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Incorporating defect specific condition indicators in a bridge life cycle analysis

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ABSTRACT

Bridges are critical assets for the safe, reliable and functional operation of transportation networks. Infrastructure asset managers are responsible for ensuring that these bridges adhere to rigorous safety standards using the finite resources available to transportation agencies. To facilitate strategy development and to present decisions to stakeholders, a life cycle analysis is commonly performed.

Many bridge owners use stochastic models that are calibrated using condition records from visual examinations, however, condition records typically report bridge condition on a single condition scale. In this study, defect specific condition scales are utilised to implement multiple defect specific condition indicators in the modelling of deterioration. These additional indicators enable the modelling of the interactions between defects during deterioration. Moreover, the indicators are used in the modelling of different defect specific maintenance interventions providing the scope to quantitatively assess the effects of strategies that favour early intervention.

A multiple defect deterioration model is presented as a dynamic Bayesian network, which is calibrated using records for metallic girders from railway bridges in the United Kingdom. A Petri net model is then used to perform a life cycle analysis, which incorporates a novel dynamic conditional approach for Petri net modelling to utilise the multiple condition indicators.

1. Introduction

The consequences of structural failure of a bridge can be devastating including serious human injury, fatalities and huge reductions in the economic and social well-being of local geographic regions [1,2]. As part of the efforts to avert such failures infrastructure owners devise asset management strategies. For large bridge portfolios it is a requisite of strategy development to perform a life cycle analysis to ascertain the cost implications of particular strategies as well as to forecast future resource requirements and to present strategies to stakeholders. The American Society of Civil Engineers Grand Challenge tasks civil engineers to “*significantly enhance the performance and value of infrastructure projects over their life cycles by 2025*” and to “*foster the optimisation of infrastructure investments*” [3].

Across academic literature and industry there have been a extensive range of decision support tools researched and developed to support asset managers in their decision making [4]. Lifecycle reliability analysis and the structural assessment of bridges are well established areas of research that guide the development of decision support tools [5–10]. Structural performance can be computed at many different hierarchical levels including cross-section, component, whole structure and network level [11]. Many transportation agencies have implemented modelling frameworks which use the component as the lowest hierarchical level. The transportation agencies assign and predict a single score for each component. An assessment of the whole structure can then be performed by assuming the components form some configuration of series–parallel system [12,13]. However, the assessment of components using one condition score is an oversimplification of the diverse physical process of deterioration. Deterioration progresses by stages, where reaching a critical deterioration threshold in one deterioration mode impacts the rate of deterioration of other modes. Such relationships between mechanisms have not been captured in models intended for network level decision support.

In this study, the deterioration of bridge condition is modelled using defect specific condition scales and indicators at component level. These multiple degradation mechanisms are not independent from each other but rather interacting processes [14,15]. The development of one defect type may increase the likelihood of occurrence and/or rate of progression of another defect type. A Dynamic Bayesian Network

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is presented which incorporates the interactions between different degradation mechanisms on metallic bridge components.

Upon obtaining the parametrisation of multiple interacting defects deteriorating, a Petri net model incorporating the inspection, maintenance and renewal processes can be used to perform a life cycle analysis. To model the Dynamic Bayesian Network within the Petri net framework a novel Dynamic Conditional Transition is defined. The additional condition indicators can be used to model targeted defect specific maintenance intervention types. Modelling defect specific interventions provides scope to quantitatively assess the effects of strategies that favour increased volumes of preventative maintenance. Moreover, the effectiveness of preventative maintenance can be modelled across all the different deterioration mechanisms not just the mechanism that was intervened on directly.

2. Bridge deterioration modelling

To analyse the deterioration of civil infrastructure, such as bridges, both deterministic and stochastic techniques have been proposed in the literature and applied by industry. However, stochastic modelling methods are favoured, especially at portfolio level, for their intrinsic ability to incorporate the fundamental uncertainty of structural bridge deterioration [16].

The calibration of stochastic models commonly draws on the use of data and/or expert judgement. For bridge condition modelling there are several potential sources of data available to bridge asset managers, which include:

- Experimental bridge measurements;
- Maintenance records from servicing and maintenance interventions;
- Condition records from visual bridge examinations.

For analysing structural deterioration, experimental bridge measurements (e.g. non-destructive testing, load tests, structural monitoring) are desirable as these records include the impact of geometric and material characteristics of bridges, traffic conditions and denote any changes over time. Nonetheless, the time and resources necessary to acquire experimental measurements are prohibitively high to scale to large bridge portfolios and as such are not currently appropriate for decision support modelling at portfolio level [11].

Previous bridge deterioration models have been calibrated using maintenance records [17]. Maintenance records outline the occurrence and types of intervention that a structure has undergone, and can be used to perform lifetime analysis without the subjectivity of condition indices. However, maintenance records for many transportation agencies are sparse and of poor quality, which limits the applicability of their use on large, mature bridge portfolios. Moreover, opportunistic maintenance, where a bridge or component is repaired before than it is strictly necessary, can bias the results of this analysis.

Many transportation agencies adopt examination regimes which require examiners to regularly record bridge condition from visual inspection; these regimes result in sizeable datasets of condition records. The calibration of deterioration models using condition records has been the most common approach due to the prevalence of condition records [11,18]. However, it is critical to note that condition records are not necessarily indicative of the structural integrity of load bearing bridge components [19–21]. Nonetheless, maintenance interventions should typically be prioritised to civil infrastructure with unacceptable and poor condition rating levels [22].

Commonly, the notion of 'overall' or 'worst' condition, scaling from 'new' condition to 'poor' condition are used by transportation agencies to record a single condition index per structure. However, the deterioration of bridges and bridge components is not a single physical process but rather the combination of several simultaneous processes which all result in the reduction of the structural integrity of the bridge/component [23]. Consolidating these processes into a single index introduces a degree of subjectivity and arbitrariness as well inhibiting the ability to ascertain the interactions between defects.

The nature of visual inspection regimes results in condition records being in the format of a longitudinal study which constrains many studies to modelling methodologies that use memoryless distributions. The use of a memoryless distribution, in particular the exponential distribution, requires the assumption that the process has a constant failure rate. However, Sobanjo [24] showed that bridge deterioration is a non-constant process, which aligns with common engineering experience.

Civil infrastructure such as bridges can suffer from both gradual/progressive deterioration and sudden deterioration [25,26]. Gradual deterioration is caused by manifest deterioration processes that result in the development of various defect mechanisms as the asset ages. Sudden deterioration is the result of latent deterioration mechanisms which result from events such as earthquakes, fires and floods. Lethanh et al. [27] extended the traditional Markovian approach for modelling gradual deterioration on multiple objects, i.e. road sections and bridges, by incorporating latent deterioration processes, with a key conclusion of the study being that latent deterioration processes are a significant factor when determining the optimal intervention strategy. Fernando et al. [28] proposed a model that incorporates both manifest and latent deterioration processes for evaluating intervention strategies for bridge components and bridges, again noting the significance of evaluating latent deterioration processes when determining an optimal strategy. The models described in this study are used to predict gradual deterioration behaviour and they do not model sudden deterioration outright. Nonetheless, the modelling of distinct defect mechanisms permits the evaluation of how vulnerable a structure may be to sudden deterioration.

As discussed in Adey et al. [29], decisions on transportation network asset management should be made in terms of the ability of the network to fulfil its function. However, due to the abundance of visual inspection data, the condition index is frequently used as a proxy of the service capacity of structures in the present and in the future.

Bridge performance can be seen as the aggregation of the performance of components which takes into account the importance of each element or component. Network level performance can be evaluated based on the performance of individual constituent bridges. Performance goals define the functionality or service level of an asset or network, while performance indicators (e.g. condition index) quantify an asset characteristic that provides information on its capability to fulfil its intended purpose both in the present and in the future. Ivanković et al. [30] provide a comprehensive review of evaluating performance indicators at different hierarchical levels.

The performance indicators used by asset managers can be expressed as a quantifiable measure from a specific characteristic or a dimensionless index that commonly results a qualitative exercise of expert judgement. For strategic models that support network level decision making, condition performance is a critical indicator, particularly as there is typically an abundance of condition records from visual inspections to calibrate models quantitatively.

The model proposed herein yields tangible benefits from evaluating condition performance indicators at component level by modelling multiple defects, which could be used in the future to support condition evaluation at system and network level, if components and bridges are aggregated appropriately. However, the aggregation of components to bridge level has been omitted from this study, as there is extensive additional work required to be able to model the correlation in degradation between components.

In this study, bridge deterioration will be modelled as a composition of simultaneous interacting processes. The quantification of the interactions between defects using conditional probabilities in a Dynamic Bayesian Network results in the model exhibiting non-constant deterioration behaviour despite the aforementioned data limitations. It is critical that non-constant behaviour is incorporated in a deterioration model when being used to evaluate the effects of different maintenance strategies. Moreover, upon modelling multiple processes simultaneously it is possible to evaluate targeted defect specific intervention strategies based on the additional condition indicators.

2.1. BayesIan belief networks

Bayesian Belief Networks (BBN) are a probabilistic graphical model based on Bayes' theorem. BBNs have been shown to be a useful method in reliability analysis, risk assessment and maintenance studies [31–33], particularly for their ability to incorporate expert knowledge.

BBNs are composed of a set of nodes and a set of arcs: the set of nodes denotes n variables $\mathbf{X} = \{X_1, \dots, X_n\}$ and the set of arcs are directed causal relationships between the variables. A Directed Acyclic Graph (DAG) is used to visualise the causal relationships between variables and the condition probabilities for variables given their causal relationships are tabulated in a Conditional Probability Table (CPT) [34,35].

The node that is at the start of an arc is known as a parent node and a node at the end of an arc is known as a child node. A node that has no parent nodes is known as a root node, a node that has no child nodes is known as a leaf node and a node with both parent nodes and child nodes is known as an intermediate node. The joint probability distribution can be calculated using recursive factorisation,

$$P(X_1, X_2, \dots, X_n) = \prod_{j=1}^{n} P(X_j | pa(X_j)), \tag{1}$$

where: $pa(X_j)$ denotes the set of all variables X_i, such that there is an arc from node i to node j in the graph [34].

2.2. Dynamic Bayesian networks

When analysing a system with a state space that can evolve temporally, a Dynamic Bayesian Network (DBN) can be used. DBNs are an extension of BBNs, which incorporate a time discretisation of the variable state space [36]. Each discretisation of time is known as a time slice or time step. The joint probability distribution can be calculated using recursive factorisation,

$$P(X_1^1, X_2^1, \dots, X_{n-1}^T, X_n^T) = \prod_{t=1}^{T} \prod_{j=1}^{n} P(X_j^t | pa(X_j^t)), \tag{2}$$

DBNs assume the Markov property, i.e. the probability distribution for a future time step is dependent on the current time step and is independent of past events. Moreover, defined CPTs for a DBN model are commonly time invariant: CPTs are not functions of time and the topology of the net remains consistent across different time steps.

2.3. Bridge deterioration Bayesian networks

Bayesian Belief Networks (BBN) are a method that can be applied to reliability engineering problems to incorporate expert engineering knowledges into a model [31]. Attoh-Okine and Bowers [37] developed a BBN that modelled the interactions between different bridge components to compute probabilities of bridge condition at the hierarchical levels of deck, sub-structure, super-structure and overall deterioration of bridge performance. However, the study did not model defect progression over time nor how they interact with each other but reported the condition of the bridge at different hierarchical levels for a specific time.

Rafiq et al. [38] presented a BBN model for bridge condition similar to Attoh-Okine and Bowers and extended it to a DBN. This study considered a UK railway masonry arch bridge, however, it used a single condition scale of Poor, Fair and Good.

Zhang and Marsh [39], proposed an additional bridge deterioration model, which used BBNs based on existing statistical models and expert knowledge to identify factors that affect the deterioration profiles of assets. The model considers visual examinations and detailed examinations and exploits the asset hierarchy similarly to the model proposed by Rafiq et al. [38], to provide a prediction of bridge strength. Additionally, the proposed BBN assigned prior probabilities to hyper-parameters which facilitates the incorporation of uncertainty in statistical variables. However, this model also used a single condition scale, and was not calibrated using real world data. There are several other studies that have proposed BBN based models for bridge deterioration, which are calibrated using expert judgement [40–42].

Calvert et al. [14] proposed a DBN model for modelling the interactions between multiple defect mechanisms of masonry elements. However, the presented case study was limited to the transition of an absent defect becoming present. This limitation was due to the constraints of the available data.

Structural Health Monitoring (SHM) requires the installation of monitoring equipment to detect damage and/or component structural failure as well as monitor structural loading, which can be used to facilitate reliability assessments of structures [43]. For network level decision making, whilst such factors are of interest, the life cycle management of a portfolio of bridges is primarily focussed on matters such as condition, serviceability, safety and predicted costs. Moreover, the incorporation of SHM activities to enhance life cycle management capabilities is a challenging task given the limited scope of deploying monitoring equipment across entire bridge asset portfolios due to prohibitive cost.

The objective of the multiple defect approach to bridge condition modelling is to provide additional insight into structural deterioration with the consideration that it is a complex phenomenon comprising many distinct and interacting processes. Moreover, the multiple defect approach should be calibrated using data that is available for the entire asset portfolio.

In this study, a deterioration model that incorporates the interactions between metallic degradation mechanisms is developed. Moreover, the attributes of the available data for metallic components enable the calibration of a DBN model that includes the interactions between defects based on defect extensiveness rather than just defect occurrence as in Calvert et al. [14].

3. Multiple defect bridge deterioration DBN model

Each bridge within a portfolio will have its own unique structural design, composition of components and material properties. To facilitate the asset management of such diverse portfolios, many transportation agencies develop standardised policies. For example, to facilitate a standardised inspection regime between different bridge structural designs, bridges can be described by a defined hierarchical decomposition. At NR a bridge's structural configuration is defined by major elements including inner supports, end supports and decks. Each major element is composed of a set of minor element, each having a designation on whether it is a '*principal load bearing element*' or not.

It is common that the costs and performance of a bridge are determined by evaluating the condition and performance of its constituent components in the first instance. For example, Fernando et al. [44] linked the condition state of components to structure performance states to determine structure level costs.

Deterioration modelling is used to project the last known condition state of a bridge element into the future. DBN modelling is an effective means to simultaneously model the conditional relationships between multiple interacting mechanisms. However, it should be noted that there a plethora of different methodologies for modelling bridge deterioration that capture the uncertainty of deterioration [45].

NR use an alpha-numeric condition scale known as Severity Extent (SevEx) to record the observed condition of each minor element of a bridge at inspection. The letter grade of SevEx denotes the defect mechanism or its severity and the number grade denotes the extent

Table 1
SevEx severity definitions for metallic bridge components [46].

Score	Severity definitions
A	No visible defects to metal
B	Corrosion less than 1 mm deep.
C	Corrosion between 1 mm and 5 mm deep.
D	Corrosion between 5 mm and 10 mm deep.
E	Corrosion greater than 10 mm but not through section.
F	Corrosion to full thickness of section.
G	Choose most extensive from: buckling, permanent distortion or displacement and tearing/fracture.

Table 2
CM severity definitions for metallic bridge components [46].

Score	Severity definitions
A	All coatings intact.
I	Presence of surface defects/abrasions. No corrosion of underlying component.
J	Flaking or blistering of top coat. No Corrosion of underlying metal.
K	Corrosion spots showing through coating.
L	Complete loss of coating to parent metal.

Table 3
SevEx/CM extent definitions for metallic bridge components [46].

Score	Extent definitions
1	No visible defects to metal/coating.
2	Localised defect due to local circumstances.
3	Defect occupies less than 5% of surface of the component.
4	Defect occupies between 5% to 10% of the surface of the component.
5	Defect occupies between 10% to 50% of the surface of the component.
6	Defect occupies more than 50% of the surface of the component.

of the observed defect. For metallic bridge components an additional scale known as Coating-Metal (CM) has been defined and is used to record the condition of any coating or paintwork on the component surface [46]. The severity definition of SevEx for metallic components can be found in Table 1, and the severity definition for CM scores in Table 2. The extent score which is common to SevEx and CM is shown in Table 3. Upon reviewing the SevEx and CM score definitions, it is clear that there are three distinct defect mechanisms captured using these condition scales:

- Loss of coating or paintwork (Severity I to L);
- Corrosion (Severity B to F);
- Structural Component Failure (SCF) — Includes: buckling permanent distortion/displacement and tearing/fracture (Severity G).

As there are three distinct mechanisms that are identifiable and have been recorded for the NR bridge stock a model with the capacity of modelling the evolution of each mechanism would be desirable. To model the occurrence of each of these defects, their extensiveness and the interactions between them, a DBN was developed. It is assumed that the paintwork condition influences the development of corrosion and the corrosion condition influences the occurrence of SCF. The model configuration was determined by analysing the NR condition scale definition and through consultation with NR structural engineers. The structure of these influences are shown in Fig. 1 as a BBN and the DBN deterioration model in Fig. 2.

The list of defect mechanisms is deemed to be exhaustive in terms of what is observable during a visual inspection of a bridges, which is the most abundant data source across a network of bridges [11], and with consideration of how SCF is defined. However, in the future with more granular reporting, a more detailed analysis could consider the specific instances of SCF.

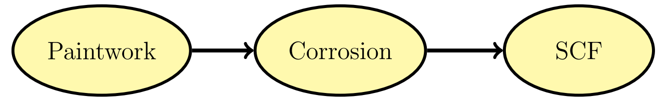

Fig. 1. Bayesian Belief Network representing causal influences between metallic defect modes.

Table 4
List of parameters for independent multiple defect deterioration model.

Defect type	Transition	Transition rate (years^{-1})
Paintwork	$Pa1 \rightarrow Pa2$	0.1761
Paintwork	$Pa2 \rightarrow Pa3$	0.1553
Paintwork	$Pa3 \rightarrow Pa4$	0.0335
Corrosion	$C1 \rightarrow C2$	0.1438
Corrosion	$C2 \rightarrow C3$	0.1160
Corrosion	$C3 \rightarrow C4$	0.0329
SCF	$F1 \rightarrow F2$	0.0092

3.1. Metallic bridge component condition scale

To avoid interactions being calibrated using sparse datasets, this study has a consolidated condition scale for each of the defect mechanisms. The conditions scales used in the study were determined by transforming the SevEx and CM condition scales by using internal NR weightings for the SevEx/CM states [46].

For this study, paintwork is described by four states, $Pa1$, $Pa2$, $Pa3$ and $Pa4$, where $Pa1$ denotes no visible defects and $Pa4$ denotes extensive paintwork damage, with $Pa2$ and $Pa3$ as intermediate states of paintwork damage. Corrosion states, $C1$, $C2$, $C3$ and $C4$ are defined in a similar manner with $C4$ corresponding as the poor condition state that would trigger major maintenance interventions.

SCF is a severe structural defect and NR policy indicates that maintenance intervention is required once a SCF mode is identified. Consequently, there are very few cases of SCF progressing beyond the SevEx state $G2$. As such it was deemed that the use of two states would be appropriate to reduce the likelihood of a model being over fitted. Thus, for SCF, there are two states: $F1$ for no failure and $F2$ for failure.

3.2. Model parametrisation

DBN are characterised by the CPTs for each node, which enable the computation of a node's probability of assuming a particular state based on the states of parent nodes.

The probability values for the CPTs of the DBN model shown in Fig. 2 are parametrised using a λ rate for the exponential distribution. The λ values were used as means of numerical stability in the optimisation function for determining the optimal probability values based on condition records. Although, it should be noted that the parametrisation of the CPTs using probabilities for the discrete time transitions is permissible and may be preferable depending on the parameter optimisation employed.

In this study, deterioration is modelled by transitions to successive condition states with no state 'jumping' permitted, i.e. a direct transition from Pa1 to Pa3 is not possible, the model requires a transition from Pa1 to Pa2 and then to Pa3. Consequently, the probability of transition occurring during one time step can be computed analytically from the exponential cumulative distribution function,

$$p_{ij|c} = 1 - e^{-\lambda_{ij|c} \cdot t}, \tag{3}$$

where $p_{ij|c}$ is the probability of transition from condition state i to j given the causal influence c, $\lambda_{ij|c}$ is its associated exponential distribution parametrisation and t is the size of the interval between the time slices in the DBN. Consequently, the probability of staying in the current condition state is $p_{ii|c} = 1 - p_{ij|c}$. Consider θ as a set of all

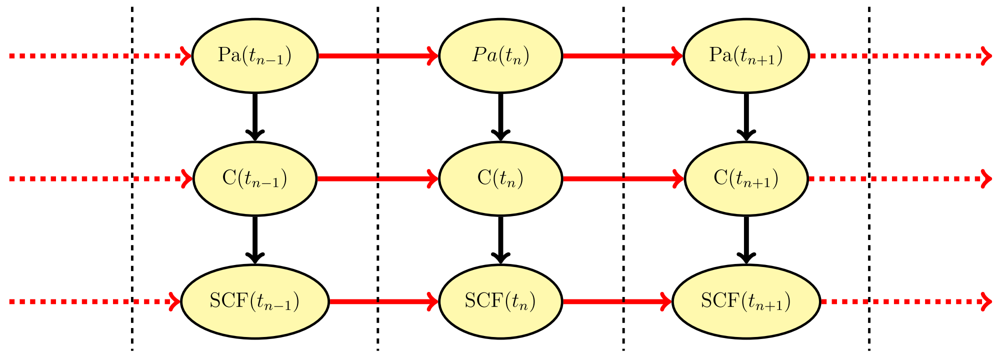

Fig. 2. DBN deterioration model, where the red lines denote temporal links. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

the values for $\lambda_{ij|c}$ in the model. To determine the appropriate set of values for θ, a method of maximum likelihood applied to panel data was applied [47–49]. The likelihood of the observed condition transitions is given by,

$$L(\theta) = \prod_{r=1}^{N} p_r, \tag{4}$$

where N denotes the number of observed condition transition records and

$$p_r = p_{i,j,t}, \tag{5}$$

i is the joint condition score at the first inspection in record r, j is the joint condition score at the second inspection in record r, t is the length of the inspection interval between the first and second inspections and N is the number of exam pair records. A joint condition score is a state space with each state unique for each permutation of the defect condition states being considered. The log-likelihood function should be used for numerical stability,

$$F(\theta) = log(L(\theta)) = \sum_{r=1}^{N} \log(p_r). \tag{6}$$

To compute the appropriate value for p_r using θ, the conditions of paintwork, corrosion and SCF at the first inspection of record r, were used as a belief state on the initial time slice. Using exact inference on the DBN populated with θ, the joint probability of all the defects being observed in a particular state at time t were calculated. A time step size of one week was used between time slices.

The θ values that maximise the likelihood were determined using a derivative-free approach, using the log-likelihood function as an objective function for a Genetic Algorithm (GA) [50].

3.3. Case study

NR are responsible for ensuring that the bridge portfolio of the British railway adheres to rigorous guidelines on the structural integrity of bridge assets. Part of the overall asset management strategy of the bridge portfolio is the execution of industry inspection policy. NR have an extensive dataset of repeated bridge condition inspections over the course of twenty years across their entire bridge portfolio.

As a case study of the metallic multiple defect DBN model, the records for all the exposed metallic main girders in the database were used to train the model. This amounts to 14,569 unique components and 24,153 pairs of exam records. To ascertain the impact of modelling the interactions between different defect mechanisms, an independent model for each defect was also calibrated using the same data.

Table 5
List of parameters for multiple defect DBN deterioration model.

Defect type	Transition	Transition rate (years^{-1})
Paintwork	$Pa1 \to Pa2$	0.1761
Paintwork	$Pa2 \to Pa3$	0.1553
Paintwork	$Pa3 \to Pa4$	0.0335
Corrosion	$C1 \to C2 \mid Pa1$	0.0050
Corrosion	$C1 \to C2 \mid Pa2$	0.1818
Corrosion	$C1 \to C2 \mid Pa3$	0.4304
Corrosion	$C1 \to C2 \mid Pa4$	0.6918
Corrosion	$C2 \to C3 \mid Pa1$	0.0471
Corrosion	$C2 \to C3 \mid Pa2$	0.0471
Corrosion	$C2 \to C3 \mid Pa3$	0.1545
Corrosion	$C2 \to C3 \mid Pa4$	0.1545
Corrosion	$C3 \to C4 \mid Pa1$	0.0331
Corrosion	$C3 \to C4 \mid Pa2$	0.0331
Corrosion	$C3 \to C4 \mid Pa3$	0.0340
Corrosion	$C3 \to C4 \mid Pa4$	0.0340
SCF	$F1 \to F2 \mid C1$	0.0015
SCF	$F1 \to F2 \mid C2$	0.0036
SCF	$F1 \to F2 \mid C3$	0.0087
SCF	$F1 \to F2 \mid C4$	0.0156

Table 6
Mean Squared Error for each model based on the predictions of final condition.

Deterioration model	Mean squared error
Independent	19.5254
DBN	5.4180

3.4. Defect DBN condition profiles

The parameter values for the independent multiple defect deterioration model are shown in Table 4 and the values for the DBN variant in Table 5. Note in the DBN model, for the $C2 \to C3$ transition the same parameter was used for conditions $Pa1$ and $Pa2$ and an additional parameter was used for the conditions $Pa3$ and $Pa4$, similarly for the $C3 \to C4$ transition. The reduced parameter count for these transitions was required to avoid over fitting due to a sparser dataset for the more advanced corrosion states with a good Pa score.

It can be observed from the transition rates for corrosion and paintwork damage that they are much more rapid in progression than SCF. This model output aligns with the engineering expectation that SCF would develop over a much longer time frame.

The model was calibrated using condition records from bridge inspections. To compare the fit between the different models, an analysis of observed final inspections compared to the predicted final inspections was performed. The process for this comparison is:

- Calculate the total number of records observed in each condition state at final inspection.

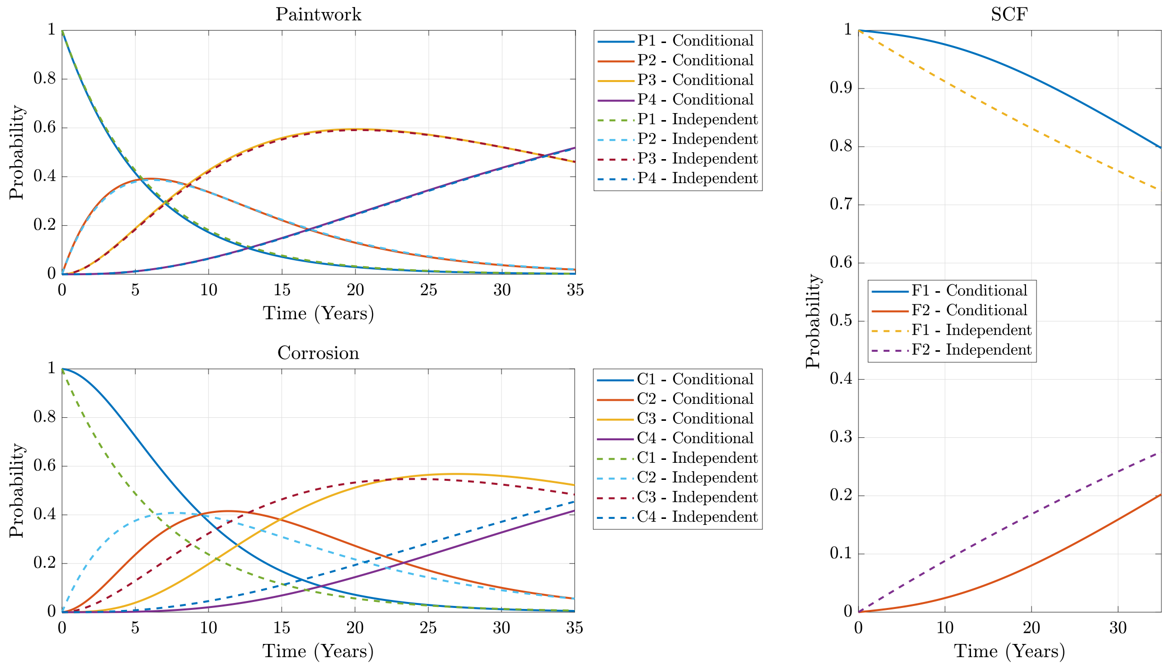

Fig. 3. Condition probability profiles for Paintwork, Corrosion and SCF for a exterior metallic girder starting in $\{P1, C1, F1\}$, calculated using both independent defect Markov chains and DBN implementations.

- Compute the probabilities for each condition state at the final inspection for each observed record using the DBN model, taking the condition at first inspection as the belief state.
- Sum the probabilities for each predicted condition state for all predicted final conditions.

To compare the goodness of fit between the two different models the Mean Squared Error (MSE) was used. The MSE is given by,

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(Y_i - \hat{Y}_i)^2, \tag{7}$$

where n is the total number of predictions, generated from the n observations, across all variables. Y is a vector of the observations across all variables and $\hat{Y}$ is a vector of the predictions across all variables. The MSE can only assume non-negative values and values closer to zero are deemed to represent the model generating a better fit. The MSE values for the independent defect model and the DBN model are shown in Table 6, with the DBN providing a better goodness of fit than the independent model.

Additionally, a log-likelihood ratio test statistic can be used to show that the improved fit of the model is statistically significant given the increase in parameters for the DBN model. The log-likelihood ratio test is given by

$$LR = -2(F_{Ind} - F_{DBN}), \tag{8}$$

where F_{Ind} is the log-likelihood of the independent model with its optimal parameter θ values and F_{DBN} is similarly defined for the DBN model. The null hypothesis for the likelihood ratio test is true when LR is small and rejected if the LR values have a significant difference. The LR statistic approximately follows a Chi-square distribution, with the degrees of freedom equal to the difference between the number of parameters used in each model. For the independent and DBN models the difference between log-likelihood scores is 211.6. Using a significance level of 5%, the null hypothesis can be rejected and thus conclude that the models are significantly different.

Fig. 3 shows the probability of being in a particular condition state for each of the defects through a 35 year time period, with the component starting in perfect condition $\{P1, C1, F1\}$. Note in this study 35 years was selected as the modelled time interval as it aligns with the interval used for NR decision support modelling. It can be observed from Fig. 3 that there is no discrepancy between the profiles for deterioration of paintwork, which corresponds to paintwork being the root variable in the DBN. For corrosion and SCF it can be observed that the rate of deterioration for each defect is less for the DBN model than independent model, for the simulated period. The reduced rate can be attributed to the reduced probability of corrosion and SCF transitions occurring when paintwork is in 'perfect' or near perfect condition. However, as time elapses the rate of corrosion would increase as the paintwork condition worsens, see Table 5. Similarly, as corrosion becomes more prevalent, the rate of SCF development would increase. The use of the DBN technique enables the modelling of the interactions between defect mechanisms and ultimately the calculation of non-constant deterioration profiles, which are more reflective of the physical process, despite being characterised by several exponential probability distributions.

4. Petri net life cycle modelling

The modelling of bridge deterioration at portfolio level is a well established discipline, with many different probabilistic techniques employed to assist the bridge management process including Markov based models [23,51,52], semi-Markov methods [53,54] and BBNs [14,37,38]. Section 3 introduced a novel multiple defect approach for modelling metallic bridge deterioration using DBNs. However, the life cycle modelling of bridges requires the modelling of not only the structural deterioration but also the inspection and maintenance regimes. Petri nets are a versatile methodology that can be implemented to model the entire life cycle of bridges under different asset management strategies. There are several contributions in literature that employ Petri nets to model the asset management of bridges [17,55,56]. General Monte Carlo simulations have the same capability to model bespoke processes and scenarios as PNs, however PNs offer enhanced model reproducibility for future analysis.

Fig. 4. Graphical representation of Petri net components.

4.1. Background

Petri nets (PN) are a method of performing graphical analysis to study dynamical systems and have been adopted for engineering, industrial and business applications [57]. A PN is described by a bipartite graph of two disjoint sets of nodes: places and transitions. The places and transitions, can be connected by directed arcs and the connection of one node type to the same node type is not permissible. Tokens are used to denote the elements in the studied system [58]. A PN has a finite set, called the marking, which denotes the token count for each place in the net.

The dynamic behaviour of the studied system, including temporal properties, is described by the rules that govern how tokens are removed from the input places of a transition and added to its output places when the transition fires. Many extensions exist for the definition of transition firing rules. A common type of transition is the stochastic transition where the firing delay is sampled from a probability distribution [59]. In graphical representations of a PN, circles are used to denote places and a rectangular shape is used to denote a transition, see Fig. 4.

4.2. PN bridge component life cycle modelling

The model proposed by Yianni et al. [55] models bridge condition on a two-dimensional scale, which considers both the type of defect and its associated magnitude. This approach produces deterioration profiles that correspond to the physical process of deterioration, however, it is limited by only monitoring the score for the worst defect present, disregarding others.

Le and Andrews [56] presented a bridge asset management model which encapsulated a series of sub-models for each bridge component, with each sub-model also defined for the component material type. The sub-models incorporated multiple degradation mechanisms dependent on the material. For metallic components the mechanisms considered included protective paint flaking, minor metal corrosion and major corrosion. Multiple mechanisms were also considered for concrete and masonry components.

To model the dependencies between the different degradation mechanisms, Place Conditional Transitions (PCT) were included in the Le and Andrews [56], PN model. A PCT is a transition which has its firing delay sampled from a probability distribution but the distribution that samples are taken from is dependent on the marking of a predefined list of places upon the transition becoming enabled [60]. Graphically the list of associated places for a PCT is denoted using black dashed arcs.

A limitation of PCTs is that if the marking of the places changes after the enabling of the transition but before the PCT fires, the firing delay is not re-sampled to reflect the updated marking. Consider a slow-acting process that is being modelled with PCTs and the process is conditional on places denoting a fast-acting process. If the PCT samples a large time for the slow-acting process, the fast-acting process could deteriorate rapidly which could have warranted a different and shorter firing delay for the slow-acting process, but this cannot be reflected for any enabled transitions. Moreover, if the fast-acting process is something that could be regularly intervened on or serviced, the PCT for the slow-acting process could end up having a firing delay sampled from a distribution based on an out-of-date marking and have a firing delay that is too short when considered against the updated marking. The latter scenario is

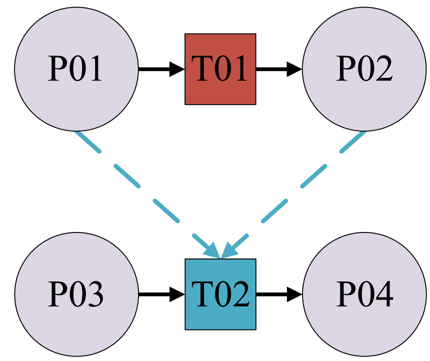

Fig. 5. PN modelling α and β using a DCT.

problematic when trying to model and evaluate different maintenance strategies and assess the benefits of early interventions.

There are several additional formalisms for incorporating Bayesian methods or conditionality into PNs. Andrews and Fecarotti [61] introduced a formalism known as BP-Net which was based on PNs and BBNs, where PN models were used to generate the probabilities for model CPTs. An alternative tool known as Bayesian Stochastic Petri Nets (BSPN) was introduced by Taleb-Berrouane et al. [62]. BSPNs are also a combination of BBNs and Stochastic PNs, although BSPNs enabled the evaluation of continuous input data, negating the need for time discretisation. However, the BSPN method was only applied to a relatively simple case study and there is limited discussion on how to extend the method to large scale and/or complex systems [63].

An accurate prediction of future condition requires the ability to dynamically update the stochastic process given changing influencing conditions. To address the limitations of PCTs and extend the methods in literature the next section proposes a new transition; *Dynamic Conditional Transitions*.

4.3. Dynamic conditional transitions

Consider two distinct processes, α and β, both of which can be described by two discrete states. However, at any given instance the state of α influences the state that β assumes, i.e. β is dependent on α. If α and β are failure mechanisms, and the state of each process is known at initial time t_0, one could predict the evolution of α and β provided a conditional probability distribution is defined for each causal state permutation.

Modelling dynamically conditional processes is not possible using existing defined transition types for PN. Whilst PCTs do sample a firing delay conditionally on the marking of a predefined set of places, if the net marking were to change before the transition fires, the transition firing delay is not resampled. To overcome this limitation, a bespoke transition known as the Dynamic Conditional Transition (DCT) is defined.

Consider the example shown in Fig. 5. P01 denotes the working state of α, P02 its failed state. Similarly, P03 is the working state of β and P04 is the failed state. T01 is a standard stochastic transition which samples its firing delay from a probability distribution and it represents α changing from the working state to the failed state. The firing operations of stochastic transitions are well defined in the literature [64]. T02 is a DCT and models the time for β to change from the working state to the failed state. The reachability graph for the PN is shown in Fig. 6.

A DCT has input arcs, output arcs and '*causal arcs*', where the causal arcs are denoted with dashed blue lines in Fig. 5. T02 would be enabled if a token is present in P02 (marking M0 or MA). Upon a DCT becoming enabled, it will attempt to fire after δt, where δt corresponds to the size of interval between a DBN time slice. After δt has elapsed during the

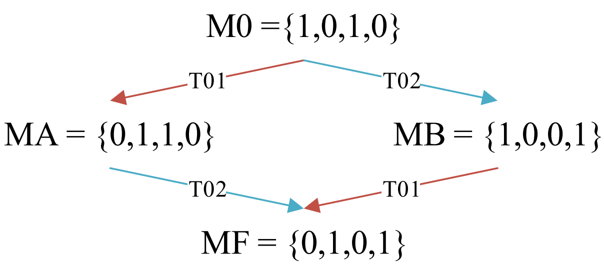

Fig. 6. Reachability graph for the PN shown in Fig. 5, where $\{\dots\}$ represents the marking of P01, P02, P03 and P04 respectively.

simulation, the DCT will analyse its *causal arc place marking* (CAPM). For example, if the PN has a marking of M0 then the CAPM for T02 would be $\{1,0\}$ ({P1, P2}). When a DCT attempts to fire, a random number, r, is sampled from $\mathcal{U}(0,1)$. Then r is compared against the DCT firing probability, f, with the value of f dependent on the CAPM. In the example shown in Fig. 5, the CAPM will be dictated by whether $T01$ has already fired or not. All possible values of f are stored in a conditional probability table.

If the value of $r \le f$, the DCT will fire. Otherwise, the DCT will not fire but will remain enabled. Whilst the DCT remains enabled, the DCT will not attempt to fire again until a further period of δt has elapsed, at which point it will determined its current CAPM, reselect f and resample r. An algorithm charting out the full firing mechanism for DCTs is shown in Algorithm 1.

A DCT provides the capability of conditional firing delay times to adapt to new markings at its conditional places as the global simulation time evolves and not just be conditional at the initialisation of the simulation, or at the time of a transition becoming first enabled.

Note that the mechanisms or processes described by stochastic transitions and that do not possess causal arcs, e.g. α, can be described by any probability distribution for firing delay, when using DCTs and not just an exponential distribution. Additionally, DCTs cannot be implemented for all structures of DBN but rather the DBNs that have temporal arcs for each variable that features on a time slice, analogous to the structure shown in Fig. 2. The state of stochastic process at the future time step must be conditional on the state of the stochastic process at the current time step, for all stochastic process.

4.3.1. DBN-DCT condition profile comparison

The metallic multiple defect deterioration model was simulated to determine condition probability profiles for 35 years. The DBN model was simulated using the parameters shown in Table 5. The model was additionally simulated using an analogous PN implementation of the model using DCTs. The probability values of being in particular condition state after 35 years is reported for each modelling method in Table 7. There is a difference in probability values between the PN and DBN models which can be attributed to issues regarding numerical precision and convergence of the PN using Monte Carlo simulations. Nonetheless, it can be observed that the percentage difference between the PN and DBN model is minimal. Consequently, the DCT implementation in a PN model of the DBN model provides a sufficiently accurate condition output to facilitate the modelling of deterioration and application of intervention activities in a life cycle model.

4.4. Multiple defect, bridge asset management PN model

A PN model was developed to model the deterioration of paintwork, prevalence of corrosion and the development of SCF, alongside the inspection, scheduling and maintenance processes for a bridge component. The PN model is shown in Fig. 7 with a key of the various PN nodes shown in Fig. 8.

Algorithm 1: DCT firing sequence for transition t_j

G, global simulation time,
$I(t_j)$, t_j marking input function (Boolean),
ζ, enabled status of t_j (Boolean),
T_e, time t_j became enabled
if $I(t_j) = 1 \wedge \zeta = 0$ **then**
  $\zeta = 1$ %Transition is enabled;
  $T_e = G$ %Time transition became enabled
while $\zeta = 1$ **do**
  if $G = T_e + \delta t$ **then**
    if $I(t_j) = 1$ **then**
      $\zeta = 1$
      Obtain CAPM
      Select f value based on CAPM
      Sample r value from $\mathcal{U}(0,1)$
      if $r \le f$ **then**
        t_j fires ;
        $\zeta = 0$
      else
        $\zeta = 1$;
        $T_e = T_e + \delta t$
    else
      $\zeta = 0$;

Table 7
Probabilities of being in a condition state after 35 years using both DBN and PN-DCTs.

Defect type	Condition state	DBN probability	PN-DCT probability	% Difference
Paintwork	$Pa1$	0.01225	0.01223	0.15219
Paintwork	$Pa2$	0.07071	0.07060	0.16266
Paintwork	$Pa3$	0.57186	0.57085	0.17532
Paintwork	$Pa4$	0.34516	0.34630	−0.32921
Corrosion	$C1$	0.02958	0.02963	−0.16363
Corrosion	$C2$	0.17192	0.17265	−0.42557
Corrosion	$C3$	0.56430	0.56307	0.21694
Corrosion	$C4$	0.23418	0.23463	−0.18964
SCF	$F1$	0.88213	0.88214	0.00001
SCF	$F2$	0.11787	0.11786	0.00291

The unrevealed condition states of paintwork, corrosion and SCF are denoted by P01–P10. The transitioning between condition states is controlled by the firing rules of T01–T07, where T04–T07 are DCTs. The configurations of these places, transitions and arcs is such that the PN is of providing an analogous condition output as the DBN model, see Section 4.3.1.

The unrevealed condition states correspond to the condition of component in real time. However, the condition of the component will only become known upon being inspected, and thus a second group of places (P11–P20) are defined to represent the revealed condition state of the component. After inspection, a maintenance strategy may require a certain intervention to be scheduled upon a revealed condition state, P29–P34 are designated to represent this. By default, the PN will schedule and execute all appropriate intervention types upon particular conditions being revealed. However, particular maintenance strategies only require some of the possible intervention types. To be able to use the same PN structure to evaluate different maintenance strategies P23–P28 are used to inhibit particular interventions when testing different maintenance strategies

Upon designating the requirement for a particular intervention to occur, there will be a delay between scheduling the intervention and it being executed, in the model T27–T32 are used to assign a time delay for this action. In this study, the delay between an intervention being scheduled and occurring was sampled from $\mathcal{N}(3, 0.5)$. P35–P37 are used to signal that the particular maintenance intervention is ongoing.

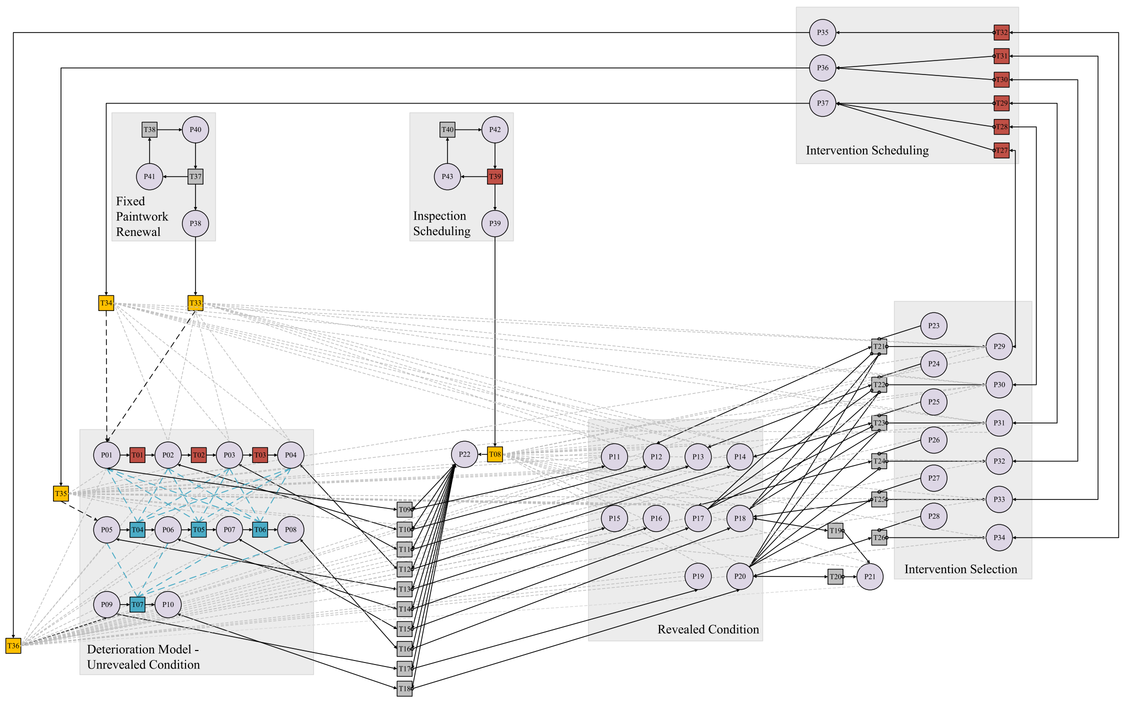

Fig. 7. Petri net for modelling the asset management of a metallic bridge component.

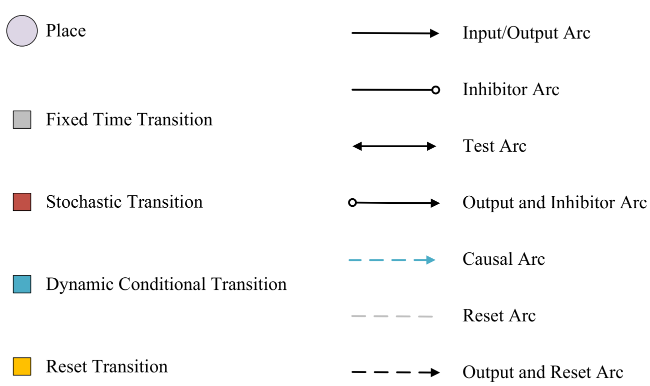

Fig. 8. Key of Petri net nodes and arcs used in Fig. 7.

Finally, after the intervention is complete, T33–T36 are used to reset the PN to reflect the updated condition scores.

As alluded to in Section 3, for the purposes of standardised procedures between different structural configurations, bridges are commonly described using a hierarchical decomposition. The bridge component model can be used as part of a whole structure model in a modular approach, whereby the whole structure model is populated with several instances of the component model to reflect its structural configuration. The whole structure model could then use the revealed condition from each component to determine the most appropriate intervention strategy for the whole structure and apply the strategy by using the intervention selection and scheduling places in the component model.

The presented PN models the life cycle of a single metallic bridge component, as the purpose of this study was to investigate the functionality of DCTs and to showcase the feasibility of quantifying the benefits of maintenance strategies that favour early intervention. Additionally, any whole structure model is dependent on the hierarchical decomposition of the structure, which is defined by the asset's infrastructure manager and is not necessarily common between infrastructure managers. Thus, to ensure maximum applicability and reproducibility only the component model is shown. However, to implement the entire asset management procedure there were some specific places and transitions required in lieu of a whole structure model. For example, the interval between inspections can vary and is normally determined by the amalgamated score of multiple components at the previous inspection. As the presented PN is for a single component, there is a local inspection loop of (P42, P43, T39, T40), which deposits tokens in P39 to initiate an inspection. However, if a whole structure model was to be deployed, all that is required is that a token is deposited into P39 to prompt an inspection of the component. The inspection interval for this case study was set as $\mathcal{N}(6, 1)$.

To enable an analysis of strategies requiring fixed-interval paintwork renewal, the following places and transitions were included in the PN model: P40, P41, T37, T38. In the case of a whole structure model these nodes could be substituted for, provided there was an output arc to deposit tokens in P38. Finally, T27–T32 could have additional input arcs to alter the scheduling behaviour of maintenance interventions based on the condition of the overall structure and/or to facilitate studies under constrained budget scenarios. The defined physical representation for each place can be found in Table 9.

The parameter values for the defect mechanisms were calibrated using a method of maximum likelihood applied to the condition data for NR metallic girders, as shown in Section 3.2. The degradation of paintwork is determined by T01–T03, which are stochastic transitions using exponential distributions with the following parameter values: $\lambda_{T01} = 0.1761$, $\lambda_{T02} = 0.1553$ and $\lambda_{T03} = 0.0335$. For the development of corrosion and SCF T03–T06 and T07 were used respectively, all of which are DCTs. The f values used for the DCTs are shown in Table 8, which shows that the probability of each DCT firing is increased by each incremental marking of its influencing defect.

4.5. Case study

The primary purpose of the PN model is to enable the evaluation of the impacts of a range of different maintenance strategies. The PN model has a versatile design such that all the different strategies can be simulated using the same net, with the only required amendment being different initial markings for a specific set of places, P23–P28 and P40,

Table 8
Conditional probability table for model DCTs. Note that $\delta t = \frac{1}{52}$ years.

	CAPM	f
T04 Fires, CAPM = {P1, P2, P3, P4}	{1,0,0,0}	9.9995×10^{-5}
	{0,1,0,0}	0.0036
	{0,0,1,0}	0.0086
	{0,0,0,1}	0.0137
T05 Fires, CAPM = {P1, P2, P3, P4}	{1,0,0,0}	9.4188×10^{-4}
	{0,1,0,0}	9.4188×10^{-4}
	{0,0,1,0}	0.0031
	{0,0,0,1}	0.0031
T06 Fires, CAPM = {P1, P2, P3, P4}	{1,0,0,0}	6.6124×10^{-4}
	{0,1,0,0}	6.6124×10^{-4}
	{0,0,1,0}	6.8001×10^{-4}
	{0,0,0,1}	6.8001×10^{-4}
T07 Fires, CAPM = {P1, P2, P3, P4}	{1,0,0,0}	3.0185×10^{-5}
	{0,1,0,0}	7.2268×10^{-5}
	{0,0,1,0}	1.7336×10^{-4}
	{0,0,0,1}	3.1122×10^{-4}

Table 9
Descriptions of the physical representation of each place in Fig. 7.

Place	Representation
P01–P04	Unrevealed — Paintwork 1–4
P05–P08	Unrevealed — Corrosion 1–4
P09–P10	Unrevealed — SCF 1–2
P11–P14	Revealed — Paintwork 1–4
P15–P18	Revealed — Corrosion 1–4
P19–P20	Revealed — SCF 1–2
P21	Revealed — Poor Condition
P22	Perform Inspection
P23–P25	Inhibit Pa Repair on Pa2-Pa4
P26–P27	Inhibit C Repair on C3–C4
P28	Inhibit SCF Repair on B2
P29–P31	Schedule P Repair on Pa2–Pa4
P32–P32	Schedule C Repair on C3-C4
P34	Schedule SCF Repair on B2
P35	Repair Paintwork
P36	Repair Corrosion
P37	Repair Buckling
P38	Fixed Renewal of Paintwork
P39	Enable Inspection of Component
P40	Pre-Fixed Renewal of Paintwork
P41	Fixed Paintwork Renewal
P42	Global Inspection Scheduled
P43	Performing Inspection

which are used to inhibit the scheduling of particular interventions. To showcase the functionality of the PN several strategies are considered:

- **Do Nothing**
- **Strategy 1** — Fixed renewal of paintwork every five years.
- **Strategy 2** — Fixed renewal of paintwork every ten years.
- **Strategy 3** — Paintwork intervention when revealed {Pa4} reached.
- **Strategy 4** — No paintwork-only interventions.

For strategies 1–4, there were two additional repair actions that were always enabled:

- Corrosion repair when condition C4 is revealed. This intervention restores corrosion to C1 and paintwork to Pa1. It is assumed that the engineers would ensure that the paintwork is fully restored to maximise the impact of taking possession of the bridge.
- Component replacement when condition F2 is revealed. This will restore the component model to the states of Pa1, C1 and F1. If C4 and F2 are revealed at the same time, component replacement is prioritised over corrosion repair.

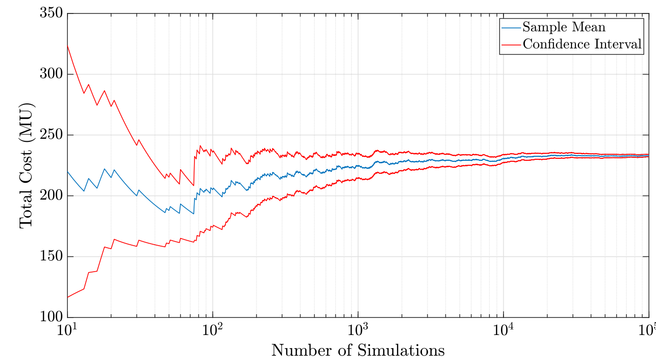

Fig. 9. Convergence Confidence Interval of 95% for PN simulation of Strategy 1.

4.6. Simulation results

The model was analysed using Monte-Carlo simulations with 100,000 simulations per strategy. The central limit theorem can be used to evaluate the confidence interval for a Monte-Carlo sample after n simulations to a particular confidence level,

$$[a, b] = \left[\frac{\overline{z} - \lambda s(z)}{\sqrt{n}}, \frac{\overline{z} + \lambda s(z)}{\sqrt{n}} \right], \tag{9}$$

where a is the lower confidence interval limit, b is the upper confidence interval limit, $\overline{z}$ is the sample mean, $s(z)$ sample standard deviation and λ is a coefficient which relate to the desired nominal confidence limit. For a confidence limit of 95%, $\lambda = 2$ [65]. The confidence limits over the course of 100,000 simulations for Strategy 1 are shown in Fig. 9. After 100,000 simulations the sample mean for Strategy 1 was 233.1 and with a 95% confidence interval of the true mean being within [232.07, 234.19]. Similar convergence was found for Strategies 2–4.

For n conditions states, an integer score can be assigned to each, $C_1, \ldots, C_n$, then the average condition of a defect at time t is determined from

$$A_C^t = \sum_{i=1}^{n} (C_i \cdot p_i), \tag{10}$$

where p_i is the probability of being in C_i at time t. The average conditions of paintwork, corrosion and SCF over time, for each strategy are shown in Figs. 10–12 respectively. From Fig. 10, it can be observed for the strategies that instigated earlier repainting of the component, lower values were obtained for average paintwork condition.

The policy for corrosion repair was consistent for each of the four strategies, i.e. to schedule corrosion repair upon an inspection revealing C4 being reached. Nonetheless, from Fig. 11, it can be observed that despite corrosion repair policy being consistent there are variations in the average corrosion condition obtained for each strategy. The variation in average condition of corrosion is due to the conditional relationship between paintwork condition and corrosion. Strategies that favour early paintwork interventions yield an improved average paintwork condition. The rate of corrosion development monotonically increases upon worsening paintwork condition. Thus, strategies that return improved paintwork condition ultimately yield lower rates of corrosion and have improved predicted average conditions for that defect mechanism.

For the SCF defect modes a similar observation can be made, due to corrosion acting as a causal influence to SCF development. Thus, the maintenance strategies that schedule paintwork renewal earlier, result in an improved average condition for paintwork which mitigate the levels of corrosion and instances of SCF developing.

An asset manger's task of maintenance strategy selection is a multi-criteria problem. Asset condition is one of many factors that must be

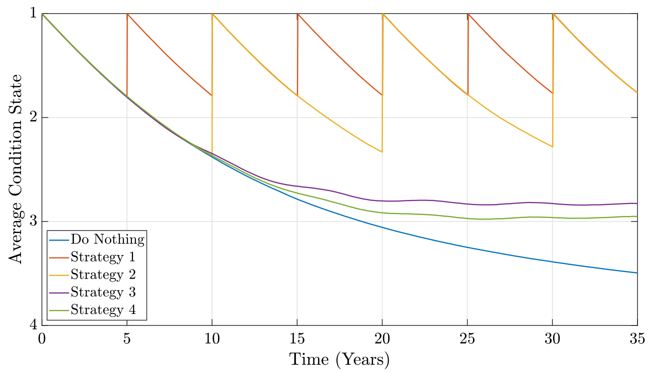

Fig. 10. Average condition of paintwork under different maintenance strategies.

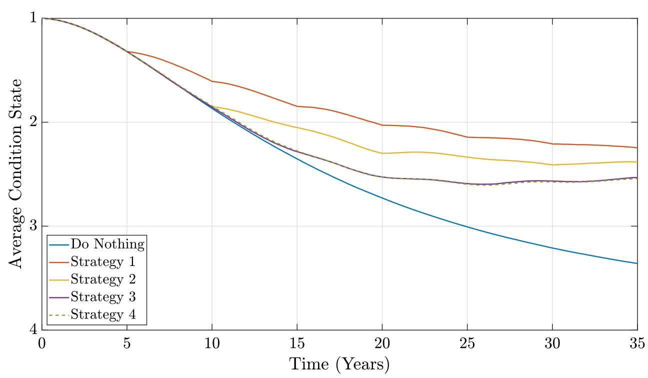

Fig. 11. Average condition of corrosion under different maintenance strategies.

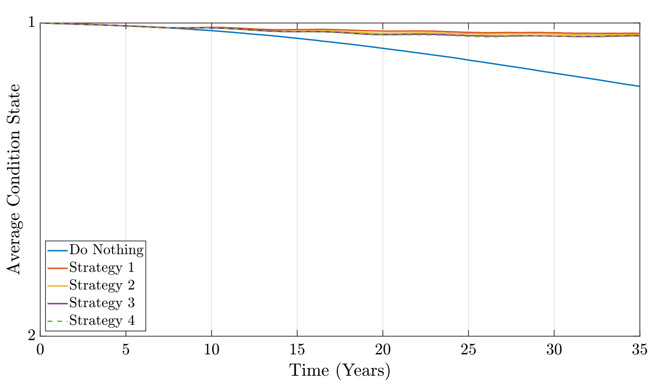

Fig. 12. Average condition of SCF under different maintenance strategies.

considered when selecting strategy and presenting decisions to stakeholders. Other factors such as service disruption and strategy cost must also be considered. Ultimately infrastructure is managed to maintain safe, reliable and operation for network usage, and the minimisation of service disruption is a key priority [66]. In this study, the minimisation of service disruption was monitored by determining the average time the bridge component spent in poor condition.

For NR condition scales, poor condition is a well defined state that triggers the scheduling of maintenance interventions and is reportable to regulators. The condition states of $C4$ and $F2$ as defined in this study correspond to the defined NR poor condition states for metallic components. The time spent in poor condition can be determined by analysing how long a poor condition state was marked during the course of simulation. An average is found by analysing each of the simulations performed during the Monte Carlo analysis.

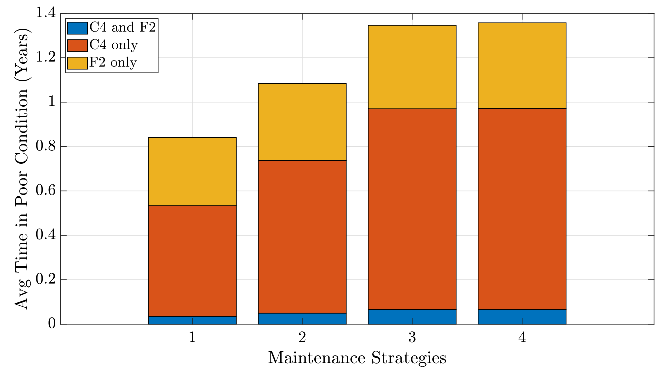

Fig. 13. Average total time in poor condition over 35 years, under different maintenance strategies.

As a baseline, the average time spent in poor condition for the 'do-nothing' strategy was 5.34 years. The average total time in poor condition for each of the maintenance strategies is shown in Fig. 13. It can be noted that the strategies favouring early paintwork intervention return the lowest average values for total time in poor condition. Moreover, the strategies that have increased values in average total time in poor condition are caused by increases in both time spent in $C4$ and $F2$. This trend conforms to the previous finding that strategies that mandate early paintwork interventions not only result in a reduction in the prevalence of corrosion but also in there being less instances of SCF developing.

Finally, another critical concern for asset managers is the cost implication of each strategy. The average cost for each strategy can be calculated by analysing the number of executed maintenance interventions during the simulated period. The number of interventions can be determined by summing the number of times that transitions T33–T36 fire throughout the duration of the simulation. The predicted average cost of each strategy can be calculated using the number of interventions and a defined cost distribution for each type of intervention. For this study, arbitrary fixed costs for each different maintenance intervention were assigned, the costs are denoted in arbitrary monetary units (MU):

- Fixed paintwork renewal — 25 MU
- Paintwork repair upon condition reveal — 50 MU
- Corrosion repair — 200 MU
- Component replacement — 500 MU

Across all model outputs there are minimal differences between Strategy 3 and Strategy 4. The similarities between strategies would indicate that there is limited benefit to waiting until the paintwork is in poor condition to repaint the component as the negative impact on corrosion would have already occurred.

Fig. 14 shows the predicted average cost of each strategy over time alongside the probability of being in poor condition. Strategy 1 results in the lowest probability of being in poor condition over the course of the entire 35 year simulation period. Nonetheless, Strategy 1 can also be identified as being the most expensive strategy, as there are regular fixed costs for paintwork renewal. The remaining three strategies all result in lower overall costs than Strategy 1, however, the probability of being in poor condition is increased. Strategies 3 and 4 obtain a lower cost than Strategy 1 and 2, however, the costs are composed of increased replacement costs which would be indicative that there was an assessment of greater risk of structure failure.

Note that the cost analysis has only considered maintenance costs. Inspection costs are the same across the four strategies, with an average of 5.33 inspections taking place over the simulated 35 years. The values for average time in poor condition, average costs and probability of being in poor condition after 35 years can be found in Table 10.

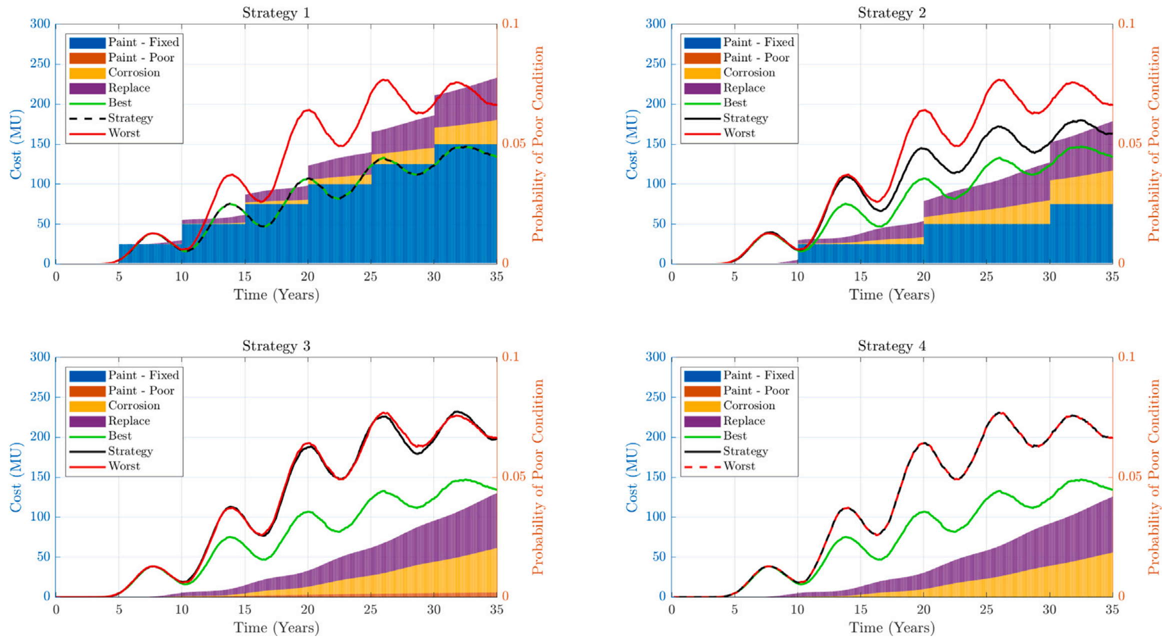

Fig. 14. Predicted maintenance costs and probability of revealed poor condition over time for Strategies 1–4.

Strategy 1 returns the lowest values for average total time in poor condition and the probability of being in poor condition after 35 years. However, Strategy 1 is the most expensive strategy and is 30.4% more expensive than Strategy 2. From analysing the cost values, Strategy 2 would be the favoured strategy in a cost constrained scenario. Strategy 2 has a 42.0% increase in overall costs when compared to the strategy with the lowest costs, Strategy 4, and yields a 20.6% reduction in the average total time in poor condition when compared to Strategy 4. Note that any reduction in average total time in poor condition would translate to increased adherence to capability and serviceability requirements.

The enhanced capability for evaluating preventative maintenance can be proven by changing Transitions T04–T07 from DCTs to stochastic transitions that sample from an exponential distribution. Considering T04–T07 as stochastic transitions and using transition rate values from Table 4, it can be found that average condition for corrosion and SCF is consistent for all four intervention strategies. Moreover, all metrics relating to corrosion and SCF would be consistent between the four intervention strategies when the deterioration mechanisms are modelled independently from each other. Thus, the inclusion of the interaction between defect mechanisms enables the quantitative evaluation of the advantages of preventative maintenance actions such as repainting.

Finally, the results seem to suggest that to reduce the prevalence of corrosion, a fixed paintwork maintenance programme is better than reactive paintwork maintenance. Moreover, reactive paintwork maintenance seems to have negligible impact on the performance indicators, i.e. Strategy 3 and Strategy 4 return similar results, suggesting by the time reactive paintwork is scheduled, corrosion is likely to have developed resulting in a diminished return on the resource investment.

Table 10
Model outputs for each strategy after 100,000 simulations of 35 years.

Strategy	Average total time in poor condition (Years)	Average maintenance cost (MU)	Average replacement cost (MU)	Average total cost (MU)	Probability of poor condition at $t = 35$ years
1	0.84	180.2	52.9	233.1	0.0448
2	1.08	117.1	61.7	178.8	0.0545
3	1.35	61.3	68.8	130.1	0.0657
4	1.36	55.8	70.1	125.9	0.0661

5. Conclusions

Infrastructure asset managers are tasked with ensuring that their civil infrastructure is maintained to conform to strict safety standards and deliver safe, reliable and functional operation. This task must be delivered whilst making optimal use of the available resources. A common approach to present management strategies to stakeholders is utilising the outputs of life cycle modelling.

In this study, a novel approach to bridge component deterioration was presented, whereby multiple condition indicators were developed that were specific to distinct defect mechanisms. The additional indicators encapsulated the interactions between defects and the reality that the absence or presence may alter the rate of development of other defects. The considered defects were the degradation of paintwork, corrosion and the occurrence of SCF defect modes. These relationships were quantified from industrial condition data for metallic girders from railway bridges in the United Kingdom and modelled using a DBN. The DBN model was found to offer improved prediction accuracy when considering the interactions between multiple defect mechanisms opposed to the defects being modelled independently. In particular, the analysis concluded that paintwork condition influenced the rate of corrosion and that the advanced corrosion would increase the probability of SCF.

To perform a life cycle analysis which modelled the condition of bridge components and the application of inspection and maintenance policy, a PN model was presented. However, to incorporate the deterioration model, a novel transition type, DCT, was defined to enable the modelling of multiple interacting deterioration mechanisms within the PN methodology. A case study of four different maintenance strategies with specific and targeted maintenance interventions was analysed. The multiple defect approach to modelling, provides additional indicators which are critical to the detailed evaluation of competing maintenance strategies, which can be defined as targeted defect specific actions. In this study, the considered model outputs for each strategy were average component condition, average total time spent in poor condition and average predicted maintenance cost.

Due to the conditional relationships between paintwork condition and corrosion, and the conditional relationship between corrosion and SCF occurrence, the effects of preventative maintenance initiatives such as fixed paintwork could be evaluated. In particular, a strategy of fixed paintwork renewal every five years was found to yield an average total time in poor condition that was 37.8% less than if paintwork was only renewed when identified as being in poor condition. Such analysis of preventative maintenance strategies is a desired modelling capability for many infrastructure asset managers.

The DBN modelling approach is the preferred technique for calibrating the conditional probability parameters in the maximum likelihood calculation, as the DBN model can be resolved analytically opposed to requiring simulations. Moreover, for a deterioration model under a do-nothing maintenance assumption the DBN model is preferred as it is computationally less expensive than the PN model. However, when performing a wider life cycle analysis, the PN model is the preferred technique as PNs are more effective in representing bespoke asset policies.

A limitation of the presented PN model was that it was defined and analysed for a single bridge component. Although, the model has been designed to have input/output functionality to facilitate inclusion into a hierarchical global structure model in the future, which should enable the reporting of additional factors such as required asset possession time for interventions. Nonetheless, before modelling at the level of the whole structure, further analysis should be performed to identify the interactions between defect mechanisms across multiple bridge components. Finally, the methodology should be extended to additional material types such as masonry and concrete, which have their own respective mechanisms and interactions.

CRediT authorship contribution statement

Gareth Calvert: Conceptualization, Methodology, Software, Formal analysis, Data curation, Writing – original draft, Writing – review & editing. **Luis Neves:** Conceptualization, Methodology, Formal analysis, Writing – review & editing. **John Andrews:** Conceptualization, Writing – review & editing. **Matthew Hamer:** Validation, Data curation, Writing – review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgements

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