Analysing the impact of local factors on the life cycle of metallic bridge girders

G. Calvert & M. Hamer
Advanced Analytics, Technical Authority, Network Rail

L. Neves & J. Andrews
Resilience Engineering Research Group, University of Nottingham

ABSTRACT: A fundamental component of a life cycle analysis of a bridge is the modelling of asset condition post-construction. To enhance the accuracy of bridge deterioration models, several studies have calibrated models based on cohorts that incorporate structural characteristics and local factors. However, it is common that these characteristics are independently modelled to avoid sparse cohorts. In this study, a bridge element deterioration model is developed that can simultaneously incorporate multiple structural and local characteristics. The incorporation of multiple co-variates is made possible by an approach that exploits the multiple defect deterioration model proposed by Calvert et al. (2021). The model is tested on a cohort of 36,075 metallic bridge girders from bridges on the British railway network. The modelling approach is shown to provide statistically significant improvements in the prediction accuracy of deterioration. Moreover, a life cycle analysis outlines the significant cost and condition differences between benign and aggressive cohorts.

1 INTRODUCTION

The asset management of civil infrastructure is a critical task for transportation organisations, with maintenance, rehabilitation, and replacement activities requiring huge amounts of resources. To forecast resource requirements and maximise the impact of allocated resources, infrastructure asset managers use strategic lifecycle costing models to support decision making. To evaluate the lifecycle of civil infrastructure post-construction one needs the means to evaluate how the asset deteriorates and a means to evaluate the effectiveness of asset interventions. The accurate evaluation of the entire lifecycle is contingent on the deterioration modelling being accurate.

There are a plethora of methodologies to model structural deterioration of bridges (Frangopol, Dong & Sabatino 2017), however, for strategic network level modelling Markov modelling calibrated using condition data from visual inspections is the most common. The use of condition data to calibrate deterioration models does have its limitations given the somewhat arbitrary condition scales used and the subjectivity of the examiners when recording the assessments. Despite the limitations of the condition data, the use of such is data is widespread amongst asset managers due to the relative abundance of data compared to more empirical measurements.

There are different hierarchical modelling frameworks for the strategic modelling of bridges (Hamer, Calvert & Neves 2022), ranging from the highest level of network level evaluations for a portfolio of bridges to the lowest level of modelling at component level. An evaluation of a whole structure can be performed by assuming that the components form some configuration of a series-parallel system. Most transportation agencies assign and predict a single condition score for each component. However, the assessment of components using a single condition score is somewhat arbitrary and does not adequately describe the diverse physical process of deterioration.

In previous studies, it has been shown that it is possible to strategically model bridge components using a methodology that enables the evaluation of multiple degradation modes simultaneously (Calvert, et al. 2020, Calvert, et al. 2021). Moreover, in previous studies it has been shown that the calibration of deterioration models using condition data should be conducted such that co-variates such as geographical location, bridge loading and structural positioning should be used to form cohorts. In this paper, a cohort analysis will be performed such that the deterioration of bridge components with multiple defect mechanisms and multiple co-variates can be evaluated simultaneously.

2 MULTIPLE DEFECT DETERIORATION MODELLING

In previous studies a Dynamic Bayesian Network (DBN) model has been used to evaluate the progression of multiple deterioration mechanisms on metallic bridge components (Calvert, et al. 2021). The defects evaluated in the modelled components included, the deterioration of paint-work/coating, corrosion and a mechanism named Structural Component Failure (SCF) which incorporated instances of buckling permanent distortion/displacement and tearing/fracture. A visualisation of the multiple defect deterioration DBN model is shown in Figure 1.

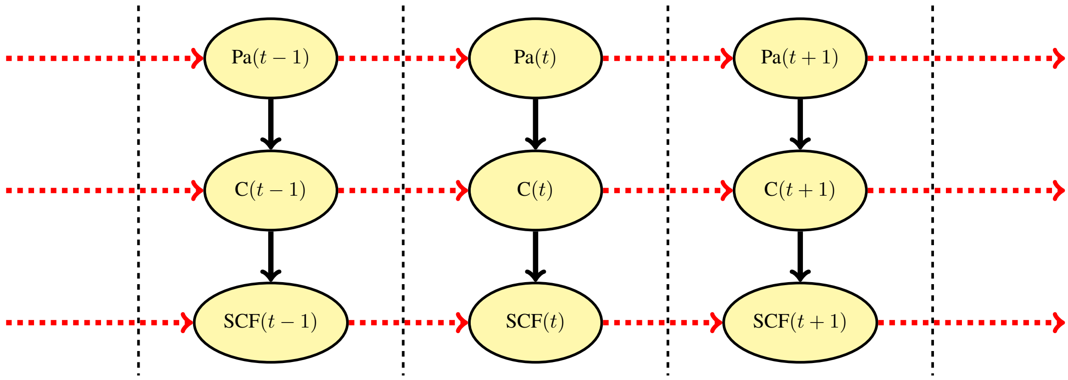

Figure 1. Dynamic Bayesian Network deterioration model.

Bridges represent a diverse asset class, with each bridge having its own distinct composition of structural elements. To facilitate intervention co-ordination and strategy development, bridges are commonly described by a hierarchical decomposition of elements. For example, at Network Rail the hierarchy for structural assets is defined by asset groups (e.g. underbridge), asset sub-groups (e.g. construction material), major elements (e.g. deck) and minor elements (e.g. inner main girder). When aggregating minor elements to determine an overall score for a bridge, particular minor elements have a designation of being a principal loading bearing element, which are used to attribute a greater weighting for elements that are structurally integral to the loading capability of a bridge.

A railway underbridge has the railway line going over the deck of the bridge. Conversely, a railway overbridge has the railway line going under the deck of the bridge. It is generally expected that an underbridge will deteriorate at a faster rate than the overbridge given that the underbridge has the loading of the railway on its deck. The MGE and MGI classifications are used to denote the exposed and inner main girders, respectively. The term of main girder is used to describe a longitudinal main girder or beam that spans between the abutments, piers or columns. The outer two beams on any deck are classified as MGE with the remaining main girders classified as MGI. For this study, main girders will be used as the component type to be analysed.

Model calibration cohorts that divide exam records by an element belonging to an underbridge or overbridge, and whether an element is an inner or exposed have been shown by previous studies to be statistically significant (Yianni, et al. 2016). For this study, such model calibration cohorts were found to be statistically significant for the multiple defect DBN model when compared to a generic cohort for main girders. This analysis was assessed by using a likelihood ratio test, the Akaike Information Criterion (AIC) and the Bayesian Information Criterion (BIC).

The DBN model parameters were calibrated using a method of maximum likelihood on Network Rail bridge condition data from visual inspections. The condition data is recorded using a condition scale known as Severity Extent (SevEx) and it can be used to note the absence or presence of each defect and the extensiveness of each defect if present. The calibrated parameters for inner and exposed main girders are shown in the table below.

Table 1. DBN Parameter Values – Transition Rates stated in $years^{-1}$.

	(Pa1 → Pa2)	(Pa2 → Pa3)	(Pa3 → Pa4)	
MGI-BU	0.1952	0.1606	0.0284	
MGE-BU	0.1769	0.1529	0.0332	
	(C1 → C2) | Pa1	(C1 → C2) | Pa2	(C1 → C2) | Pa3	(C1 → C2) | Pa4
MGI-BU	0.005	0.1969	0.3523	0.9526
MGE-BU	0.005	0.1753	0.4274	0.7014
	(C2 → C3) | Pa1	(C2 → C3) | Pa2	(C2 → C3) | Pa3	(C2 → C3) | Pa4
MGI-BU	0.0957	0.0957	0.1172	0.1172
MGE-BU	0.0453	0.0453	0.1545	0.1545
	(C3 → C4) | Pa1	(C3 → C4) | Pa2	(C3 → C4) | Pa3	(C3 → C4) | Pa4
MGI-BU	0.0219	0.0219	0.0247	0.0247
MGE-BU	0.0341	0.0341	0.0367	0.0367
	(F1 → F2) | C1	(F1 → F2) | C2	(F1 → F2) | C3	(F1 → F2) | C4
MGI-BU	0.0038	0.0054	0.0060	0.01030
MGE-BU	0.013	0.0035	0.0094	0.0157

3 ADDITIONAL DETERIORATION FACTORS

The deterioration models in this study are calibrated using inspection records rather than experimental data, although it is still critical that the aforementioned properties that alter deterioration behaviour are considered in the model calibration. Previous studies have analysed additional properties that can influence deterioration such as traffic volumes, asset age, coastal proximity, structure type amongst others (Huang, Mao & Lee 2010, Morcous, Rivard & Hanna 2002, Yianni, et al. 2016) and shown that their consideration is statistically significant to calibrated deterioration models. However, the early studies were often limited to analysing properties independently, which is problematic for scenarios when more than one property has been identified as influencing deterioration, as an asset manager wants to incorporate all of the properties simultaneously.

3.1 *Coastal Proximity*

Bridges situated in close proximity to the coast are exposed to high atmospheric salinity and prevailing winds, which can accelerate the deterioration of structural components. To determine the proximity of a bridge to the coast, the co-ordinates of the bridge were evaluated against 51,043 reference co-ordinates of the coastline from the Global Self-consistent, Hierarchical, High-resolution Geography Database (GSHHG). Upon determining the proximity to the coast for all bridges, the bridges were split into two cohorts: CP1 – Less than or equal to 10 km from the coast and CP2 – More than 10 km from the coast.

3.2 *Material*

Across a network of bridges and even a bridge, metallic bridge elements can be constructed out of different metal materials. These different metals will corrode at different rates. For example, Agrawal, Kawaguchi & Chen (2010) analysed highway bridges in New York state, where from approximately 1968, metal bridges were constructed using weathering steel, which was a different steel composition than was typically used before 1968, called 'steel'. In the Weibull-based analysis, weathering steel was found to deteriorate at a slower rate than the steel after 20 years.

The Network Rail portfolio contains metal bridges constructed out of cast iron, wrought iron, early steel, weathering steel and steel. 'Early Steel' is steel that was manufactured prior to 1956 and 'Steel' denotes steel manufactured from 1956 onwards. For the purposes of this study, three cohorts were formed based on material type: M1 – Wrought Iron, M2 – Early Steel and M3 – Steel. Cast iron was omitted from the study due to discrepancies in the recording of condition for this material at Network Rail.

3.3 *Track Category*

For road bridges, it is common to consider the traffic volume and road system when determining cohorts for model calibration (Scherer & Glagola 1994). Road traffic volume is commonly measured using Annual Average Daily Traffic (AADT). The road system indicates the type of road system a bridge is situated on e.g. interstate/motorway, primary or secondary. Moreover, Zhang & Cai (2012) shown that increased vehicle speed has a negative effect on fatigue reliability of bridge components.

Track categorisation considers annual tonnage for a section of track and the designated line speed for trains on that section of track. The categories are used to specify requirements relating to design, maintenance, renewal and inspection of track. For railway underbridges, track category can be used as an indicator of traffic loading and route type. Tonnage is measured using Equivalent Million Gross Tonnes Per Annum (EMGTPA), which accounts for the variations caused by different rolling stock. The calculation that Network Rail uses for EMGTPA is similar to the calculation for "theoretical traffic load" specified by the International Union of Railways (UIC 2019). Line speed is measured in miles per hour and track sections with a greater permitted line speed are typically located on strategically important routes e.g. mainline services. At Network Rail there are seven track categories, Cat 1, 1A, 2, 3, 4, 5 and 6. For this study, there are two track category cohorts considered: TC1 – (Cat 1, 1A and 2) and TC2 – (Cat 3, 4, 5 and 6).

The boundary between the track category definitions is a line speed of 91 mph between 0 and 7.2 EMGTPA. For annual tonnage greater than 7.2 EMGTPA, the line speed is defined as $-55 \cdot log(w) + 200$, where w is the annual tonnage in EMGTPA of the track section. The boundaries for categories are based on historical and experimental data.

4 INCORPORATING MULTIPLE FACTORS INTO MULTIPLE DEFECT MODEL

For this study, the condition records of 36,075 main girders are considered. When additional properties are incorporated into the model, the records used in model calibration are split into smaller cohorts. The inclusion of coastal proximity, material type, track category and being an inner or exposed girder in a more detailed model will increasingly limit the size of the available data for specific instances of model calibration.

If distinct rates or a scaling factor permutation were calibrated that did not maintain the monotonic increase, the model could output the perverse scenario that the more degraded an influencing defect is, the slower the corresponding defect degradation rate is. For example, if the rate for $(C1 \rightarrow C2)|Pa3$ is 0.675 and the rate for $(C1 \rightarrow C2)|Pa4$ is 0.55, the model would be returning a lowering rate of corrosion as the paintwork condition degrades. This scenario would ultimately disincentivise paintwork maintenance interventions when performing a life cycle analysis, which goes against engineering judgement. To include multiple properties simultaneously, they could be strategically input into the model on a per defect basis.

The multiple defect model shown in Figure 1 incorporates the underbridge/overbridge and exposed/inner status of the component for all of the defects in the deterioration model. However, each of the additional properties that influence deterioration is then input to the existing model for a particular defect type. The paintwork scaling factors are specific to the proximity of the bridge component to the coast. The corrosion scaling factors are specific to the material type that the bridge component is constructed out of. The SCF scaling factors are specific to the component's bridge track category.

The relationship between the local, structural and material properties is shown in Figure 2. This particular model configuration ensures that there are minimal additional parameters being added to the model to avoid the over parameterisation of the condition data. However, if a girder being close to the coast results in increased paintwork degradation, corrosion will occur at a greater rate due to the worse paintwork condition. Similarly, if a particular material type corrodes at a faster rate, the instances of SCF occurring will increase due to the causal influence between those defects.

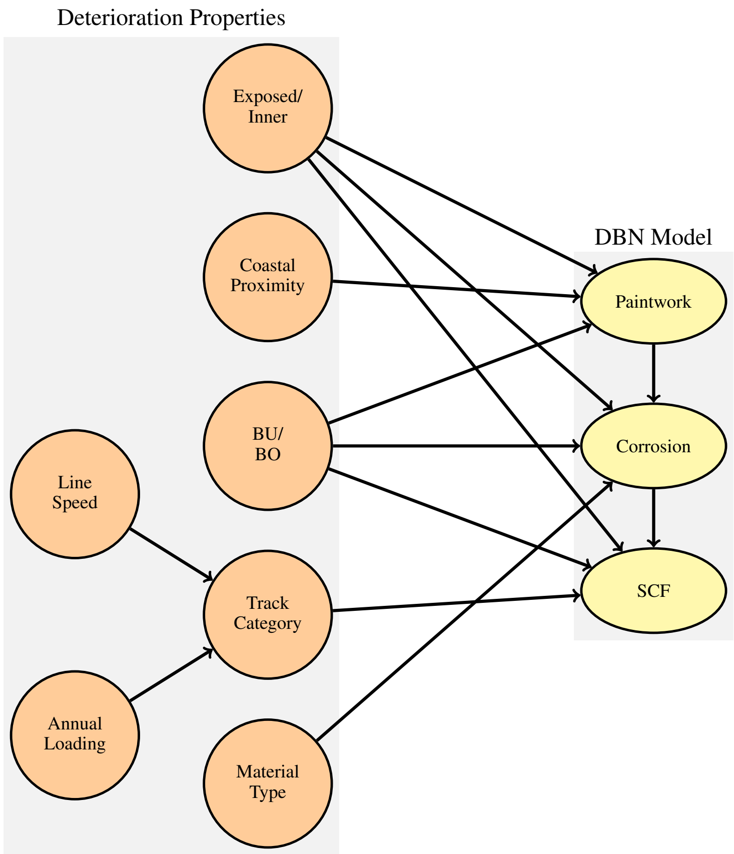

Figure 2. Influencing properties for defect deterioration model.

As a case study, the enhanced multiple defect deterioration model from the previous section was calibrated using the Network Rail condition records for railway underbridges. The scaling factors that maximised the log-likelihood function for the condition records used in calibration are shown in Table 2 for paintwork, corrosion and SCF.

Table 2. Scaling factors for DBN model based on additional characteristics.

	Pa Scaling Factors		C Scaling Factors			SCF Scaling Factors	
	CP1	CP2	M1	M2	M3	TC1	TC2
MGI	1.3580	0.9096	1.4048	1.2562	0.8108	1.6822	0.7235
MGE	1.2223	0.9210	1.4031	1.2966	0.7621	1.1430	0.9354

It can be observed that for each of the scaling factors, components with the more aggressive properties, i.e. CP1, M1, M2 and TC1, have a value greater than one and the components with the less aggressive properties, i.e. CP2, M3 and TC2, have a factor value less than one. This enables the components with aggressive properties to deteriorate at a faster rate than the baseline rate and conversely, the components with less aggressive properties can deteriorate at a slower rate than the baseline rates. Consequently, each component would have a contextualised deterioration rates for its composition of local, structural and material properties.

Engineering expertise would suggest that the closer a bridge is to the coast, the greater the rate of deterioration, similarly, wrought iron and early steel would deteriorate faster than steel and finally that the greater the bridge loading or line speed is, the greater the rate of deterioration. This is observed in the deterioration factor values and the values obtained in the initial case study adhere to the following inequalities,

$$\gamma_{Pa}^{CP1} \geq \gamma_{Pa}^{CP2}, \tag{1}$$

$$\gamma_{C}^{M1} \geq \gamma_{C}^{M2}, \tag{2}$$

$$\gamma_C^{M2} \geq \gamma_C^{M3}, \tag{3}$$
$$\gamma_{SCF}^{TC1} \geq \gamma_{SCF}^{TC2}, \tag{4}$$

where γ is a scaling factor and the subscript indicates the defect and the superscript denotes the relevant deterioration factor cohort.

4.1 *Model Selection*

For the initial case study for underbridges there are two models, Model A with 28 Parameters (Baseline transition rates) and Model B with 42 Parameters (28 Baseline parameters, 7 scaling factors for MGI and 7 scaling factors for MGE). The likelihood ratio test statistic is 875.5, which gives a p-value that is infinitesimal ($< 10^{-5}$) and suggests that the difference between Model A and B is statistically significant. This is again supported by Model B having the lowest value for AIC and BIC, making it the preferred candidate model despite its increased parameters.

4.2 *Life Cycle Analysis*

To evaluate the implications of main girders being modelling with additional characteristics, a life cycle analysis was performed to evaluate the effects of the different deterioration properties under different maintenance strategies. The following cohorts of deterioration properties were considered:

- Cohort 1 - MGI-BU Baseline
- Cohort 2 - MGI-BU, M1, CP1, TC1 (aggressive properties)
- Cohort 3 - MGI-BU, M3, CP2, TC2 (benign properties)
- Cohort 4 - MGE-BU Baseline
- Cohort 5 - MGE-BU, M1, CP1, TC1 (aggressive properties)
- Cohort 6 - MGE-BU, M3, CP2, TC2 (benign properties)

The different cohorts will be assessed using three different maintenance strategies, Strategy A - Fixed renewal of paintwork every five years, Strategy B - Fixed renewal of paintwork every ten years and Strategy C - No paintwork-only interventions. A life cycle analysis was performed using a Petri model which simulated the deterioration of a component, inspection regime and application of each maintenance strategy. The Petri net model is described in (Calvert, et al. 2021).

To compare between the different cohorts and strategies, there are two Key Performance Indicators (KPI) considered for the 35-year simulation period: Average total Time in Poor Condition (ATPC) and Average Total Costs. The study KPIs are presented in Figure 3 as a scatter plot, where it can be observed that there are three clusters formed from different cohorts and maintenance strategies. The red ellipse includes the KPIs for Cohorts 2 and 5 under strategies A, B and C; these cohorts represented the most aggressive scaling factors, with wrought iron, a coastal proximity of within 10km of the coast and belonging to a track category with the greatest loading/highest line speeds. Conversely, the green ellipse includes the cohorts from the least aggressive scaling factors. The yellow ellipse includes the KPI results for the baseline parameters for inner and exposed main girders.

From Figure 3 it is observable that both the scaling factors and the maintenance strategy have a great impact on the resultant KPIs. The traditional breakdown of inner and exposed main girders returns a smaller difference in KPIs when compared to the differences between KPIs between the same element type and different deterioration properties. For any of the simulated results, for any given strategy, the following expressions hold true,

$$Cost_1 - Cost_3 < Cost_2 - Cost_1, \tag{5}$$
$$Cost_4 - Cost_6 < Cost_5 - Cost_4, \tag{6}$$
$$ATPC_1 - ATPC_3 < ATPC_2 - ATPC_1, \tag{7}$$
$$ATPC_4 - ATPC_6 < ATPC_5 - ATPC_4, \tag{8}$$

where the numeric subscript denotes the cohort identifier. From (5) and (6), it can be stated that the savings in total cost for the least aggressive cohort compared to the baseline is less than the added expense of the most aggressive cohort compared to the baseline. Similarly, from (7) and (8), the reduction in ATPC for the least aggressive cohort to the baseline is less than the increase in ATPC for the most aggressive cohort compared to the baseline. Such observations have huge importance when allocating resources in a constrained budget scenario. The difference in cost and ATPC between the least aggressive and baseline cohorts, and the difference between the most aggressive and baseline cohorts were expected not to be equal. Moreover, there are more components that feature in the less aggressive cohort than the most aggressive cohort. Consequently, it would make sense that the values obtained by the least aggressive cohort are closer to the baseline values, as the baseline cohort is ultimately an average result based on the composition of all cohorts, so will be skewed to larger cohorts.

For each cohort there is a general trend that the ATPC increases from Strategy A to B to C. However, the reduced ATPC comes at a cost, with a trend that Strategy A is the most expensive and Strategy C is the least expensive. These observed trends correspond with what engineering expertise would predict as Strategy A dictates a more regular preventative maintenance schedule.

It can be stated that the cohorts (Cohorts 2 and 5) with the most aggressive properties, i.e. CP1, M1 and TC1, return the upper limit for total cost and ATPC. Conversely, the cohorts (Cohorts 3 and 6) with the least aggressive properties, i.e. CP2, M3 and TC2, returns the lower limit for total cost and ATPC. It was expected that the least aggressive and most aggressive cohorts would act as bounds for cost and ATPC indicators. Moreover, the baseline cohorts (Cohorts 1 and 4) return values for total cost and ATPC between the two limits, which conforms with the expectation that the baseline cohorts serve as an average based on the asset composition of the calibration data.

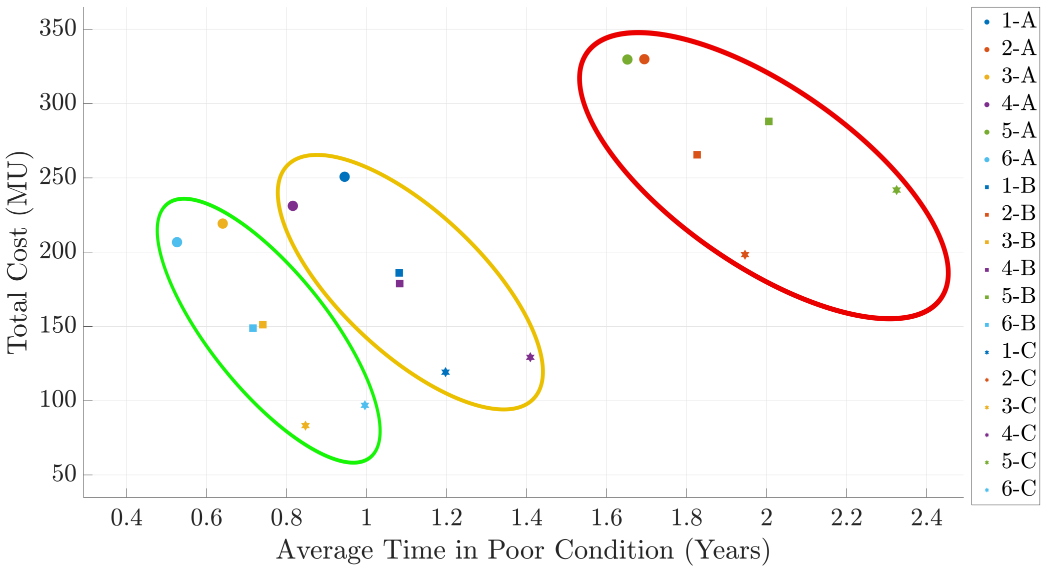

Figure 3. Scatter plot of cost and condition KPIs, where $i - j$ denotes the Cohort ID and Strategy ID respectively.

5 CONCLUSION

The study in this paper analysed deterioration rates for main girders from metallic bridges. An initial set of deterioration rates were calibrated for the traditional cohort breakdown of underbridges/overbridges and inner/exposed main girders using condition records from the bridge inspection regime on the British railway. Statistical analysis confirmed that the inclusion of these structural properties increases the accuracy of the multiple defect deterioration model without over fitting the model due to the additional parameters.

Existing literature has shown that there are additional properties aside from the aforementioned structural properties that alter the deterioration rates of bridge components. In this study the deterioration factors of coastal proximity, component material type, bridge loading and railway line speed were considered. Commonly, properties that alter deterioration rates are identified by calibrating models by data cohort splitting, however, this typically results in the inability of including multiple factors due to data sparsity. This paper presented a novel approach to incorporate multiple deterioration factors by including the factors on a per defect basis with the defects also having causal influences. The incorporation of the deterioration factors was shown to provide a statistically significant improvement in model accuracy.

Finally, the enhanced deterioration model with the multiple deterioration factors integrated into a wider asset management Petri Net model to perform a life cycle analysis. The life cycle analysis revealed that the different deterioration factors returned quite diverse values for the considered KPIs of average total time in poor condition and average total cost. Moreover, the incorporation of the deterioration factors in the life cycle analysis enables increased decision support capabilities for asset managers by facilitating targeted intervention strategy development particularly for constrained budget scenarios and developing equitable resource allocation for different administrative regions. In future work and in the advent of additional data, additional deterioration properties may be identified and included in the metallic bridge component deterioration model. Moreover, properties may be identified for additional material types.

ACKNOWLEDGEMENTS

Gareth Calvert completed his PhD research at the University of Nottingham. This work was supported by the Engineering and Physical Sciences Research Council [EP/N50970X/1]. Additional support was received from Network Rail.

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