the firing of transition T_SL_3_3 will mark the place in the rail PN of that segment representing the initiation of maintenance ahead of the planned schedule and subsequently the place conditional transition in the rail PN equivalent to that labelled T_SL_3_1 will fire immediately. In the same manner rail replacement started in the segment will initiate replacement of sleepers ahead of the planned schedule.

3.2 Analysis

The superstructure line model presented and three of its variants were used for the analysis. The first variant of the baseline model had an option to perform opportunistic maintenance of sleepers introduced. Concurrent maintenance of assets, *i.e*, simultaneous replacement of rails and sleepers, was another intervention option considered. A maintenance strategy incorporating both opportunistic and concurrent maintenance options was introduced in the third variant of the model. MC simulations of 60 year operational life cycle for all four models were performed.

Table 5 and Table 6 list expected values of the total number of days and average durations of ESRs calculated over the whole lifetime respectively. As one can see from the results presented, the number of days ESRs are imposed and the average duration of each ESR instance due to poor state of rails are much greater than those due to sleepers. It is interesting to note that for sleepers the difference in terms of durations of ESR between the two parts of the line (at location #1 and location #2) is very significant. These observations suggest that in order to reduce disruptions for train passengers the focus should be placed on changing the intervention strategy to ensure a better condition of rails. Additionally, efforts should also be made to tailor interventions of sleepers in order to reduce ESRs in the second part of the line.

Table 5: Expected Number of Days Spent with ESRs imposed over the Lifetime – Scheduled Interventions only

	Line	**Section in Location #1**	**Section in Location #2**
Rails	1614.4	333.8	330.7
Sleepers	274.1	6.3	128.8
Superstructure	1875.6	340.7	464.9

Table 6: Expected Average Duration (expressed in days) of ESR imposed– Scheduled Interventions only

	Line	**Section in Location #1**	**Section in Location #2**
Rails	45.1	46.5	46.5
Sleepers	9.0	9.1	9.0
Superstructure	28.4	43.5	21.7

Overall, the results demonstrate the advantage of having an integrated model of the superstructure as oppose to individual asset models to assess durations of ESRs. The superstructure model predicts infrastructure performance by eliminating periods of ESRs that overlap between the two asset groups (*e.g.* $1614.4+274.1\neq1875.6$). When predicting the duration of ESR at a line level the overlaps among individual sections are also eliminated as indicated in Table 5 (*e.g.* $3\times340.7+2\times464.9\neq1875.6$).

Table 7 and Table 8 demonstrate the impact of different intervention strategies on ESRs over the lifetime of the superstructure. For example, with the introduction of concurrent maintenance the total duration of ESRs in the line reduced by 21 days from 1875 to 1854. Periods of ESRs reduce even more if instead of concurrent maintenance opportunistic maintenance programme is used. However, adopting both opportunistic and concurrent maintenance programmes provide no additional benefits in terms of reduction of the number of days ESRs are imposed over the lifetime of the superstructure. In any case, the results prove that introducing concurrent and/or opportunistic maintenance as a way to improve cost-efficiency will not only reduce maintenance costs but it will additionally provide cost savings as a result of reduction in ESRs and, subsequently, train delays. It is interesting to note, that even though the total duration of ESRs reduces with the introduction of opportunistic maintenance, the average duration of ESRs increases, particularly, in the sections in the second part of the line. In this case adjusting intervention response times could be considered as an option for reducing prolonged periods of ESRs.

Table 7: Expected Number of Days spent with ESRs imposed over the Lifetime of the Superstructure under different Maintenance Strategies

	Line	**Section in Location #1**	**Section in Location #2**
Scheduled interventions only	1875.6	340.7	464.9
Concurrent interventions performed	1854.2	342.3	446.5
Opportunistic interventions performed	1808.1	345.3	411.0
Opportunistic + concurrent interventions performed	1843.8	351.5	443.2

Table 8: Expected Average Duration (expressed in days) of ESRs imposed over the Lifetime of the Superstructure under different Maintenance Strategies

	Line	**Section in Location #1**	**Section in Location #2**
Scheduled interventions only	28.4	43.48	21.72
Concurrent interventions performed	28.19	43.38	21.24
Opportunistic interventions performed	31.70	43.52	24.96
Opportunistic + concurrent interventions performed	29.42	43.64	22.75

Another set of performance parameters was obtained to assess the intervention activities. The effects of different intervention strategies on the numbers of interventions and the downtime of the superstructure are summarised in Table 9 and Table 10 respectively. With the introduction of concurrent and opportunistic maintenance activities along the scheduled maintenance work, the number of interventions carried out in the line increases. The largest increase of additional 142 (3%) activities occurs as a result of the introduction of opportunistic interventions. Intervention numbers in the last two sections of the line (location # 2) follow the same pattern (increase in 5% from 1336 to 1405 activities) as that of the line; while the numbers of maintenance activities carried out in the first three sections of the line (location # 1) remain the same for all maintenance strategies. Most of the variation in the numbers of intervention activities can be attributed to more frequent repairs of sleepers. Alternatively, the downtime of the superstructure either remains the same or decreases as a result of carrying out opportunistic and/or concurrent maintenance. The largest improvement in the downtime in the line (decrease by 10%) is achieved when opportunistic maintenance activities are included in the work bank. These findings imply that despite an increase in the numbers of interventions their durations are shorter. Such a maintenance strategy would be very beneficial in the parts of the network where train intensity is high providing shorter windows for maintenance.

Table 9: Expected Number of Intervention Activities over the Lifetime of the Superstructure under different Maintenance Strategies expressed in Days

	Line	Section in Location #1	Section in Location #2
Scheduled interventions only	4893	741	1336
Concurrent interventions performed	4894	741	1337
Opportunistic interventions performed	5035	741	1405
Opportunistic + concurrent interventions performed	4905	741	1342

Table 10: Expected Number of Days of Downtime over the Lifetime of the Superstructure under different Maintenance Strategies

	Line	Section in Location #1	Section in Location #2
Scheduled interventions only	227.4	33.7	70.4
Concurrent interventions performed	227.4	33.6	70.4
Opportunistic interventions performed	204.7	33.4	61.7
Opportunistic + concurrent interventions performed	215.1	33.5	64.3

4. Summary and Conclusions

In the paper a framework for modelling the railway infrastructure and changes in its state over time has been presented. The proposed framework uses a hierarchical modular platform where models combining degradation and intervention processes of individual assets are at the lowest hierarchical level. They can be deployed as stand-alone asset state models or as building blocks to construct infrastructure models for any level of the network granularity with a varying degree of complexity. The advantage of the approach is the flexibility to construct very detailed system–wide models for any part of the railway infrastructure.

The models are constructed using the PN technique and are executed by the means of MC simulations. By performing the simulations the infrastructure performance can be predicted and alternative asset management strategies investigated. Further investigations can be carried out on how to modify the strategies in order to improve infrastructure performance and, if associated costs are known, what impact they will have on the expenditure.

In the paper the development of the superstructure model has been described followed by the model application example for the investigation of the infrastructure performance under different maintenance strategies. The analysis has produced a set of performance parameters of the superstructure and its constituent elements at different hierarchical levels of the network. The results demonstrate essential advantages of the modelling framework proposed. In terms of accuracy in predicting the superstructure (system) performance and information available to support asset management decisions, the system-wide model is superior to individual asset models. Furthermore, having the multi-asset system model different maintenance strategies, including opportunistic and concurrent maintenance, which require interdependencies among different assets and different parts of the infrastructure to be accounted for, can be modelled.

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