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A Petri-Net-based Modelling Approach to Railway Bridge Asset Management

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Abstract

Management of a large portfolio of infrastructure assets is a complex and demanding task for transport agencies. Although extensive research has been conducted on probabilistic models for asset management, in particular bridges, focus has been almost exclusively on deterioration modelling. The model being presented in this study tries to reunite a disjointed system by combining deterioration, inspection and maintenance models. A Petri-Net (PN) modelling approach is employed and the resulting model consists of a number of different modules each with its own source of data, calibration methodology and functionality. The modules interconnect providing a robust framework. The interaction between the modules can be used to provide meaningful outputs useful to railway bridge portfolio managers.

Keywords: Rail, Bridges, Asset Management, Maintainability, Whole Life Cycle Costing, Petri-Net

1. Introduction

Railway structures are integral to the efficient running of the transport network. Railways are used for both industry and commuters so their use is critical from a social and economic perspective. Trains can carry very heavy loads and the schedules mean that the frequency of trains is relentless on supporting structures. With the future introduction of moving block signalling systems the frequency of trains will only increase which means the stress on civil structures will increase too.

A significant challenge is to be able to predict structural deterioration. There are already industry guidelines (Network Rail, 2012) on the thresholds to inspect structures and maintain structures, but there is limited understanding of how structural defects evolve over time. Different elements will deteriorate in different ways and so grouping the elements helps to assign a deterioration profile to those elements. Additionally, some defects are more or less likely to lead to other defects and knowing which defect an element suffers from and then monitoring the defects development gives a great insight into predicting structural deterioration.

There are three main material types used for railway bridges: masonry, metallic and concrete. This study uses concrete main girders as its exemplar element because concrete bridges are becoming increasingly more popular and the main girders are the elements that experience most structural loading and are critical to bridge safety. However, the techniques and methods used in this study can be applied to all railway bridges.

2. Stochastic Models

2.1. Markov Based Models

A number of different modelling approaches have been used for bridge asset management, but the most popular type is stochastic modelling. Frangopol et al. (2004) makes it clear that stochastic models are superior to other modelling techniques for structural deterioration. Stochastic models use random variables and probability distributions to predict the deterioration over time. Frangopol et al. (2004) states that it would be better to model deterioration in terms of a time-dependent stochastic process. Morcous et al. (2010) reports from Ditlevsen (1984) that structural deterioration is a complex process and there is a considerable amount of uncertainty in the structures "micro-response" which means that stochastic models offer practicality and reliability.

Markov based models have been used for bridge deterioration for 25 years. Jiang and Sinha (1989) were one of the first to study bridge deterioration with a Markov based model. They used a population of 5,700 bridges in Indiana, USA, from which 50 were randomly selected as samples. The paper discusses the methodology of generating the transitional probability based on condition score data of bridges of different ages. The bridge conditions were scored by guidelines set out by the Federal Highway Administration (FHWA), 0-9 with 9 being the rating of a new bridge. They noticed that as the bridge ages the deterioration rate also changes. The paper follows on to say that Markov based approaches would be useful in this stochastic situation. The paper has been widely cited as

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pioneering the technique, however there was no application on bridge condition data.

Cesare et al. (1992) developed the technique further by incorporating a repair policy into the model. The study used 850 bridges in New York state totalling over 2,000 spans. The Markov chain model was designed with 7 states ranging from 1, potentially hazardous, to 7, new condition. Their approach splits the asset into major components e.g. superstructure, deck and piers. The model assumes that deterioration of each element is independent of all other bridge elements. The repair policy is implemented with a repair matrix that improves the condition by either 10% or 20% of the bridge condition scores in condition state 3 or less. There is little clarification about the repair policies but the authors claim to be able to predict the evolution of the average condition state of a set of bridges and the condition for a specific bridge. This approach was used by the Association of State Highway and Transportation Officials (AASHTO) to create Pontis which serves as the most widespread Bridge Management System (BMS). It is used to manage over 500,000 bridges in 45 US states (Sobanjo and Thompson, 2011).

Scherer and Glagola (1994) attempted to apply the Markov approach to real-world data from 13,000 bridges in Virginia. The paper uses the same 7 states used in Cesare et al. (1992). However the author uses the condition of the whole bridge rather than bridge components. The author then comments that the Markov chain approach creates S^n states where S is the number of states and n is the number of assets in the study. This would have created $7^{13,000}$ states which contemporary computers would have struggled to simulate. To tackle this issue the author creates a number of classes based on: road system, climate, traffic loading, bridge spans, bridge age and bridge type. The total number of classes is 216 and a typical bridge example was chosen for each class. This reduces the number of states to 7^{216}. The paper tried to address the issue with Markov state inflation (S^n) by grouping the bridges and then selecting typical examples from each group. The paper does identify the issue of a bridge that moves between groups over its lifetime due to deterioration.

Morcous (2006) studied the Quebec transport bridges, totalling 9,678 structures, including bridges of different types and culverts. Overall the data included 500,924 element inspections from 1997 to 2000. The performance indicator ranged from 0-100 with a higher number indicating a better condition. All inspection changes that indicated an increase in condition were striped out to eliminate the effects of maintenance or inspector variance. The paper lays out some assumptions: firstly, bridge inspections are assumed to be carried out at a pre-determined fixed interval. Secondly, future bridge condition depends only on present condition, ignoring historical conditions, highlighting the "memoryless" Markov property. Morcous (2006) states that these assumptions affect the reliability of the predictions and that the assumptions were designed to reduce the computational complexity and streamline the decision-making operation. The paper analyses the inspection interval to compute a normally-distributed inspection interval with a mean just over 2 years. The paper calculated the Transition Probability Matrix (TPM) using the frequency approach. This paper incorporates a different approach using Bayes' rule which is used to adjust the TPM for the variance in inspection frequency. This is then compared to the before and after effects of Bayes' rule. The paper closes with a figure of 22% for the improvement possible in estimating the service life of the bridge decks (the most critical component) with the inclusion of Bayes' rule in the adjustment of the TPM.

The models that have been discussed are Markov based models. Markov models form the basis for the prediction module found in many BMS systems. They have had unparalleled adoption in the field of infrastructure facilities. Morcous (2006) makes it clear that the Markov approach is the most commonly used of all the stochastic models for predicting performance in bridges, highways, sewerage and water distribution. That is not to say that Markov models are without limitation. Additionally, some of the techniques used to simplify Markov model computation are not directly Markovian limitations, but are limitations to using the Markov approach in structural deterioration modelling. Some of those limitations include:

- Markov chain based models assume that time intervals are discrete intervals, the bridge population is fixed and the TPM probabilities are static which can be inaccurate (Morcous et al., 2002).

- Transition probabilities in the TPM are difficult to accurately calculate and can often require manipulation by expert judgement (Frangopol et al., 2004).

- Often inspection data where the condition has increased is disregarded due to difficulty in reliably ascertaining which assets were repaired and what repair action was applied (Robelin and Madanat, 2007; Morcous et al., 2002).

- The condition states are defined as discrete states but often there will be borderline candidates and critical elements which require expert judgement for correct classification, which can be subjective. Frangopol et al. (2004) argues that a more detailed, continuous, measurement criterion would be superior.

- The Markov modelling approach suffers from a rapid expansion of states when interactions between elements are considered. The number of model states follows S^n where S is the number of states and n is the number of elements. Even though this is often not a problem for modern bridge management systems, it is still a limitation of the technique (British Standards Institution, 2012).

2.2. Petri-Net Based Models

PNs were developed by Petri (1962). They have had increasing application in transportation, manufacturing and business for modelling dynamic, distributed systems (British Standards Institution, 2012). PNs are not as common as other conventional modelling techniques and being the main method employed in this work, they are described in detail in Section 3. Recent work demonstrated that PNs are appropriate for deterioration modelling (Andrews, 2013). The approach used four states to describe the asset deterioration process: new, degraded needing maintenance, degraded needing speed restrictions and degraded needing line closure. The model was designed for track deterioration rather than structural deterioration, however the author mentions that the PN modelling technique has a great deal of flexibility and the PN model presented in the paper is significantly more developed than others found in literature.

Rama and Andrews (2013b) used a number of simple PN subnets to model the railway infrastructure in a hierarchical, modular structure. A number of different sub-net modules were created for component deterioration, maintenance, inspection and renewal. A modelling framework was presented where the hierarchy was laid out. At the top level the whole railway is subjected to track, rail and geometry inspections. Then, at the lower levels, depending on that particular 1/8th of a mile section, sleepers, fastenings and ballast are modelled. Each of the sub-nets connects to one another and a resource allocation PN is created to manage occupied maintenance staff. For each section of track, the appropriate sub-net modules are amalgamated. The paper mentions that having a library of PNs specific to individual assets could be beneficial to generating a detailed, realistic model of the whole system.

Le and Andrews (2014b,a) created a bridge model using a PN approach. A number of PN sub-nets were generated for the components that make up the bridge (e.g. deck, girders and abutments). Each component was detailed with deterioration, inspection and maintenance processes. For each bridge asset the elements are considered and the corresponding sub-PNs chosen to create a complete bridge model. The state descriptions in this model were not related to deterioration, but the maintenance action required for rehabilitation, similar to Yang et al. (2009). This model uses Coloured Petri-Nets (CPNs) to track different individual bridge elements within the same sub-net. The advantage of CPNs here is that coloured tokens within a sub-net could hold tuple information. This can be used in analysis, for example, the number of maintenance occurrences before element replacement. The model inputs are deterioration characteristics for different bridge components and the maintenance/renewal strategy parameters. The author uses Monte Carlo sampling for all stochastic transitions. A simulation duration of 60 years was used and the results converged after roughly 200 simulations; this took under 10 minutes to perform.

Overall, there is a strong case that structural deterioration is a stochastic process and therefore a probabilistic method is preferred. Due to numerous Markov limitations, explained in section 2.1, there is a suitable draw to using PNs to model structural deterioration.

3. Petri-Nets

PNs are directed bipartite graphs. A bipartite graph is valid if its vertices can be grouped into two subsets U and V. Each arc connects a vertex from subset U to a vertex in subset V. They are built with two types of nodes: places and transitions. In bridge modelling, places are representative of element condition (e.g. as new, good, poor). Tokens are arguably the most important feature of a PN model. A token, representing a bridge or element, occupies a place. Through this, the condition of the element is defined at any given time. I.e. a token in a place marked as new" means that a particular bridge element is in an as new" condition. Transitions are used to move tokens from place to place mimicking deterioration, for instance. The arcs are graphical representations of relationships between places and transitions. No two places or transitions can be directly connected with an arc (Reisig, 2013). These components can be seen in Figure 1.

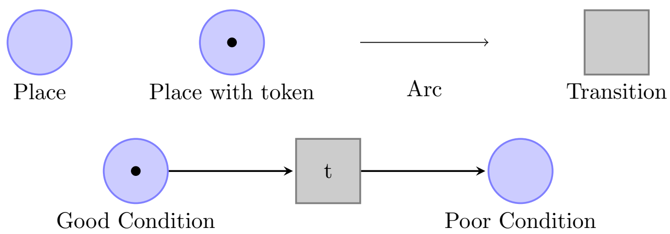

Figure 1: Components of a Petri-Net with a simple example.

3.1. Coloured Petri-Nets

CPNs are an extension to simple PNs previously discussed. They were developed by Jensen (1997) as the amalgamation of simple PNs and programming languages. British Standards Institution (2004) discusses the advantage of CPNs as a way of avoiding the exponential increase in number of states with the number of elements.

In simple PNs, the tokens are anonymous and indistinguishable, their importance comes from their presence/absence in the place. However with CPNs, there is an additional constraint: transitions can only be activated if all the input places have the correct number of tokens and the tokens must match the transition criteria, known as the "guard". An example of this in bridge modelling may be for minor interventions. After a certain amount of minor interventions, a more major intervention may have to be carried out. Therefore, a counter place may accumulate tokens based on the number of minor interventions, when the threshold is reached, the transition fires to inhibit further minor interventions. The phrase "coloured" in CPNs does not necessarily mean that each token has its own colour; but only tries to clarify that now tokens can be of different types with different data sets and characteristics. The data held within the token in known as the token “tuples”. The tuples within the token could be modified by the transition, for instance if one of the pieces of information in the token was the age of the asset, that number could increase within the tuple when the transition fires.

The transitions become more sophisticated in CPNs as they do not simply consume and produce tokens at the allocated time, but they now perform functions on the data within the token itself. This affords CPNs a great deal of flexibility beyond simple PNs. A basic example of a CPN can be seen in Figure 2. The transition has two input places, each containing a token. The transition has a guard to satisfy which is that the input tokens both have to have integers larger than one. The token in the top place contains two pieces of information: an integer number and a string. The token in the bottom place only contains an integer number. The integer is bound to w and the string to s. The guard is satisfied, so upon firing, the transition consumes the input tokens and generates a token in the output place. This output token contains an integer and a string. The integer is the product of the two input token integers. The string remains unmodified in this example. The binding of the tuples, the satisfying of the transition and the subsequent modification of the tuple information is known as occurrence. This functionality enables a huge variety of features to be incorporated into PNs which affords it a high level of flexibility. More details about advanced CPN functions are described in Le and Andrews (2014b).

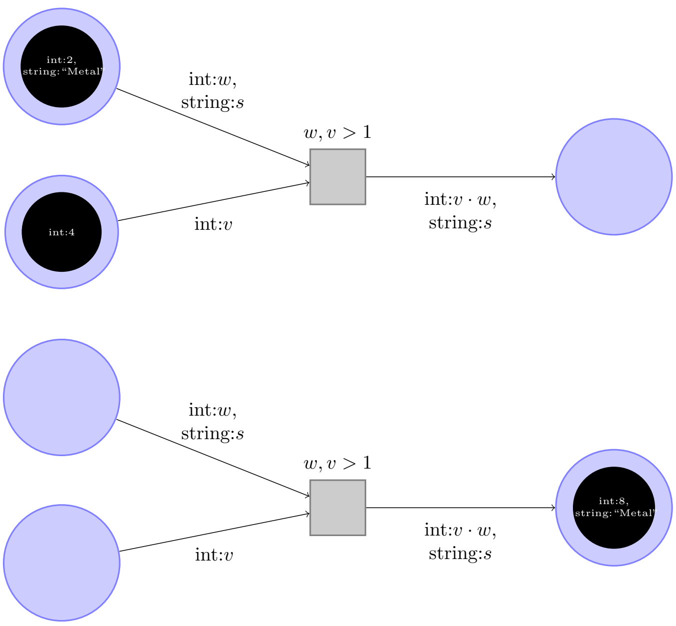

Figure 2: Simple example of a CPN before the transition fires (a) and after the transition fires (b)

4. Deterioration, Inspection and Maintenance Policies

4.1. Condition States

Network Rail (NR) inspect each Sub-Minor element of each bridge and give it a rating according to its condition. The condition of elements is determined during inspection with a conditional matrix, which ranks the condition based on Severity Extent Rating (SevEx). Each time an element is inspected, its condition is recorded. For concrete bridges, the example used in this study, the SevEx ratings go from A1 (perfect condition) to G6 (permanent structural damage). The first character refers to the type of defect and the second refers to the extent of the defect, the full SevEx ratings can be seen in Table 1. The most common defects seen in concrete elements are cracking and spalling, Nielsen et al. (2013) found them to be as high as 89.9% of all concrete defects.

Table 1: SevEx defects for concrete structures (Network Rail, 2012)

Severity	Defect Definition
A	No visible defects
B	Surface damage, Minor spalling, Wetness, Staining, Cracking <1mm wide
C	Spalling without evidence of corrosion, Cracking $\geq$ 1mm wide without evidence of corrosion
D	Spalling with evidence of corrosion, Cracking $\geq$ 1mm wide with evidence of corrosion
E	Secondary reinforcement exposed
F	Primary reinforcement exposed
G	Structural damage to element including permanent distortion
Extent	**Definition**
1	No visible defects
2	Localised defect due to local circumstances.
3	Affects <5% of the surface of the element.
4	Affects 5%-10% of the surface of the element.
5	Affects 10%-50% of the surface of the element.
6	Affects >50% of the surface of the element.

4.2. Inspection Interval

The current NR policies lay out guidelines for when inspection should be scheduled. NR uses two classes of inspection. The first, detailed inspections, are performed within touching distance. Each of the elements are inspected and the SevEx score recorded. The second, visual inspections, are carried out annually. An inspector uses the last detailed inspection to make sure that no major changes to element condition have occurred. No scoring is carried out on visual inspections. Henceforth, any reference to an inspection is referencing detailed inspections. Network Rail (2010b) describes how the condition of the structure is then converted to a risk level and that corresponds to an inspection interval. Rather than have to convert from the condition state to a risk level to determine the inspection interval, a back-calculation was done so that the inspection interval could be directly related to the condition state. This was then incorporated into the model so that the inspection schedule could be determined during simulation.

Table 2 shows the SevEx states and their associated inspection regime. The SevEx states of better conditions are deemed to be lower risk and have a maximum inspection interval of 12 years for concrete elements. The SevEx states of medium conditions are of a medium risk and are recommended to be inspected no later than 6 year intervals. Finally, the worse SevEx states have a higher risk and must be inspected no less frequently than every 3 years.

Table 2: Table showing the SevEx states and their corresponding inspection interval

Interval (years)	States
12	A1, B2-B5, C2-C3, D2
6	B6, C4-C6, D3-D5, E2-E5, F2-F3
3	D6, E6, F4-F6, G2-G6

4.3. Maintenance Actions

The current NR policies lay out guidelines for when maintenance should be scheduled. This is decided upon by an index number known as Bridge Condition Marking Index (BCMI). An A1 condition would relate to an BCMI of 100 and a G6 would relate to an BCMI of 0. The maintenance thresholds in Network Rail (2010a) give the maintenance thresholds in terms of BCMI. The fundamental condition that all elements must meet or exceed is known as the “Basic Safety Limit” which varies for different materials. To determine the correct maintenance action, the SevEx condition must be converted to the BCMI and then checked against the thresholds in Network Rail (2010a). To be able to determine the appropriate maintenance action in the PN model, the thresholds were back-calculated, through the BCMI to determine the SevEx conditions that they relate to. This was carried out so that the appropriate maintenance action could be determined during simulation.

Whilst exploring the database of inspections, it was evident that there were repair works carried out above the condition threshold for intervention. In discussions with the NR Principal Engineers, it became clear that there were two avenues for intervention: 1) the elements that had breached the NR condition threshold and 2) the elements that were above the threshold but the local maintenance team had decided they should intervene. Therefore, in essence, there are two types of intervention, Minor and Major intervention. In Table 3 the SevEx state thresholds for different maintenance actions are represented. There is a great deal of similarity between the thresholds seen in Tables 2 and 3 which suggests the same set of principles were employed by NR policy makers.

Table 3: Table showing the SevEx state thresholds for different maintenance actions.

Maintenance Action	States
Minor Repair	B2-B4, C2-C3, D2
Major Repair	B5-B6, C4-C6, D3-D5, E2-E4, F2-F3
Replacement	D6, E5-E6, F4-F6, G2-G6

5. Data Source

The data used for this study was amalgamated from a number of different datasets. The Civil Asset Register and Reporting System (CARRS), Structure Condition Monitoring Index (SCMI), Cost Analysis Framework (CAF) and MONITOR databases were used, provided by NR. CARRS contains general asset information e.g. the location of the bridge, the material category, territorial classification, etc. The SCMI database contains information regarding the condition of the structure following an inspection. CAF and MONITOR contain work items split between smaller jobs and larger interventions, these were used to determine scheduling and work times as well as costs. Snapshots of the databases were provided covering different time periods so the databases had to be combined and cleaned to ensure that duplicates were removed as well as erroneous data entries. The combined database contains inspections between 1998 and 2014. In total there were records of inspection of 25,949 bridges. Each bridge comprises a number of major elements; the number of major elements which were inspected totalled 273,427. Each of the major elements can be broken down into minor elements; minor elements which were inspected totalled 563,150. The number of inspections on minor elements totalled 1,397,748.

The exemplar element in this study is concrete main girders. There are 4,434 concrete bridges recorded in the population and the main girders are one of the most critical minor elements. The number of repeat inspections on concrete main girders totalled 407,708. This was used to calibrate various model parameters including structural deterioration.

To be able to understand how structural deterioration evolves, one inspection is not enough as a change in condition is required. The vast majority of elements (82.68%) have only had two inspections. The percentage of elements with three inspections is 15.83%. The number of elements that have had 4-6 inspections is 1.49%. The database ranges roughly 16 years and most elements are inspected every 6 years so 2 inspections per element would be expected. The elements that are in the range of 4-6 inspections usually have an inherent asset defect (e.g. structural subsidence) that causes a number of issues to occur hence the increase in inspections. Overall however, there is a large portfolio of structures to inspect so the number of elements with multiple inspections grows continuously.

6. Petri-Net Model

The model which has been developed uses a bottom-up approach rather than a top-down approach. To that effect, the model is asset and sub-asset level rather than at the network level. The model represents an asset with the PN tokens representing elements of the asset. To model a complete bridge, each element of the bridge would be represented by a token in the model. The model is primarily condition based as this is currently the main driver of the decision making processes since it is often the only available information for large bridge stocks. The limitation of this approach has been described, amongst others, by Neves and Frangopol (2005). The capability to model interactions between elements has been incorporated into the model, however has not been used in this study. For example, element interaction could occur during maintenance; one girder that requires replacement may lead to another that is in a moderate condition being repaired too. In this study, elements are considered individually as oppose to groups of elements with interactions. Finally, this model can be used to optimise maintenance and inspection strategies using a multitude of algorithms including Genetic Algorithms (GAs) (Elbehairy et al., 2006), Dynamic Programming (Sniedovich, 2010) and Particle Swarm (Yang et al., 2012) although not considered in this study.

The PN bridge model uses a number of CPN features, but is referred to as a PN model for simplicity. The CPN features are used in two ways: 1) each token contains tuple information about the element i.e. each token represents an element of the bridge and contains all the relevant information about that element within the token e.g element type, material and location 2) there are advanced transition functions built into the model which can aid in modelling complex decision-making processes without making the resulting model unduly complex e.g: probabilistic outcomes, condition dependant delays and condition transposing.

The PN bridge model comprises of a number of "modules". Each module has a different purpose e.g. element deterioration, inspection, maintenance, etc. They vary in their formation and modelling approach and so each module is explained individually. Figure 3 describes the general overview of the modules and how they interact.

Figure 4 gives an example of how the modules interact to form the bridge model framework. Consider a bridge element with a deterministic starting condition of $A1$. This condition, according to current policy, requires an inspection every 12 years (see Table 2). Transition times are generated, based on historic data, for the possible movement (i.e. to condition states $B2$, $B3$ and $C2$). The transition with the probabilistically defined shortest time is selected. This transition fires at $t = 5$ which moves the system state from t_1 to t_2. At this point, the transition times are generated for the possible movement to condition states ($B3$, $C2$ and $C3$). Again, the shortest transition time is chosen

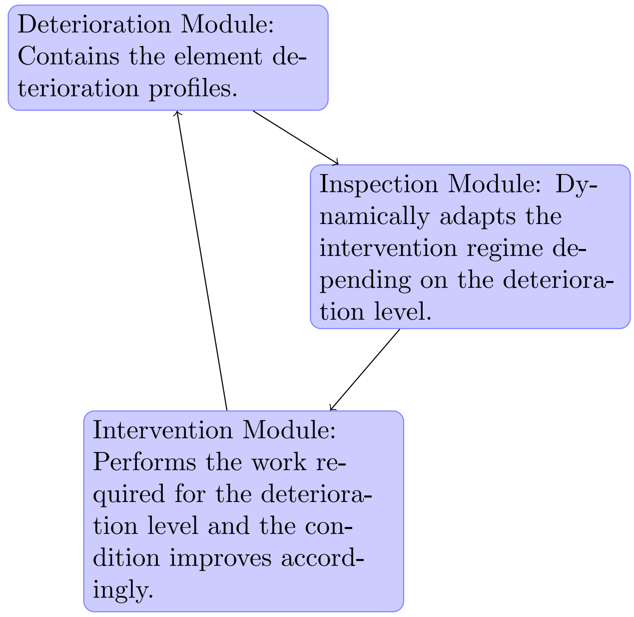

Figure 3: A general overview of the PN model and its component modules. Each of the modules performs a different function and interacts with the other modules as shown.

and the element deteriorates to condition $B3$ at $t = 10$. Transition times are generated for the possible movement to condition states ($B4$, $C3$ and $C4$). However, at $t = 12$, the scheduled inspection takes place. This reveals the condition of the element to the bridge managers. According to current policy, an element in condition $B3$ would be eligible for a Minor Intervention (see Table 3). The inspection takes place at $t = 12$, however there is an associated delay to carry out the intervention whilst bridge possessions are scheduled and materials ordered. The intervention is carried out at $t = 13$ which, in this example, improves the condition of the element to the $A1$ condition. Although not implemented in this study, the model includes the capability of introducing a number of different condition improvement profiles. Another inspection is scheduled in a further 12 years. The deterioration starts again with the transition times from condition $A1$ to condition states $B2$, $B3$ and $C2$ generated.

6.1. *Deterioration*

6.1.1. *Calibrating Deterioration*

One way to format the historic data is to use a time-based approach (Agrawal et al., 2010; Niroshan et al., 2014; Rama and Andrews, 2013a), which is typically used with PNs. Each structure is routinely inspected and so a record can be built up of the health of each element that the structure comprises of. However, NR inspect their structures roughly every 6 years which is not regular enough to capture the data to use this approach. This means that lifetime distributions cannot be obtained from the data. Due to this limitation, the movement between condition states of the structure is assumed to be of a constant rate and is equivalent to a constant failure rate,

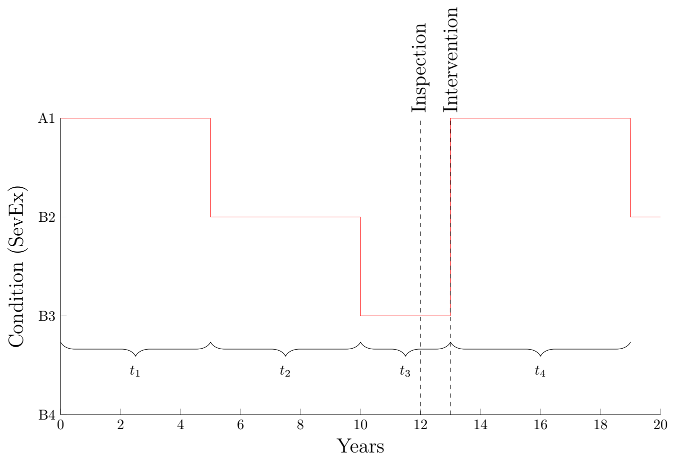

Figure 4: An example of a single bridge element. The effects of the deterioration, inspection and intervention modules are demonstrated.

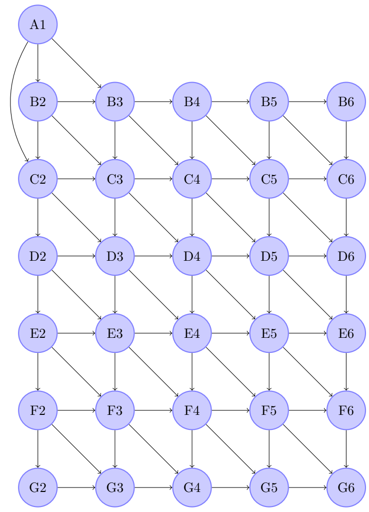

Figure 5: Condition states and their allowed progression; each of the states are connected to its neighbouring states, but only if it represents deterioration.

λ. In this situation, failure is defined as moving from one condition to another e.g. B2 to B3.

Most models that incorporate structural deterioration use a one dimensional condition state scale e.g. new, good, poor (Cesare et al., 1992; Morcous, 2006; Le and Andrews, 2014a). However, structures fail by multiple failure modes, as seen in Table 1. Different defects deteriorate at different rates and are more or less likely to lead onto other defects. For this reason keeping the failure modes separate was an important part of the deterioration module. This study uses a 2-D condition scale comprising the defect type and the magnitude of the defect. Although this approach enhances the realism of the deterioration, it also makes calibration more difficult. However it was seen that the advantages gained from having condition states that were more true-to-life outweighed the problematic calibration process.

There has also been a review of the time steps used in the model. NR inspect their structures roughly every 6 years, however for the model a more regular time step is required. Additionally, having a smaller time step should give more transparency to the model as degradation can be followed more closely. The following assumption has been implemented: the condition of an element can only move to the immediately neighbouring states. To satisfy this assumption, a time step of one month was selected as it was seen as the longest unit of time that would not enable an element to move beyond one condition state. Most bridge management models (Le and Andrews, 2013; Agrawal et al., 2010; Cesare et al., 1992) choose 1 year time steps, however this would not satisfy the constraint previously mentioned, in particular regarding duration of maintenance actions. Figure 5 shows the condition states with the movements that are possible between them.

In practice, the element condition movements have been calculated from historic data. The assumption being used is that the condition of an element can only move to the immediately neighbouring states because of the monthly time interval. The Mean Time to Failure (MTTF) was then calculated for the positions being considered, using the following equation:

$$MTTF_{B2\rightarrow B3} = \frac{t \cdot n_{B2}}{m_{B2\rightarrow B3}} \tag{1}$$

where t is the time interval, in this case 72 months between inspections, n_{B2} is the total number of elements residing in state $B2$ at the beginning of the time interval, and $m_{B2\rightarrow B3}$ is the number of elements that move from $B2$ to $B3$. The MTTF is then used to calculate the failure rate:

$$\lambda_{B2\rightarrow B3} = \frac{1}{MTTF_{B2\rightarrow B3}} \tag{2}$$

where λ is the failure rate. Here $\lambda_{B2\rightarrow B3}$ represents the rate of an element moving from state $B2$ to $B3$. Each transition is embedded with its corresponding λ value which is then used to generate the transition time in the PN deterioration module from the exponential distribution. Historical data was used to obtain the occurrences between each condition state e.g. the number of elements that move from condition B2 to condition B3. These were then used to compute the MTTFs. The failure rates are the reciprocal of the MTTFs which are embedded into the PN transitions so that the same deterioration profile can be replicated in the model. Some of these values can be seen in Table 4.

The deterioration profile for concrete girders, the critical element in this study, can be seen in Figure 6. This graph shows the probability of being in different conditions over time with no intervention. This is useful to be able to see how defects evolve over time. The simulation was done with the element starting in a new (A1) condition.

Table 4: Extract of the movements from state to state along with the MTTF and corresponding failure rate.

State From, To	Number of Occurrences	MTTF (years)	Failure rate (years,10^{-2})
A1,B2	2335	292.2835	0.3421
A1,B3	23550	28.9801	3.4506
A1,C2	317	2152.9400	0.0464
B2,B3	1103	50.6817	1.9731
B2,C2	62	901.6451	0.1109
B2,C3	706	79.1813	1.2629
B3,B4	5046	62.0154	1.6125
B3,C3	3627	86.2779	1.1590
B3,C4	1437	217.7661	0.4592

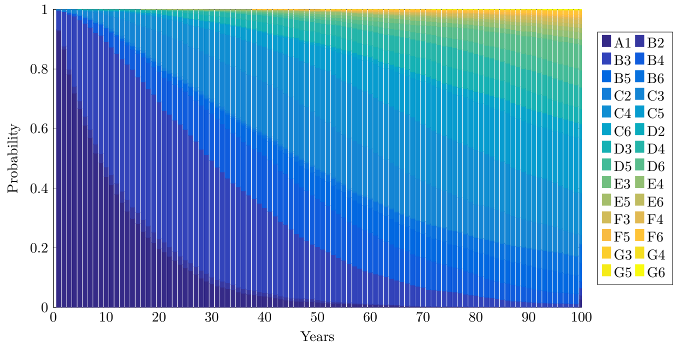

Figure 6: A demonstration of the deterioration of a concrete girder, the critical element in this study. The element begins the simulation in a new (A1) condition. The graph shows the probability of being in different condition states over time.

6.1.2. Quality of Fit of the Deterioration Module

To calibrate the deterioration of the concrete main girders, the exemplar element in this study, the data was randomly split into two sets. The total dataset included 407,708 repeat inspection records and a random sample of 75% (305,781 records) was chosen as the calibration dataset. The remaining 25% (101,927 records) was used as a test dataset. Micevski et al. (2002) states that split sample analysis is a robust test as it uses historical data not considered in the calibration data set which makes them independent. The calibration dataset was used to generate the failure rates, λ, which are what is embedded in the model transitions. The results were compared with the test data to see if the results were independent of one another based on the χ^2 test. The χ^2 test uses the following equation:

$$\chi^2 = \sum_{i=1}^{n} \frac{(Obs\lambda_i - Exp\lambda_i)^2}{Exp\lambda_i} \quad (3)$$

where χ^2 is the Pearson's cumulative test statistic; n is the number of MTTF parameters; $Obs\lambda_i$ is the observed failure rate and $Exp\lambda_i$ is the expected failure rate. The test was carried out at the 5% significance level and only movements from state to state with occurrences greater than 5 were considered (Cochran, 1954). The resulting p-value was <0.001 which suggests that the deterioration module passes the goodness-of-fit test using the calibrated and test data sets.

6.1.3. Deterioration Module

The deterioration module is arguably the most important as it contains the deterioration profile over time with typical usage. The places of the deterioration module, shown as the blue nodes in Figure 7 represent the condition states. They are alphanumeric and map to the NR SevEx ratings which go from A1 (perfect condition) to G6 (permanent structural damage). Tokens reside in the places and in this study, each token represents a different structural element. The transitions, shown as the grey squares, show the movement possible between conditions following the assumption discussed in Section 6.1.1. In Figure 7 the transitions link the conditions so over time the element will move from condition state A1 to B2 and then from B2 to B3 or C3. $T1 - T8$ are stochastic transitions and contain their representative λ parameter used to generate an exponential based delay time. One can notice in the figure that there are two coloured tokens, one green and one orange, they represent two different elements at different stages of deterioration, B2 and B3 respectively.

NR inspect each Sub-Minor element of each bridge and give it a rating according to its condition. The deterioration module replicates this system of conditions. The reason for this is that: 1) it allows for efficient transposing from the historical conditions database 2) it allows for the results of the PN model simulation to be exactly comparable to the system already used by NR 3) each SevEx condition has a well defined definition and finally, 4) by keeping the same data as the original format, no conversion is required where there is a loss of precision typically.

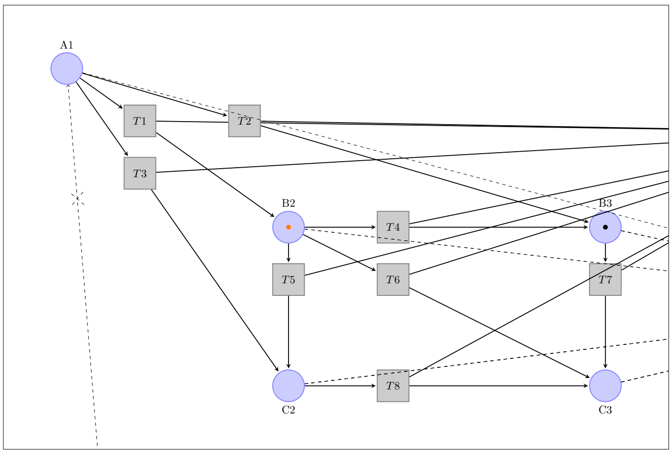

Figure 7: The deterioration module of the PN bridge model. Only states A1 to C3 are shown for clarity, however there are 31 states in total (A1 to G6).

6.2. Inspection Module

The inspection module triggers inspections of the minor elements. The inspection module follows guidelines set out in Network Rail (2010c). It uses the SevEx condition and relates that to a table present in Network Rail (2010a) which stipulates the inspection interval which must not be exceeded. The inspection module in the PN, seen in Figure 8, uses the same condition based inspection regime. Transition $T11$ uses dashed input arcs to analyse Minor element conditions. Depending on the marking of the places, the transition firing delay is determined. The better the condition, the less important the inspection is deemed to be and therefore the more lax the inspection regime. The more severe the condition, the more important it is to oversee the deterioration and so the tighter the inspection regime. I.e. a bridge in good condition is deemed to require less observation than a bridge in poor condition.

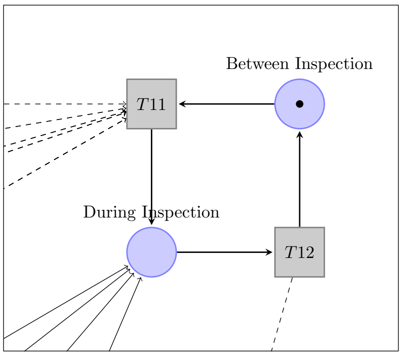

Figure 8: The inspection module shown using the most recent policy from Network Rail (2010a).

6.3. Intervention Module

The intervention module is the most complex module as it contains a number of advanced CPN functions, seen in Figure 9. The intervention module initiates when a maintenance action has been decided upon. This decision is simulated in the model and depends on the element condition, as seen in Table 3. When a maintenance action has been decided upon, a token is fired into a trigger place, "Intervention Planned", which then enables the rest of the module to function. There are three types of intervention: Minor Repair, Major Repair and Replacement. Transition $T17$ is designed to assess which type of maintenance action has been scheduled e.g. Minor Repair, from which an associated delay time is selected in the model e.g. 4 months. With each maintenance action there is an associated delay whilst the possession of the asset is requested and the materials ordered. These delay times are obtained from historical data. This enhanced functionality is shown in the figure with dashed input arcs.

Transition $T18$ is designed to simulate a maintenance team going out to perform the maintenance. When the team(s) get to the site, the first task is to assess the deteriorated elements. This is represented in the model by dashed input arcs from the Minor element condition places to determine the token position. They will have prepared and have the resources for the maintenance action that was scheduled. If the element is in the condition they were expecting, then the work can commence and the condition of the element improves accordingly.

An important addition to the model that was recommended by industry experts was the possibility of not being able to carry out the scheduled maintenance action. If the maintenance teams arrive on site, inspect the element and the condition of the element has deteriorated further; then the maintenance team(s) will not have the necessary time or resources to repair the element. For instance, if the possession time requested was 6 hours and the element has degraded to the point where 8 hours are required to carry out the work, then maintenance must be postponed. In this situation, the maintenance action must be re-scheduled and the maintenance teams must return. The complexity of the intervention module is represented by the many dashed input and output arcs; there are a large number of factors that the intervention module must communicate with.

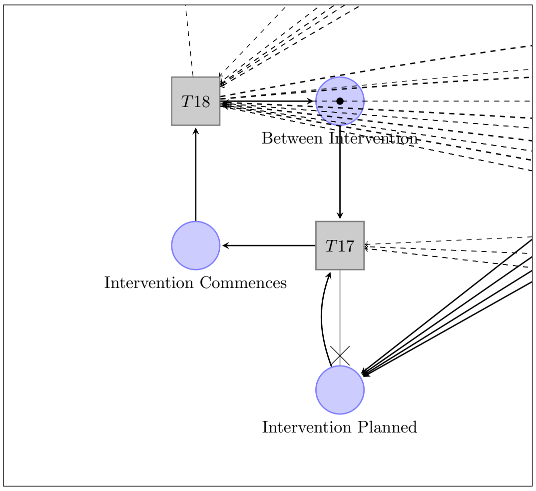

Figure 9: The intervention module has a number of advanced features, shown with dashing input and output arcs, to mimic the complex processes involved in repairing elements.

7. Model Outputs

Example simulations can be run through the model to show the effects of deterioration, inspection and intervention and how they interact. On an asset there are many components that each have their own deterioration profile. For the example simulation shown in the outputs below, a single concrete main girder is presented for clarity. The model is configured with the current NR practices and policies. The NR intervention strategy selected is quite rigorous; whenever the structure is below an A1 condition, it can be repaired.

Figure 10 shows the probability of being in different states over time. As the element starts in a good condition, the chance of it being in a good condition is high to begin with. An element in condition A1 would be inspected after 12 years, at which point it could have degraded to a worse state. At the 12 year point, it would be inspected and subsequently maintained, hence the increase in the expected condition at roughly 12 years. The graph then takes on a saw-tooth pattern where the structure degrades until it gets inspected and potentially maintained. The frequency of this saw-tooth is the same frequency of the NR inspection regime. Some of the sawtooths are not perfectly smooth due to the stochastic nature of the deterioration process. In some of the simulations the deterioration has been more severe and so the inspection regime has changed to either 3 or 6 years depending on its condition, hence the more regular interventions. The simulation can be run with real-world case studies to be able to predict the deterioration and subsequent inspections and interventions.

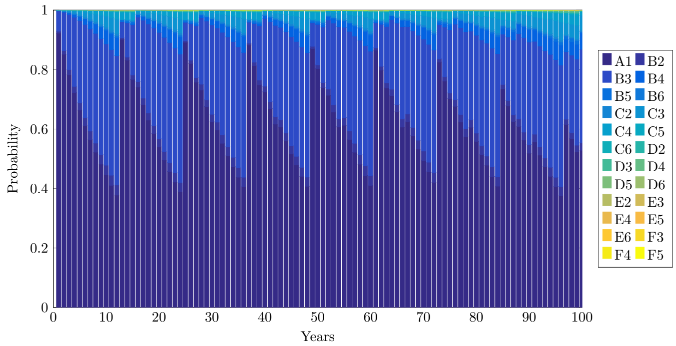

Figure 10: Graph to show the probability of being in different states over time.

Figure 11 shows the distribution of intervention types each year over the simulation period. This graph only shows the cases where intervention has been done. Considering we are starting with a element in good condition, the vast majority of the graph shows that only minor repairs would be required. It can be noticed that there are some major repairs developing over time as the element ages. Lastly, there is a minimal probability of the element requiring a replacement. This is useful for being able to plan work items and predict work schedules, a useful tool for railway bridge managers.

Figure 12 shows the nominal and cumulative cost per year of interventions and inspections. The bars of the stacked bar chart are regular to the 12 year frequency, as seen in Figure 10. The bars are split into the cost of Replacements, Minor Repairs, Major Repairs and Replacements. There are actually very few replacements, but due to their high cost, their effect seems disproportionate. This graph is useful to visualise the Whole Life-Cycle Costing (WLCC) of the structure, allowing a railway bridge manager to understand when and where the major costs are coming from. Being able to predict future costs is a vital feature when requesting funds from the Office of Rail Regulation (ORR).

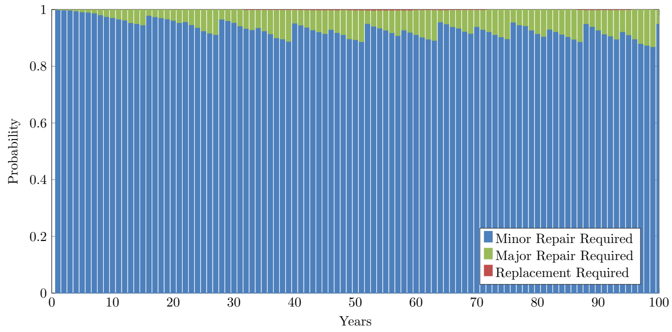

Figure 11: Graph to show the probabilities of different types of intervention over time.

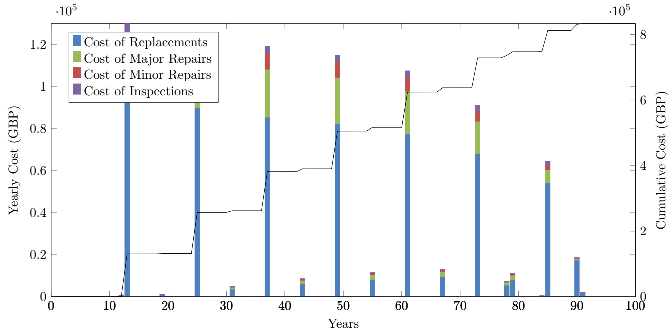

Figure 12: Graph to show the nominal and cumulative cost per year of interventions and inspections.

8. Conclusion

There are a wide variety of different systems, policies and practices that the model needs to encompass so a modelling approach that is very flexible was required. One key advantage regarding flexibility is the ability to model a changeable number of elements; adding an element is as simple as adding another token. The main focus was to strike a balance between the model being true-to-life, but not overly complicated, whilst still bringing together all the different processes that affect bridges and bridge management.

An understanding of the complex deterioration process had to be obtained before being able to calibrate the model. Using a 2-D system of condition states allowed a much more intuitive deterioration profile to be achieved even though it was challenging to calibrate.

The current industry policies had to be back-converted to be able to be incorporated into the model itself, but this then allowed dynamic inspection intervals as well as a multitude of maintenance actions to be simulated along with the structural deterioration. Together these modules make up a significant backbone of a railway bridge model.

Finally, the results of the simulations show an element that starts in a new condition and is inspected and repaired according to industry guidelines. This is backed up by a significant amount of historical data which affords the model some confidence from railway bridge managers. This model can be used to run examples of bridge assets starting in any condition, with custom inspection and maintenance policies and the outputs compared. This allows bridge portfolio managers to get an estimate of when work will be required, what that work will be and the cost of that work which is invaluable knowledge when managing a portfolio of assets.

9. Future Developments

The model presented displays a high degree of flexibility and is able to mimic many complex processes. A possible model improvement would be the addition of opportunistic maintenance. The model includes “clustered” maintenance which is when an element gets repaired, all the subordinate components of that element get repaired too. This is designed to mimic the hierarchical maintenance policies used by NR. By incorporating opportunistic maintenance, when an element requires repair, other elements that are near to requiring repair are also maintained. This would be more realistic for certain components of the bridge, but not for others. For instance, with girders, the exemplar element in the study, it is unlikely for multiple girders to be maintained at once due to the time and resources required for repair. However, for bridge bearings, it may be more suitable to incorporate opportunistic maintenance as they are more likely to be replaced in batches whilst possession of the bridge is in progress.

An additional model improvement would be a resource allocation module. The current system for maintaining railway bridges in the UK is with regional maintenance depots. However each region encompasses a different amount of area and varying numbers of bridges. Additionally, each regional maintenance depot has a different amount of available resource e.g. equipment, plant and workforce. It may be difficult to quantify these resources especially as they can change as equipment and plant become unavailable. This means that the model would have to take into account the region the bridge is in and then allocate the resources accordingly. However, the resources are dynamically allocated bridge by bridge so there would have to be some consideration for other assets in the area requiring those same resources.

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