PRELIMINARY STUDY ON BRIDGE HEALTH PREDICTION USING DYNAMIC OBJECTIVE ORIENTED BAYESIAN NETWORK (DOOBN)

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The availability of bridges is crucial to people's daily life and national economy. Bridge health predication plays an important role in bridge management because maintenance optimization is implemented based on prediction results of bridge deterioration. Conventional bridge deterioration models can be categorised into two groups, namely condition states models and structural reliability models. Optimal maintenance strategy should be carried out based on both condition states and structural reliability of a bridge. However, none of existing deterioration models considers both condition states and structural reliability. This study thus proposes a Dynamic Objective Oriented Bayesian Network (DOOBN) based method to overcome the limitations of the existing methods. This methodology has the ability to act upon as a flexible unifying tool, which can integrate a variety of approaches and information for better bridge deterioration prediction. Two demonstrative case studies are conducted to preliminarily justify the feasibility of the methodology.

Keywords: Bridge health prediction, Dynamic object oriented Bayesian network (DOOBN), Condition States, Structural reliability

1. INTRODUCTION

Bridges are regarded as critical components of a transport network. The availability of bridges is crucial to people's daily life and to the national economy. Any damages or faults during the service lives of bridges could lead to severe consequences such as transport paralysis, costly maintenance or even catastrophic loss of life or casualties. Nonetheless, due to aggressive environmental conditions, ever-increasing and changing traffic loading effects and bridge itself aging, lifelong maintenance care becomes critical. In Australia, the maintenance cost for over 33,500 bridges could be approximately AUD$ 100 Million per annum[1]. However, a large portion of this maintenance cost has been wasted due to ineffective maintenance. Financial funding for bridge maintenance also suffers from constraints. As the concern for economically sustainable maintenance practices increases, bridge managers/owners have resorted to bridge management systems (BMS) for maintenance decision making. Bridge management systems have been developed to assist decisions making starting from bridge design , material selection, maintenance optimization, rehabilitation and replacement (MR&R) for bridge networks under financial constraints[2]. To a great extent, the quality of the decisions made by BMS depends on the ability to predict the future health condition of a bridge, i.e., bridge deterioration plays a chief role in any bridge management process. The capabilities and reliability of bridge deterioration modelling techniques are crucial for the effectiveness of bridge management system[3].

Various bridge deterioration models have been developed for BMS. These models can be largely categorised into two groups, namely condition states models and structural reliability models. Condition states models include stochastic process models, Markov chain models, fault tree and artificial intelligence models. They mainly focus on deterioration process of a bridge element in visual terms, such as, corrosion and crack, while, structural reliability models, which are based on limit state functions, mainly concentrate on load carrying capacity of a bridge in terms of strengths and stresses. Condition states models are currently dominant in bridge management systems. However, some researchers are confident that future bridge management systems will be based on time-dependent structural reliability[4].Experience gained in different countries shows that the major part of the maintenance work on existing bridges depends on the load-carrying capacity (or structural reliability) of the bridge system rather than the condition states of the bridge elements alone[5]. Comprehensive assessment of bridge deterioration requires probabilistic modelling in terms of both condition states and structural reliability. So far, there are not generally applicable model yet. And each model has its advantage and disadvantage. Furthermore, better maintenance optimization strategies are based on comprehensive assessment of bridge deterioration. However, none of the existing bridge deterioration models are capable of addressing bridge deterioration process using condition states and structural reliability jointly.

To fill this gap, a DOOBN-based methodology is proposed in this paper for modelling bridge deterioration processes in terms of both condition states and structural reliability. DOOBN, which is an extension of Bayesian Network (BN), has shown various advantages. For instance, it can deal with dependencies among complex system and avoid “state space explosion”. As a unifying and intuitive modelling tool, DOOBN can integrate expert knowledge and observation information. It also has bi-directional updating ability and can account for temporal variability. Moreover, DOOBN is easy to be expanded for the purpose of maintenance optimization.

The remainder of this paper is organised as follows. Section 2 briefly introduces BN theory and the extension of BN, DOOBN. Section 3 presents bridge deterioration knowledge which includes deterioration mechanism in bridge and description of bridge deterioration in mathematical formula. The proposed DOOBN-based methodology for bridge deterioration is illustrated in Section 4. To prove the feasibility of the proposed methodology, two demonstrative case studies are conducted (section 5). Finally, section 6 gives the conclusions and perspectives.

2. BAYESIAN NETWORK THEORY

BN is a probabilistic model in the form of directed acyclic graphs (DAG) with the directed edges and a table of conditional probabilities of each variable on all its parents[6]. Figure 1 gives a simple example of BN. Each node represents a probability distribution of a variable, which may in principle be continuous state or discrete state. An arrow between two nodes indicates conditional dependence relationship of the variables that are represented by the nodes. The dependence relationship is represented by a set of conditional probability distribution. For instance, the probability of a dependent variable B being in a particular state given for each combination of the states of variable A is expressed as P(B|A). Nodes with arrows directed from other nodes are called child nodes (e.g. nodes B and C in Figure 1). Nodes without any arrows directed into them are called root nodes (e.g. node A in Figure 1). Prior probability tables or functions are held by root nodes.

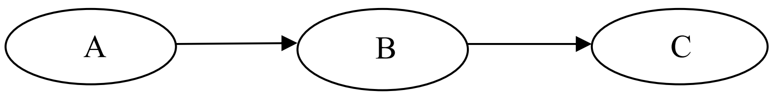

Figure1. A simple BN consisting of three variables

As an extension of conventional BN, an Object Oriented Bayesian Network (OOBN) contains, in addition to the usual nodes, instance nodes[7].The basic construction block in an OOBN is an object, which can be a physical or an abstract entity, or a relationship between two entities[8]. The object represents either a node or an instantiation of a network class (instance nodes). An example BN class for structural reliability of bridge components is shown in Figure 2, where input nodes are ellipses with shadow dashed and output nodes are ellipses with shadow bold line borders. An instantiation of this network class is also given in the Figure 2, which has one input $D_{(t-1)}$, and two outputs Cmp and $D_{(t)}$.

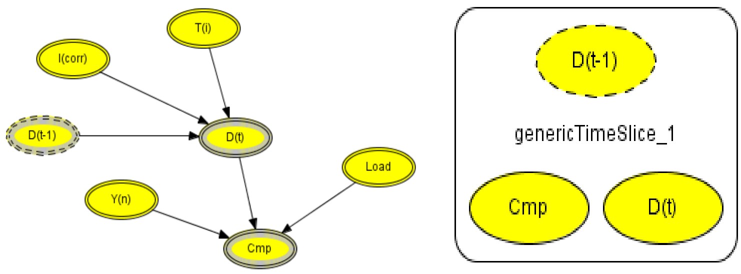

Figure2. A simplified BN class and its instantiation for structural reliability of bridge components

To address temporal behaviour of an OOBN, time slices are added to represent each period of interest and make an OOBN into a Dynamic Object Oriented Bayesian Network (DOOBN). Figure 3 shows a two-slice DOOBN. The input comes from output in previous time slice, and temporal behaviour can be described.

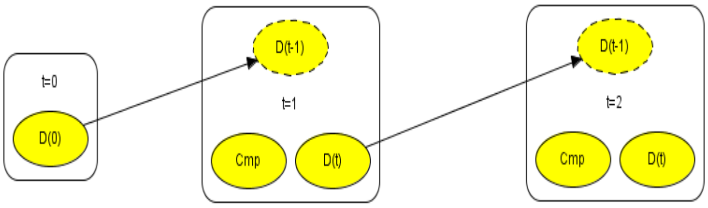

Figure3. A simple two-slice DOOBN for structural reliability of a bridge component

3. BRIDGE DETERIORATION KNOWLEDGE

In this paper, only bridges made of reinforced concrete and steel are considered. If bridge deteriorations are assumed to be a result of uniform corrosion, the deterioration processes of bridges can be described by the following equations:

- Reinforced concrete

Once the corrosion has occurred, the diameter of reinforced steel bar at any time D_t is reduced over time and modelled as a function of time as follows[9].

$$D_t = D_0 - C_{corr} i_{corr} (t - T_{corr}) \quad (1)$$

where D_0 is the initial diameter of reinforcement steel bars, C_{corr} is a corrosion coefficient, i_{corr} is the corrosion rate, T_{corr} is corrosion initiation time. The cross-section area of reinforced steel bar at any time A_t is given by

$$A_t = \frac{n\pi {D_t}^2}{4} \quad (2)$$

- Steel

If the effect of paint and coating is not considered, a power function is commonly used to describe corrosion propagation[10].

$$C = A \cdot t^B \quad (3)$$

where C is corrosion loss after t years, A is the corrosion loss after one year, and B is a regression coefficient numerically equal to the slope of Eq 3 in log-log plot. Both A and B are based on the environment and the type of steel. Eq 3 enables recalculation of geometric parameters, such as, plastic section area and web area for the purpose of reliability estimation.

4. PROPOSED METHODOLOGY

A DOOBN-based methodology for bridge deterioration prediction has been developed in this section. The flowchart of the proposed methodology is shown in Figure 4. Overall, the proposed methodology is defined through four modelling steps: bridge system analysis, formulation of DOOBN, parameter learning and inference for bridge deterioration. The first step aims to analyse the bridge system hierarchically to facilitate the formulation of DOOBN. Based on bridge system analysis, DOOBN is formulated through four aspects: behaviour, observation, maintenance and environment. The parameter learning accounts for discretization of continuous nodes, estimation of CPTs and priori probability of root nodes. Finally, inference algorithms are operated for bridge deterioration prediction.

4.1 Bridge system analysis

- *Hierarchical decomposition*

Hierarchical decomposition of a bridge is necessary for systematically modelling of the bridge. In light of a complex bridge, different decomposition strategies have been used. The bridge engineers who have their own understanding of bridges decompose the bridge based on their expert knowledge. Some standard regulations and guides for BMSs have been available to assist people to decompose a complex bridge. In this research, the strategy, which categorise bridge elements based on their functions, is preferred since bridge elements such as structural elements and non-structural elements can be distinguished. Therefore, the decomposition method proposed by Morcous[11] is adopted. It consists of seven levels of granularity: root bridge, bridge massing, bridge sub-system, bridge assembly, bridge sub-assembly and bridge element.

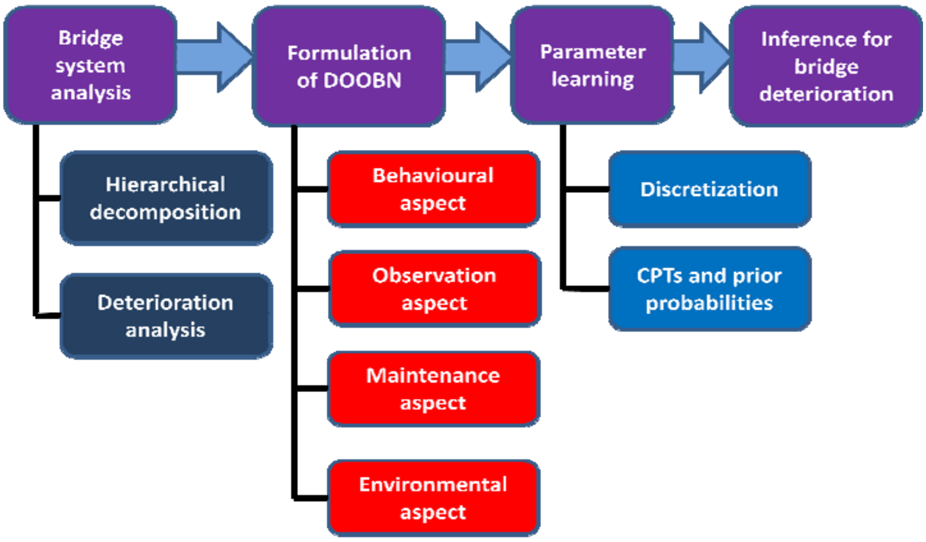

Figure 4.Flowchart of the proposed framework

- *Deterioration analysis*

Based on hierarchical decomposition of bridges above, this section identifies deterioration processes of bridge elements and develops limit state functions for bridge structural elements. The deterioration processes of bridge elements over time could be obtained from literature and expert knowledge. However, to systematically analyse the deterioration processes, it is better to implement Failure Mode and Effects Analysis (FMEA)[12], FMEA helps analyse each bridge element in details from failure causes to failure consequence.

For bridge structural elements, limit state functions need to be developed for structural reliability analysis. Limit state functions are always in the form of Resistance-Load. However, limit state functions should be formulated in details for each bridge element. As each element may have more than one failure mode, the development of limit state functions starts from selection of critical failure modes. Generally, failure modes of shear and moment are often considered. The performance functions for moment and shear failures in ultimate limit states are given by Equation 4 and Equation 5, respectively.

$$g_m = M_u - M_{dl} - M_{ll} \tag{4}$$

where M_u, M_{dl}, M_{ll} are moment capacity, moment due to dead load and moment due to live load, respectively.

$$g_{sh} = V_u - V_{dl} - V_{ll} \tag{5}$$

where V_u, V_{dl}, V_{ll} are shear capacity, shear due to dead load and shear due to live load, respectively.

4.2 Formulation of DOOBN

4.2.1 Behavioural aspect

This section aims to formulate DOOBN in terms of a bridge's behavioural processes. Based on bridge system analysis results, the modelling starts from bottom level (bridge elements) to top level (an entire bridge structure) and consists of two major modules: bridge element module and bridge system module. The first module focuses on formulation of bridge elements. The second module focuses on the formulation from bridge assembly to the entire bridge. Based on the formulation of bridge elements, bridge assembly is easily formulated. In addition, the entire bridge is gradually formulated based the formulation of bridge assembly.

- Bridge element module

For non-structural elements, as they do not bear any load, only their condition states are considered. Figure 5 shows a DBN of a non-structural element with temporal node C_k , which represents the non-structural element with discrete health states according to its deterioration processes from perfect states to failed states.

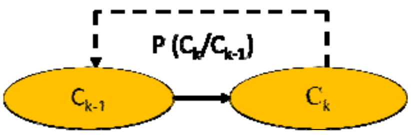

Figure 5.The DBN model of a non-structural element in a compact way

For structural elements, both condition states and structural reliability should be considered. The overall health states of a structural element are conditional on both its condition state and structural reliability (Figure 6).

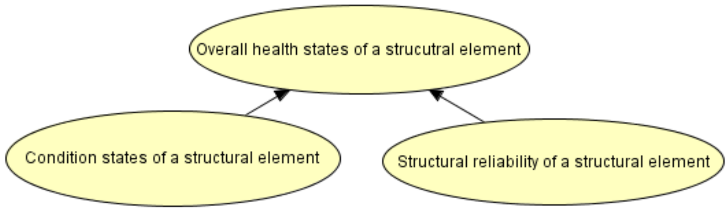

Figure 6.BN model of a structural element considering both condition states and structural reliability

The node for condition states of structural elements are modelled in the same way as non-structural elements. Since each structural element may have more than one failure mode in structural reliability, a network class is adopted to express overall structural reliabilities of structural elements with all types of failure modes. Figure 7 gives an example of a structural element with failure modes of shear and moment.

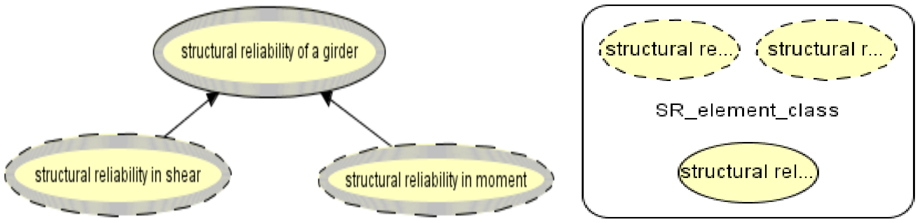

Figure 7.A network class and its instance node for structural reliability of a structural element

The further modelling of structural reliability in each failure mode is based on limit state functions. As mentioned in Section 3, bridge deteriorations are only assumed to be a result of uniform corrosion. Live load is assumed to be time-invariant. A generic limit state function that describes time-variant structural reliability with any types of failure mode as a function of time *t*, a set of time-invariant parameters **L**, and a set of time-variant model parameters $\mathbf{R}_t=\mathbf{R}(t)$,can be written as

$$gt = g(t) = f(t, \mathbf{L}, \mathbf{R}_t) \tag{6}$$

where **L** denotes all the parameters relating to Load and $\mathbf{R}_t$ denotes all the parameters relating to the resistance. This generic limit state function can be represented as DOOBN in Figure 8.In this figure, SR represents structural reliability in terms of one failure mode with two health states: safe and failed. R and L represent all the parameters related to resistance and load, respectively. Time node t represents change of time, which links to the deterioration of resistance over time.

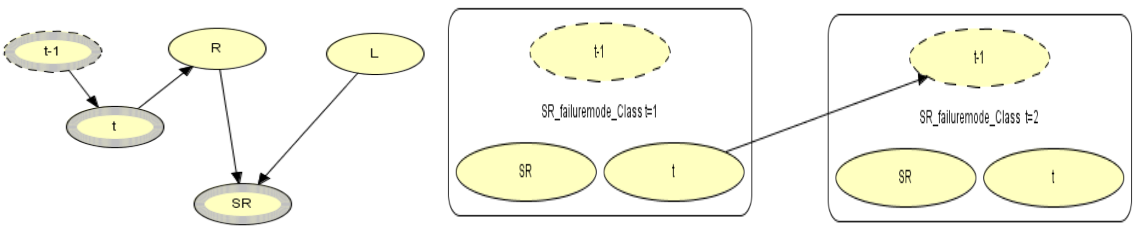

Figure 8.DOOBN modelling of a genetic limit state function that describes time-variant structural reliability in any type of failure modes

- Bridge system module

This module models the relationship between an assembly/sub-assembly and the entire bridge. In an assembly of a non-structural system, only condition states of non-structural elements need to be considered. A network class can be used, which has all the relating elements as inputs and the assembly as an output. However, in an assembly or sub-assembly of a structural system, both structural reliabilities and condition states of structural elements have to be considered. For modelling other bridge entities such as bridge system, bridge massing and the entire bridge, the modelling methods are the same as the one for bridge assembly. The bridge entities are modelled as a network class through OOBN and defined with discrete health states. Figure 9 illustrates the network class for an entire bridge. As the entire bridge is the highest level of modelling, no output nodes are defined further.

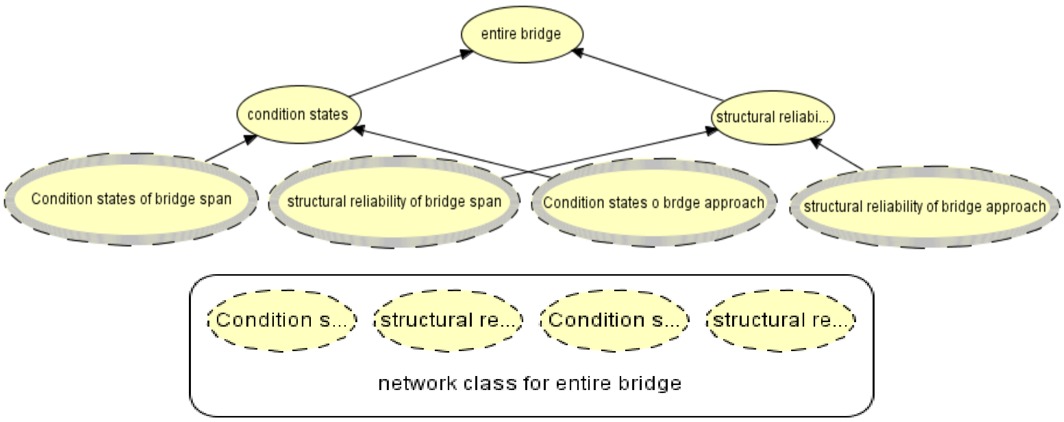

Figure 9.An network class modelling of an entire bridge and its instance node

4.2.2 Observation aspect

DOOBN is capable of computational and robust Bayesian updating when observation information (new evidence) is available, which is the major advantages of DOOBN. Observation information can be obtained through visual inspection, NDT (Non-Destructive Technology) and SHM (Structural health monitoring).Visual inspection provides straightforward information for bridge engineers, while both NDT and SHM provide indirect information which need to be further processed. Examples of such observations are fatigue crack size, corrosion rate, strain gages and failure/survival events.

For direct observation information from visual inspection, health conditions of an observed bridge element are determined by observation information directly. While for indirect observation information, observation information is conditional on health conditions of an observed bridge element. A direct edge representing conditional relationship between observation information and a bridge element is created. Furthermore, observation information is independent of the past and it is possible that observations may not be always available all the time.

4.2.3 Maintenance aspect

A maintenance variable is defined for each bridge element with five states: replacement, perfect repair, minimal repair, imperfect repair and no maintenance, to take into account planned/unplanned maintenance actions. Furthermore, replacement and perfect repair will bring bridge element into new state. Minimal repair and no maintenance keep a bridge element in the same state as before. Imperfect maintenance brings a bridge element into the state better than past state but worse than new state. In this research, imperfect maintenance is represented by the probability over possible health states of a bridge element. In addition, a maintenance variable has a direct impact on both condition states and structural reliability of a bridge element.

4.2.4 Environmental aspect

To take into account environmental factors, such as, traffic volumes, traffic loads, temperature, moisture and humidity, an environmental variable is defined with four states: benign, low, moderate and severe. The four environmental states are described as the ones in the PONTIS BMS[13]. Each bridge element is assigned with an environmental variable to address the impact of environment. Both condition states and structural reliability of a bridge element are affected by the environmental variable. In fact, the environmental condition has an influence on parameters for calculation of structural reliability. For instance, severe environment may bring high corrosion rate and earlier corrosion initiation time for corrosion in reinforced steel.

4.3 Parameter learning

After formulation of DOOBN in four aspects, this section is carried out with the purpose of estimation of CPTs and priori probabilities of root nodes for the DOOBN. Due to the limitation of current inference algorithms and slow convergence rate, continuous nodes cannot be dealt with efficiently. Furthermore, current inference algorithms do not allow continuous parent nodes to have discrete children nodes. However, this problem actually happens in this research. Therefore, continuous variables should be replaced by equivalent variables defined in finite states.

4.3.1 Discretization

The continuous variables in this research include some variables relating to estimation of structural reliability and some observation variables. Univariate discretization is chosen in this paper and is carried out sequentially from parent nodes to children nodes. Equal length intervals are chosen. Next, the discretization interval length is determined within the probable values range to make sure that the discretized distribution represents the original continuous distribution in a reasonable and accurate way. The probability of each discrete state is assigned with cumulative distribution probability over the corresponding discretization interval.

4.3.2 Estimation of CPTs and prior probabilities

Overall, learning processes for CPTs and prior probabilities in this research are based on three sources: statistic database, expert knowledge and physical laws. Eventually, a combination of the three sources can be used to get better estimation.

- Statistic database

CPTs can be estimated from statistic database. If all the variables in DOOBN are observable, maximum-likelihood (ML) is applicable. However, what makes the learning process difficult is that some of the variables are hidden. In this case, parameter learning methods such as gradient ascent and expectation maximization (EM) have to be applied[14]. Obviously, the quality of learning depends on the quantity and quality of available data. However, it is a difficult task to collect enough statistics data for estimation of CPTs.

- Expert knowledge

Bridge maintenance engineers may have a prior knowledge about deterioration processes of a bridge, which is called expert knowledge. Expert knowledge can be used straightforwardly to derive prior probabilities, transition probabilities between different condition states and conditional probabilities between different bridge elements. The efficiency and quality of this solution are totally dependent on expert abilities. However, due to the updating ability of the proposed DOOBN approach, the estimation of CPTs can be renewed when new data are available.

- Physical laws

In this research, physical laws are used to estimate the conditional probabilities of variables in structural reliability. Since modelling structural reliability is based on limit state functions and knowledge of corrosion in bridge deterioration, the conditional probabilities could be derived from the basic equations, such as, Equation 1-5, which also means the conditional relationships are deterministic.

4.4 Inference for bridge deterioration

After all the CPTs and prior probabilities have been specified, the network is run to predict the deterioration of the entire bridge structure and bridge elements in the future. This section is to implement inference algorithms to update the deterioration prediction of an entire bridge and bridge elements based on observed evidences. Moreover, inference algorithms can be used to update the deterioration estimations at current and past time as well.

However, a detailed description about the inference algorithms is beyond this research. In fact, numerous commercial softwares have been available, for instance, Hugin Expert, Bayesialab and Bayes Net Toolbox. These inference algorithms have been already implemented in these software packages. With the help of commercial softwares, prediction of bridge deterioration can be easily carried out.

5 CASE STUDIE

5.1 Deterioration modelling for condition states of a bridge deck system

A simple bridge deck system includes bridge deck, bearing, expansion joints and drainage system. There are failure dependencies phenomena among bridge deck, bearing, expansion joints and drainage system ,which are described as follows[15]: the malfunction of bridge drainage system can cause excessive rust or corrosion, which can lead to malfunction of both bearing and expansion; furthermore, the frozen bearing resists horizontal deck movement, and the expansion joints in malfunction prevent normal expansion and contraction, both of which could accelerate the deterioration of bridge deck and lead to malfunction. The DBN modelling is shown in Figure 10. Each bridge element is defined with a finite number of discrete conditions. Moreover, data for prior probabilities of each bridge element are available[15]. However, data with regards to CPTs are unavailable at all. Therefore, in this case study the CPTs are simulated with consideration of deterioration processes of each bridge element. Furthermore, the CPTs were assumed time-invariant and maintenance actions are not considered in this case study.

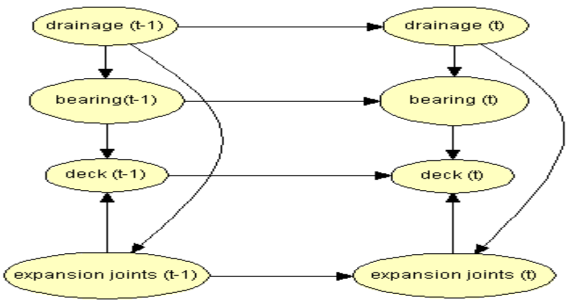

Figure 10.Failure dependencies modelling as a DBN

At initial time the four bridge elements were assumed in "good" condition. The deterioration of the four elements over 50 years was predicted using inference algorithms in the software "GeNIe and SMILE" (Figure 11). A main merit of DBN is the Bayesian updating alibility when new evidence is available. If the bearing is observed in corrosion at 10th year, the deterioration processes of the four elements are also renewed (Figure 12).From the figure, we can see that due to the deterioration of bearing, the deterioration of the deck is accelerated, and the beliefs in "good" condition for both drainage and expansion joints also decrease.

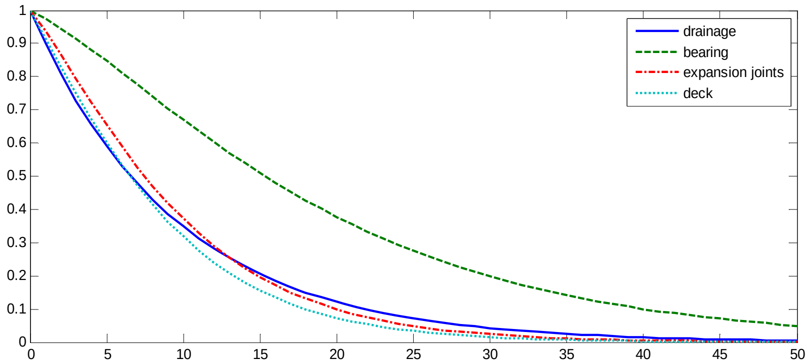

Figure 11.Probabilities of the four bridge elements in "good" condition over 50 years

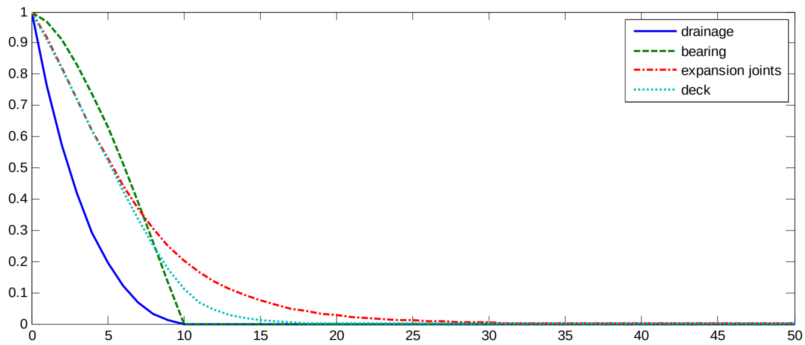

Figure 12.Updated probabilities of the four bridge elements in "good" condition over 50 years with an observation that bearing is in corrosion when t=10 year

5.2 Deterioration modelling of structural reliability in shear for a steel girder

In this case study, a limit state equation for shear failure in a steel girder was chosen from PhD thesis written by Estes[9].

$$g = V_{capacity} - V_{Demand} = 10.55F_y - 18.04\lambda_{conc} - 5.26\lambda_{asph} - 2.89\lambda_{steel} - 28.33V_{trk-i}DF_iI_{beam} \tag{7}$$

where F_y is yield strength of steel in girders; λ_{conc} is uncertainty factor for weight of concrete on deck; λ_{asph} is uncertainty factor for weight of asphalt on deck; λ_{steel} is uncertainty factor for weight of steel girders; V_{trk-i} uncertainty factor for live load shear in girder; DF_i is uncertainty for live load girder distribution; I_{beam} uncertainty factor for impact on girder. To take into account temporal behaviour of bridge deterioration due to corrosion, Equation 7 is rewritten into Equation 8 according to Equation 3.

$$g = 18.183F_y\left(0.58 - \frac{At^B}{12700}\right) - 18.04\lambda_{conc} - 5.26\lambda_{asph} - 2.89\lambda_{steel} - 28.33V_{trk-i}DF_iI_{beam} \tag{8}$$

where t is time variable; A is the corrosion loss after one year; B is a regression coefficient numerically. All the parameters can be found from [9].After rewriting Equation 8 into Equation 9-14, The DOOBN is shown in Figure 13, where SR denotes time-variant structural reliability and has two states: safe and failed.

$$g = R - L \tag{9}$$

$$R = 18.183F_y\left(0.58 - \frac{d_{corr}}{12700}\right) \tag{10}$$

$$d_{corr} = At^B \tag{11}$$

$$L = V_{dl} + V_{ll} \tag{12}$$

$$V_{dl} = 18.04\lambda_{conc} + 5.26\lambda_{asph} + 2.89\lambda_{steel} \tag{13}$$

$$V_{ll} = 28.33V_{trk-i}DF_iI_{beam} \tag{14}$$

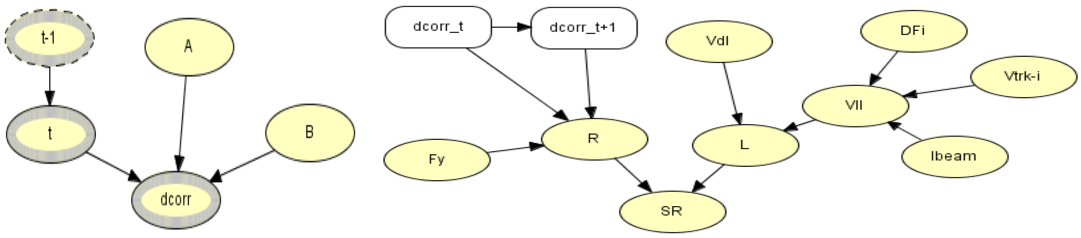

Figure 13.Shear structural reliability modelling of a steel girder as a DOOBN

By implementing inference algorithms, the DOOBN predicts deterioration of the steel girder over 50 years in terms of reliability index. The results are compared with results obtained with FORM (Figure 14). The comparison demonstrates the accuracy of the DOOBN approach.

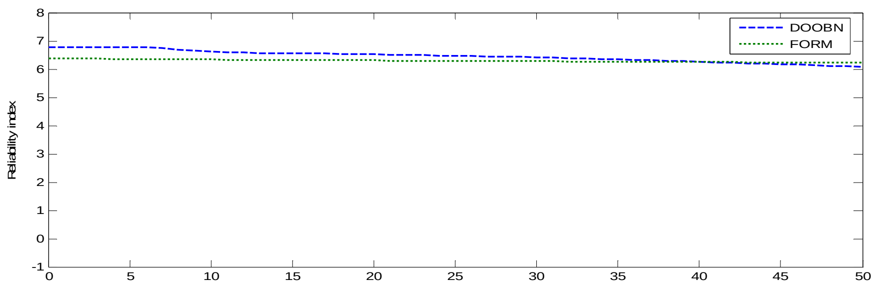

Figure 14.Comparison of prediction results between DOOBN and FORM

6 CONCLUSION AND DISCUSSION

A DOOBN-based methodology has been proposed in this paper to address bridge deterioration processes using both condition states and structural reliability jointly. The entire methodology includes four steps: bridge system analysis, formulation of DOOBN, parameter learning, and inference. Two case studies have been conducted to preliminarily validate the proposed methodology. From the first case study, we can see that DBN is capable of modelling failure dependencies between bridge elements. Temporal variability in failure dependencies and new observation information can be taken into account. The second case study demonstrates that the DOOBN can accurately predict bridge structural reliability. The approach allows the modelling of temporal behaviour of bridge deterioration processes caused by corrosion. The outcome of the case studies illustrates that the methodology developed in this study poses a great potential for bridge health prediction.

Further investigation on applicability of the approach in practical bridge health prediction using real life data is proposed in the next stage of study. The extended study aims to validate bridge deterioration model in terms of both condition states and structural reliability. For instance, the discretization schema in parameter learning may not be optimal. Appropriate data sources have to be chosen for estimations of CPTs and prior probabilities.

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