Quantifying the Impact of Variability in Railway Bridge Asset Management

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ABSTRACT: Bridge asset management is often a challenging and complicated task due to the diversity, multitude and variation of bridge configurations. Much research has been carried out in the field of asset management which has resulted in a wealth of models to help with the decision making process. However, often these models oversimplify the process, resulting in a decision making tool that trivialises the complexity of the decisions. The purpose of this study was to ascertain what the main sources of variability are in the process and then quantify the impact of them in terms of the Whole Life-Cycle Cost (WLCC). The study focuses on human-induced variability to ensure the results are directly influenceable by bridge portfolio managers. The sources of variability identified include misdiagnoses of defects as well as imperfect repairs and variability in costs, all of which are aspects that bridge portfolio managers are exposed to. The sources of variability are quantified and then incorporated into an existing railway bridge WLCC model, established in a previous study, which uses a flexible Petri-Net (PN) approach which is able to incorporate the complex logic and probabilistic aspects. The model itself is able to replicate some of the more complicated decisions which have to be made in bridge asset management, especially those which influence the decisions around rehabilitation. The resulting model, enhanced with the probabilistic variability, is able to reveal the impact of variability on the asset condition, WLCC and even understand where operational complexities are occurring within the system. Incorporating human-induced variability into any model will inevitably increase the financial and operational burden predicted by the model, however, recognising and modelling these aspects is a crucial step in providing bridge portfolio managers a more robust and accurate decision making tool which can more accurately replicate the real world system.

1 INTRODUCTION

The rail infrastructure in the UK is key to commerce, enabling the mobilisation of both people and materials. Management of the railway can be difficult due to, firstly, its extended heritage resulting in many legacy systems, assets and techniques (Network Rail 2010d). Secondly, the infrastructure utilises diverse asset groups covering signalling and control groups, electrification and power management systems, structures and structural support groups and the track itself. Finally, due to the increasing demand of the infrastructure, especially when considering the step changes with the introduction of European Train Control System (ETCS) (Technical Strategy Leadership Group (TSLG) 2012).

Due to the complexity of managing the infrastructure, decision support tools are becoming more critical. This study focuses on the management of railway bridges, specifically focusing on the variability in the process and how the variability impacts the operational and finance aspects of managing bridges over their life-cycle.

There have been a number of studies that have modelled bridge asset management, each using different modelling methods and assumptions (Frangopol, Kallen, & van Noortwijk 2004, Miyamoto, Kawamura, & Nakamura 2000, Morcous, Rivard, & Hanna 2002). However, what often occurs during the creation of these models is that the system, and the decision making process, is oversimplified in the model. This often means that the resulting model, although accurate in its replication of individual processes, does not consider the overall system complexity. Because of this, the usefulness of the model is often limited from the perspective of a bridge portfolio manager. One of the major factors often overlooked when modelling bridge portfolio management is that it relies on human recognition, identification and decisions, which are prone to error and variability. Trying to incorporate this human-induced variability into a bridge management model would help improve the usefulness of the model outputs to bridge portfolio managers.

2 LITERATURE REVIEW

To be able to analyse variability within a system, a great deal needs to be understood about the system and the decisions which are made within that system. Some of these decisions will be governed by industry standards and organisational policy, but other decisions will rely on human interpretation and decision making. Madanat 1993 and Ben-Akiva, Humplick, Madanat, & Ramaswamy 1993 identify two fundamental sources of variability within models: 1) the certainty of the current asset condition and 2) the forward prediction of the asset condition. The studies both identify that the variability in asset condition can arise from measurement errors, defect diagnosis errors and data input errors, amongst others. The authors state that variability of inspections had not been incorporated into any bridge maintenance and rehabilitation model until then. Misdiagnosis during an inspection can lead to major consequences with regards to incorrect maintenance being scheduled. The authors argue that policies are designed to recommend a suitable maintenance action which means that a misdiagnosis can only lead to scheduling a maintenance action that is less suitable. The studies both assume that the condition reported by the inspections can contain errors. The reported condition is only probabilistically related to the actual condition of the asset. The authors perform a parametric study to ascertain the effect of variability on the final model outputs. The results of the study are that as the standard deviation widens, which represents a greater amount of variability, the higher the WLCC of the asset over its lifetime. Although this study parametrised and quantitated the variability, the WLCC could have been considered in more detail.

Phares, Washer, Rolander, Graybeal, & Moore 2004 and Moore, Phares, Graybeal, Rolander, & Washer 2001 investigated the variability in inspection results carried out on highway bridges. For this study, they collaborated with 49 bridge inspectors who had been trained to the National Bridge Inspection Standards (NBIS), which is the standard in the USA. The inspectors were asked to carry out 10 different field tests across a range of different types of bridges. The asset condition reported by each of the inspectors was compared against the Federal Highway Administration (FHWA) Non-destructive Evaluation Validation Center (NDEVC). The NDEVC condition was used as the known/true asset condition and each of the inspectors reported condition scores was compared against it. The results showed that 78% of the condition scores reported by the inspectors were correct at a 95% probability. The authors conclude that the vast majority of condition ratings (95%) will be within two condition scores of the true condition, using the NBIS condition scale. This study is significant in quantifying the variability of visual inspections.

Neves & Frangopol 2010 analysed the variability of inspections on bridge assets. The analysis showed that there are a number of factors which influence the quality of inspections including: the experience of the inspector, the ease of access of the asset elements, the topology/configuration of the bridge and the types of defects. Using these factors, a probability of misdiagnosis was calculated. The results showed that a good quality inspection only has a 5% probability of misdiagnosis whereas a poor quality inspection produces a 40% probability of being misdiagnosed.

A number of studies have identified that there is a great deal of variability in the management of bridge assets. Madanat 1993 identified that the misdiagnosis of defects has both a financial and operational impact where it increases stress on the maintenance teams. Phares, Washer, Rolander, Graybeal, & Moore 2004 and Moore, Phares, Graybeal, Rolander, & Washer 2001 quantified the variability of visual inspection according to a known condition. The results from this were used by Neves & Frangopol 2010 to develop different quality bands for inspections with probabilities of misdiagnoses calculated. It is clear that variability has a major impact on the management of bridge assets, but it has mostly been overlooked in traditional bridge models which is evident from the low numbers of studies that address it as the main focus. Therefore, attempting to incorporate variability in a bridge WLCC model is worthwhile.

3 NR BRIDGE MANAGEMENT POLICIES

3.1 Condition States

Network Rail (NR), the UK's largest railway owner and operator, separate each of their bridges into individual elements, which are each inspected and scored. The condition scoring system used is a 2-dimensional, discrete condition system known as the Severity Extent Rating (SevEx). One axis contains the type of defect and the other axis details the extent of the defect. The SevEx matrices vary depending on the material composition of the element. Concrete bridges are used in this study as the exemplar material type as they are becoming the de facto standard for new bridges and therefore their management is becoming increasingly more important. The SevEx matrix for concrete elements ranges from A1, an "as new" condition to G6, which refers to a permanent structural defect. The majority of defects within the concrete SevEx matrix relate to cracking and spalling. When the elements get inspected, the SevEx condition is recorded for each one. The historical condition recordings are all stored within a database, which will be discussed on Section 4.

3.2 Inspection Policy

There are two types of inspection which are standard within the railway industry for bridge assets: 1) visual examinations, which occur yearly to ensure asset safety and 2) detailed examinations which are scheduled according to the asset condition. During detailed examinations the element conditions are recorded; detailed examinations are the focus of this study.

NR determine the inspection interval based on the condition of the asset (Network Rail 2010b). Assets in good condition (condition states A1, B2-B5, C2-C3 and D2) are inspected every 12 years, those in medium condition (B6, C4-C6, D3-D5, E2-E5 and F2-F3) are inspected every 6 years and assets in poor condition (D6, E6, F4-F6 and G2-G6) are inspected every 3 years. This system was developed using a risk based approach and has been back-converted to the SevEx condition matrix for ease of comparison in this study.

3.3 Maintenance Actions

NR determine the appropriate maintenance action based on the condition of the asset (Network Rail 2012a). There are three main maintenance types which are performed: 1) Minor repairs, which are carried out on elements in condition states B2-B4, C2-C3 and D2, 2) Major repairs, which are carried out on elements in condition states B5-B6, C4-C6, D3-D5, E2-E4 and F2-F3 and 3) Replacements, which are carried out on elements in condition states D6, E5-E6, F4-F6 and G2-G6. The threshold for a replacement to be carried out is set by the Basic Safety Limit (BSL) within the industry standards for safety (Network Rail 2010a). This process has also been developed using a risk based approach, and back-converted to the SevEx condition matrix for ease of incorporation in this study.

4 DATA SOURCE

A variety of data sources were used in this study, ranging from asset registers, Civil Asset Register and Reporting System (CARRS), to inspection databases, Structure Condition Monitoring Index (SCMI), and work order databases, MONITOR and the Cost Analysis Framework (CAF).

As mentioned in Section 3.1, bridge assets are split into their constituent elements via a defined hierarchy (Network Rail 2012b). There is a total of 25,949 bridge assets within the dataset. The total number of minor elements in the dataset is 563,150. The total number of inspections on minor elements is 1,397,748 within the dataset.

Concrete bridges were chosen as the exemplar material type for this analysis. There are 4,434 concrete bridges in the dataset. The main girder elements were chosen as the exemplar element as they are often the Primary Load Bearing Element of concrete bridges. In the dataset there are 407,708 inspections of concrete main girders.

5 VARIABILITY OF INSPECTIONS AND INTERVENTIONS

5.1 Variability of Inspections

Detailed examinations are carried out by trained inspectors who assess each element in detail. Most railway bridge assets in the UK are inspected in person, as oppose to using remote condition equipment, and there are differences between inspectors in both their physical recognition of defects (i.e. differences in eyesight) even if their technical training and competence is the same.

Detailed examinations are carried out within touching distance of the element (Network Rail 2010c). Each of the elements has their condition recorded according to the SevEx scale and is often accompanied by a photograph. A senior inspector will review the recorded conditions and the photographs; these members of staff often have risen to the position with many years experience and so their identification of defects and the severity of the defects is good, but not infallible.

The studies, mentioned in Section 2, performed by Phares, Washer, Rolander, Graybeal, & Moore 2004 and Moore, Phares, Graybeal, Rolander, &

Washer 2001, studied the variability of defect identification on bridge assets. The results were that the inspectors were correct to within two condition states. The condition scale used in this study was linear whereas the condition scale used by NR is the 2-Dimensional SevEx scale. Transposing the results found by the authors to the SevEx scale results in an equivalent variability of ±1 condition state. Therefore, for a particular condition state, there may be up to 8 surrounding states within the ±1 condition range, as seen in Figure 1.

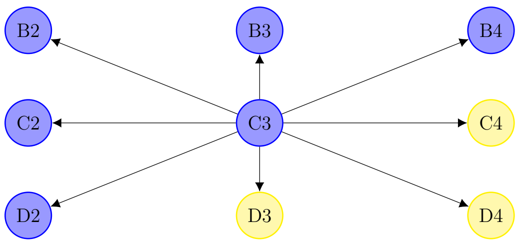


Figure 1: Variability associated with a reported condition score.

In the example shown in Figure 1, a C3 condition is reported by the inspector as the element condition. However, due to variability of the examination process, the C3 being reported could relate to any of the condition states shown. The maintenance action recommended for an element in a C3 condition would be a minor repair. However, the maintenance action which is recommended for an element in condition states C4, D3 and D4 would be a major repair. Therefore, the consequence of an erroneous identification is that it could lead to the wrong type of maintenance being scheduled.

Table 1 shows the results of the analysis carried out on the SevEx condition matrix to identify the probability of each condition state leading to the wrong type of maintenance action being scheduled, using the ±1 variability. Where a condition state is on the border of two different maintenance actions, the probability of a misdiagnosis leading to an erroneous maintenance action is higher. Condition states that are not near borders are not as critical because an erroneous condition identification would still result in the same maintenance action. On average, using the ±1 variability range, maintenance actions are scheduled correctly 72% of the time.

5.2 Imperfect Interventions

Often bridge management models either do not consider maintenance as an explicit action or assume that maintenance is perfect (i.e. maintenance improves the condition to a predefined condition state, often the "as new" or A1 condition) Morcous & Lounis 2006, van Noortwijk & Klatter 2004, Le & Andrews 2013. Although this assumption is an oversimplification of the system, to dispense with the assumption requires an evidence-

Table 1: Probabilities of scheduling the correct maintenance action when considering inspection variability of ±1 condition state.

State	B2	B3	B4	B5	B6
Probability	1.00	0.80	0.40	0.80	1.00
State	C2	C3	C4	C5	C6
Probability	0.80	0.63	0.63	0.75	0.80
State	D2	D3	D4	D5	D6
Probability	0.40	0.63	0.75	0.63	0.40
State	E2	E3	E4	E5	E6
Probability	0.80	0.75	0.63	0.63	0.80
State	F2	F3	F4	F5	F6
Probability	0.60	0.50	0.63	0.88	1.00
State	G2	G3	G4	G5	G6
Probability	0.33	0.60	0.80	1.00	1.00

based approach. Therefore, data analysis was carried out using historical maintenance and inspection records to determine the variability in the condition uplift after an intervention.

The inspection data available for this study includes both deterioration and condition uplift. In the previous section it was determined that there is some variability regarding the accuracy and repeatability of element inspections. To ensure this analysis only considers situations where there has been an uplift in condition due to an intervention, rather than due to any variability within the inspection procedure, only element condition uplifts of more than one condition state were considered. The exemplar element used throughout this study is the concrete main girder, on which this analysis was performed. The total number of element inspections which was used for this analysis was 49,300.

The analysis results are presented in Table 2 where it can be seen that interventions which return the element condition to A1, the "as new" state, which represents a "perfect repair", only accounts for 43% of the condition uplifts. This is in stark contrast to what most bridge management models assume as the result shows that perfect repairs do not even occur in the majority of occurrences. The next most populous condition state is B3, which accounts for 29% of all condition uplifts following an intervention.

Table 2: Probabilities of resulting condition states following an intervention.

State	A1	B2	B3	B4	C2	C3	D2
Percent	43%	6.5%	29%	10%	0.4%	11%	0.1%

5.3 Summary

It has been determined that misdiagnoses of defects can lead to incorrect maintenance actions being scheduled. Transposing the results to the SevEx condition matrix shows that only 72% of maintenance actions are appropriate for the condition of the element. In addition to this, an analysis has been carried out on the condition uplift following an intervention. This demonstrated that a "perfect repair" only occurs 43% of the time, which is in stark contrast to the assumption made by many other bridge management models that all interventions result in perfect repairs. These aspects will now be incorporated into an existing WLCC model to quantify the impact that these sources of variability have on the overall system.

6 WLCC PN MODEL

PNs, created by Petri 1962, have been gaining in popularity in modelling systems within the communications, manufacturing and engineering sectors (British Standards Institution 2012). An existing WLCC model will be used in this study which uses the PN approach (Yianni, Rama, Neves, Andrews, & Castlo 2016). The advantage that the PN approach brings to this type of study is that the logic and probabilistic elements can be more easily incorporated than in other modelling approaches, as demonstrated by Andrews 2013. The more advanced features of the model use the Coloured Petri-Net (CPN) techniques introduced by Jensen 1997.

The PN WLCC model uses a number of different modules which each mimic a different aspect of bridge management, ranging from the deterioration module to the inspection and maintenance modules. Each of these has been designed and calibrated using a combination of historical data, expert judgement and industry standard policies. The details which follow in this section are specifically in relation to the modules of the PN model which are affected by the variability discussed within this study. The model itself is simulated using a Monte Carlo (MC) approach and the outputs are aggregated to provide a yearly overview, which gives an insight into the overall system behaviour. The full model, and details of all the individual modules, are given in detail in Yianni, Rama, Neves, Andrews, & Castlo 2016.

6.1 Maintenance Action Module

The maintenance action module simulates the events immediate after an inspection, during which the appropriate maintenance action is decided upon. As detailed in Section 5.1, the variability of inspections can lead to incorrect maintenance actions being scheduled. The probability of a defect misdiagnosis occurring is 28%.

Within the statistical model, each of the PN transitions have been enhanced with probabilistic capabilities and have had the probabilities from Table 1 embedded within them. These are shown in Figure 2 by transitions $S13 - S16$. The effect of this is that there is a probabilistic outcome for the maintenance actions, calibrated with the probabilities calculated in Table 1. This ensures that the same probability of an incorrect maintenance action being scheduled in the real-world system is mirrored within the statistical model.

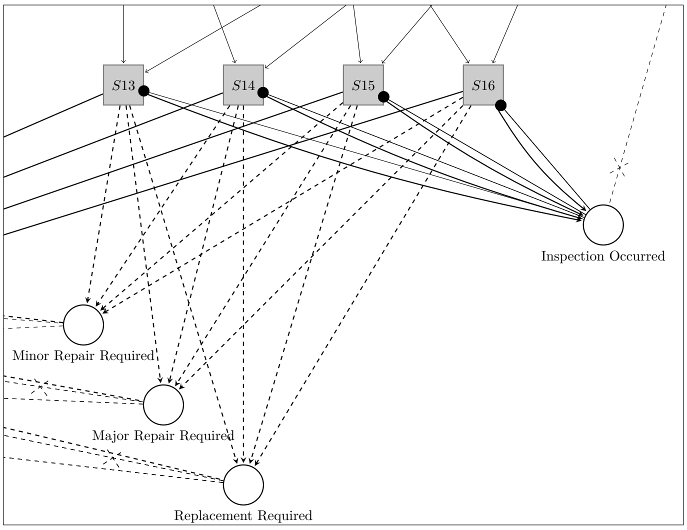


Figure 2: The maintenance action module captures the variability in the outcome of the inspection procedure.

6.2 Intervention Module

The intervention module is activated once a maintenance action has been determined, following an inspection. The module is modelled on maintenance teams arriving on site to carry out an intervention and performing an initial investigation to ascertain if the condition of the element and the maintenance action are compatible. The transition, marked $S18$, contains a complex CPN guard which checks the type of maintenance action which has been scheduled against the condition of the element. This allows it to determine if the correct maintenance action has been scheduled or not. The variability in inspection, which this model is enhanced with, affects both the maintenance action module and the intervention module.

The intervention module has been embedded with the results of the imperfect repair analysis, as seen in Section 5.2. In the model, there is a probabilistic output to the condition module which means that the condition uplift following an intervention is calibrated to the probabilities seen in Table 2. This ensures that the condition uplift follows the same profile as that seen in the real world system.

7 IMPACT OF VARIABILITY ON WLCC

Two simulation scenarios were considered for the analysis: 1) the control scenario, which does not consider the human-induced variability and 2)

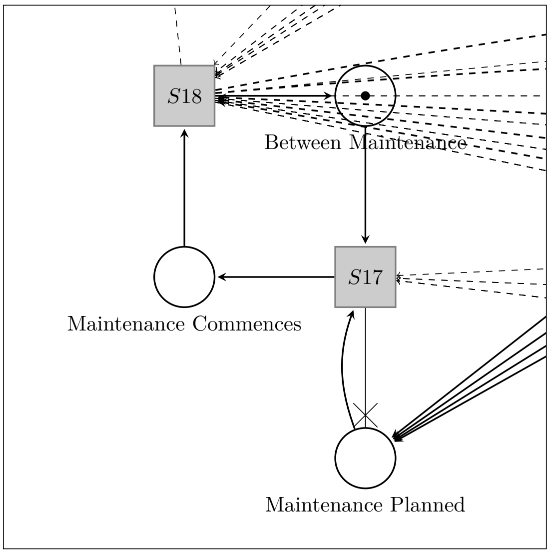


Figure 3: The intervention module is affected by variability of inspections, variable intervention costs and imperfect repairs.

the enhanced scenario, which does consider the human-induced variability, using the results from the previous sections. This allows an effective comparison to quantify the effect of variability on the WLCC of bridges. To simulate an entire bridge asset, an equal number of PN tokens to bridge elements would be entered into the model. For illustrative clarity, the outputs shown in this section were calculated based on a simulation with a single concrete girder element, the exemplar element used throughout this study. The model is simulated using a MC simulation approach over a 100 year timespan.

Figure 4 shows the model output which aggregates the element condition states. It can be seen in Figure 4(a), the control scenario, which does not consider imperfect repairs, that the element spends the majority of the simulation period, ~60%, in condition state A1. This is because the element experiences repeated condition uplifts, following “perfect repairs”, to the A1 “as new” condition, after every intervention. When considering Figure 4(b), the scenario with imperfect repairs, which is more accurate to the real-world system, there is much more of a spread across a number of condition states. The A1 condition, over the 100 year simulation period, is lower at only ~40%. The enhanced scenario is a more realistic model scenario and helps to boost the accuracy of the model.

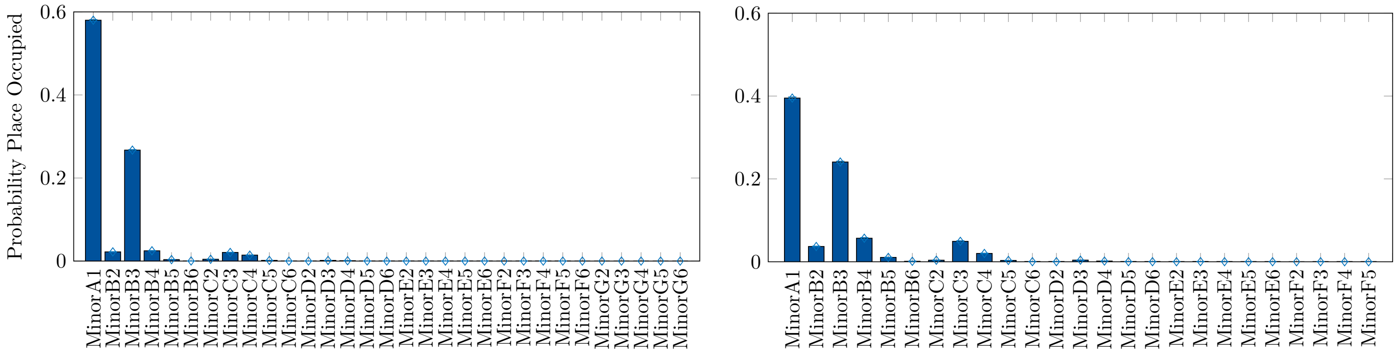
Figure 5 shows the probability of the element condition over time, aggregated by year. This output is able to demonstrate both the effect of imperfect repair and the effect of incorrect maintenance actions being scheduled. Both scenarios begin the simulation with the element in an A1 condition, slowly deteriorating, with an inspection occurring after 12 years, as is stipulated in the industry policy on bridge inspections. At this point the element is rehabilitated with a minor repair. The condition uplift following these repairs differs based on the scenario. In Figure 5(a), the control scenario, the perfect repairs uplift to an A1 “as new” condition. In Figure 5(b), the enhanced scenario, the uplift can result in a number of different condition states, as defined from the results in Section 5.2. For this reason, the sawtooth pattern, which represents probabilities, is much more defined in the control scenario than the enhanced scenario.

Misdiagnoses of defects can result in the scheduling of an inappropriate maintenance action. The occurrence of inappropriate maintenance actions is evident in the sawtooth patterns within Figure 5. When an inappropriate maintenance action has been scheduled, the maintenance teams are unable to carry out the procedure as they would have insufficient time and resources. Therefore, there is a chance that the maintenance teams would need to return to perform the appropriate maintenance action. Although subtle, there is evidence of this in Figure 5 on the downward slopes of the sawtooths. Where the downward slopes of the sawtooths are smooth, as in Figure 5(a), this indicates the natural progression of deterioration, without any additional interference. However, where there are blips midway down the slope, this indicates an increased probability of the maintenance teams having to return to perform a maintenance action, as in Figure 5(b). As the occurrence of this is only infrequent, the increase in probability is small, hence the subtlety in the output. The enhanced scenario has more evidence of these blips due to inappropriate maintenance actions. Although subtle in the figures, the financial and operational implications are significant.

Figure 6 shows the financial costs over time. It can be seen that the cumulative cost difference between Figures 6(a) and 6(b) is almost double across the 100-year timespan being simulated. This is because in Figure 6(b) there is a much greater chance of: 1) incorrect maintenance actions being scheduled which would result in additional costs of materials and financial compensation due to structural possession and 2) the effect of imperfect repairs meaning that the condition of the structure does not reset to an A1 condition after every intervention, which inevitably reduces the time required before the next intervention is required.

8 CONCLUSION

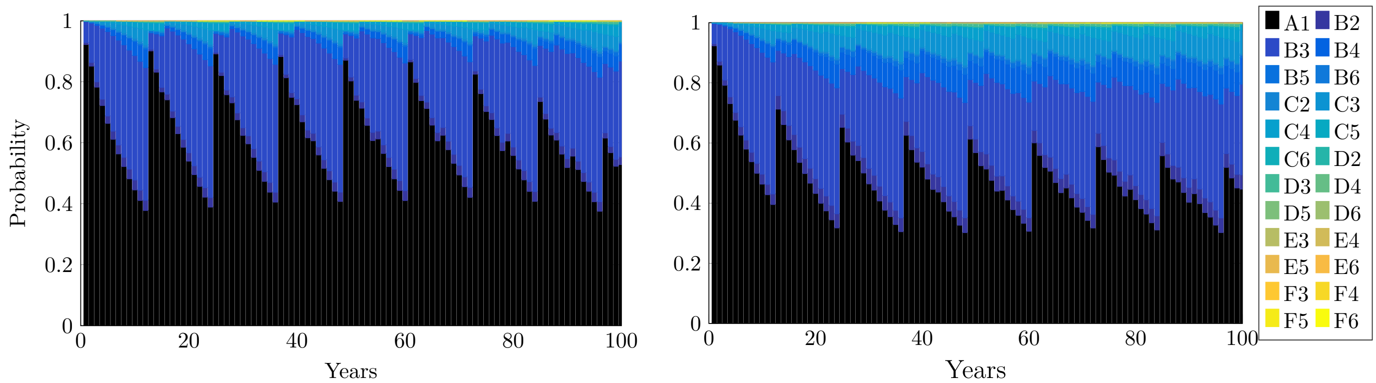
Modelling a complex system, such as bridge asset management, is most effective when the balance between capturing the major processes, but not making the model overly complex, is struck. Some of the assumptions made in existing bridge management models oversimplify the process which estranges it from the real system to the point where it cannot be considered analogous to the original



(a) Control scenario, without variability.

(b) Enhanced scenario, considering variability.

Figure 4: Probability of the element residing in each condition state, aggregated over the entire simulation period.



(a) Control scenario, without variability.

(b) Enhanced scenario, considering variability.

Figure 5: Probability of the element condition over time, aggregated by year.

system. This reduces its usefulness as a decision support tool for bridge portfolio managers.

The purpose of this study was to investigate the sources of variability within bridge asset management, focusing on human-induced variability, the results of which can help advise where bridge portfolio managers should focus their efforts going forward. The following sources of variability were investigated: 1) variability in defect diagnoses causing the wrong type of maintenance to be scheduled and 2) variability in the intervention process as not all repairs are of equal quality and therefore the associated condition uplift is different. Expert judgement and historical data was used to calculate the variability in the processes.

Using an existing WLCC model, two scenarios were simulated and their outputs compared. The results show that, when comparing the two scenarios, the enhanced scenario, which considers human-induced variability, predicts greater financial and operational burden than the control scenario, which does not consider human-induced variability. The enhanced scenario is much more accurate to the real-world system and considers many more of the complexities.

Overall, it is understood that bridge portfolio management is a complex task. The human-induced variability has a significant impact on the management of the bridges as it results in inefficient and ineffective inspection/maintenance teams, which reduces budgetary efficiency too. The results of this study show that even moderate amounts of human-induced variability quickly build up in the system to make the whole process much more complex and much more capital intensive to manage.

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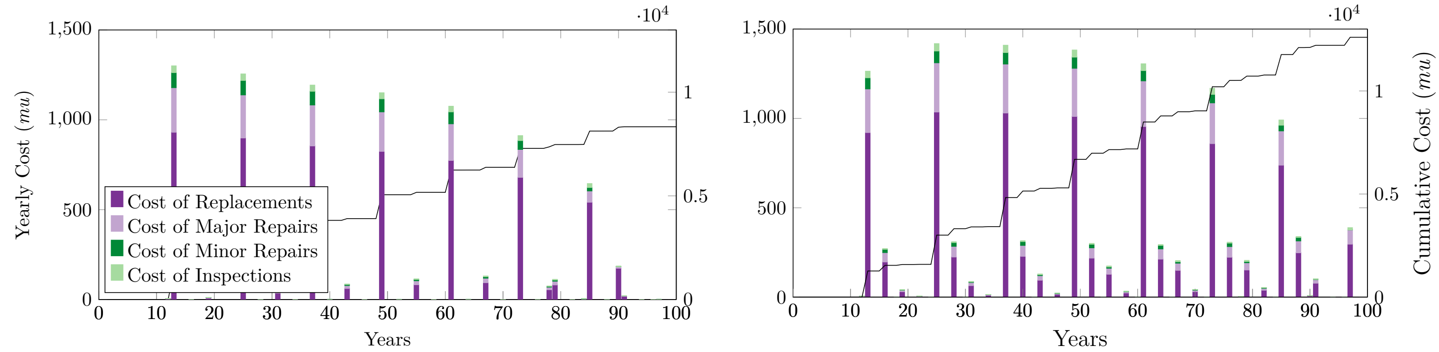

(a) Control scenario, without variability.

(b) Enhanced scenario, considering variability.

Figure 6: Cost output of intervention and inspections per year.

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REFERENCES

Andrews, J. (2013). A modelling approach to railway track asset management. Proceedings of the Institution of Mechanical Engineers, Part F: Journal of Rail and Rapid Transit 227(1), 56–73.

Ben-Akiva, M., F. Humplick, S. Madanat, & R. Ramaswamy (1993). Infrastructure management under uncertainty: Latent performance approach. Journal of Transportation Engineering 119(1), 43–58.

British Standards Institution (2012). Analysis techniques for dependability — Petri net techniques. Technical report.

Frangopol, D. M., M.-J. Kallen, & J. M. van Noortwijk (2004). Probabilistic models for life-cycle performance of deteriorating structures: review and future directions. Progress in Structural Engineering and Materials 6(4), 197–212.

Jensen, K. (1997). A brief introduction to coloured Petri Nets. In E. Brinksma (Ed.), Tools and Algorithms for the Construction and Analysis of Systems, Number 1217 in Lecture Notes in Computer Science, pp. 203–208. Springer Berlin Heidelberg.

Le, B. & J. Andrews (2013). Modelling railway bridge asset management. Proceedings of the Institution of Mechanical Engineers, Part F: Journal of Rail and Rapid Transit 227(6), 644–656.

Madanat, S. (1993). Optimal infrastructure management decisions under uncertainty. Transportation Research Part C: Emerging Technologies 1(1), 77–88.

Miyamoto, A., K. Kawamura, & H. Nakamura (2000). Bridge Management System and Maintenance Optimization for Existing Bridges. Computer-Aided Civil and Infrastructure Engineering 15(1), 45–55.

Moore, M., B. M. Phares, B. Graybeal, D. Rolander, & G. Washer (2001). Reliability of visual inspection for highway bridges, volume I: Final report. Federal Highway Administration.

Morcous, G. & Z. Lounis (2006). Integration of stochastic deterioration models with multicriteria decision theory for optimizing maintenance of bridge decks. Canadian Journal of Civil Engineering 33(6), 756–765.

Morcous, G., H. Rivard, & A. Hanna (2002). Modeling bridge deterioration using case-based reasoning. Journal of Infrastructure Systems 8(3), 86–95.

Network Rail (2010a). Handbook for the examination of Structures Part 11A: Reporting and recording examinations of Structures in CARRS. NR/L1/CIV/006/11A.

Network Rail (2010b). Handbook for the examination of Structures Part 1C: Risk categories and examination intervals. NR/L3/CIV/006/1C.

Network Rail (2010c). Handbook for the examination of Structures Part 2C: Condition marking of Bridges. NR/L3/CIV/006/2C.

Network Rail (2010d). Network Rail Asset Management Policy Justification for Civil Engineering Policy.

Network Rail (2012a). Policy on a Page: Structures.

Network Rail (2012b). Structures Asset Management Policy and Strategy. pp. 219.

Neves, L. C. & D. M. Frangopol (2010). Optimization of bridge maintenance actions considering combination of sources of information: Inspections and expert judgment. In Bridge Maintenance, Safety, Management and Life-Cycle Optimization: Proceedings of the Fifth International IABMAS Conference, Philadelphia, USA, 11-15 July 2010, pp. 374. CRC Press.

Petri, C. A. (1962). Communication with Automation. Ph. D. thesis, Mathematical Institute of the University of Bonn, Bonn, Germany.

Phares, B., G. Washer, D. Rolander, B. Graybeal, & M. Moore (2004). Routine Highway Bridge Inspection Condition Documentation Accuracy and Reliability. Journal of Bridge Engineering 9(4), 403–413.

Technical Strategy Leadership Group (TSLG) (2012). Rail Technical Strategy. Technical report, Rail Research UK Association.

van Noortwijk, J. M. & H. E. Klatter (2004). The use of lifetime distributions in bridge maintenance and replacement modelling. Computers And Structures 82(13–14), 1091–1099.

Yianni, P. C., D. Rama, L. C. Neves, J. D. Andrews, & D. Castlo (2016). A Petri-Net-based modelling approach to railway bridge asset management. Structure and Infrastructure Engineering 0(0), 1–11.