Condition deterioration prediction of bridge elements using Dynamic Bayesian Networks (DBNs)

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Abstract—**The ability of bridge deterioration models to predict future condition provides significant advantages in improving the effectiveness of maintenance decisions. This paper proposes a novel model using Dynamic Bayesian Networks (DBNs) for predicting the condition of bridge elements. The proposed model improves prediction results by being able to handle, deterioration dependencies among different bridge elements, the lack of full inspection histories, and joint considerations of both maintenance actions and environmental effects. With Bayesian updating capability, different types of data and information can be utilised as inputs. Expert knowledge can be used to deal with insufficient data as a starting point. The proposed model established a flexible basis for bridge systems deterioration modelling so that other models and Bayesian approaches can be further developed in one platform. A steel bridge main girder was chosen to validate the proposed model.**

Keywords- Bridge deterioration models; Condition ratings; Dynamic Bayesian Networks (DBNs); Expert knowledge

ACRONYM

BMS	bridge management system
CPTs	conditional probability tables
DBNs	Dynamic Bayesian Networks
DAG	directed acyclic graphs
EM	Expectation-maximization
HMM	Hidden Markov Model
MLE	maximum likelihood estimation
NDT	Non-Destructive Technology
PoD	probability of detection

I. INTRODUCTION

Over the last several decades due to increasing urbanisation, a large number of bridges for transport networks have been built. The sustainable maintenance of these bridges has been drawing increasing attention recently because of constrained budget funding and ineffective maintenance. Bridge management systems (BMS) are designed to consider decisions in the design and selection of materials, maintenance optimization, and the rehabilitation and replacement (MR&R) of bridge networks under financial constraints [1]. In BMS, bridge condition ratings, estimated from visual inspection in the form of numerical codes, have been commonly used as an indicator of bridge deterioration describing the extent and severity of bridge damages. Significantly, the ability of bridge deterioration models to predict future condition determines the quality of maintenance decisions. Nonetheless, aggressive environmental conditions, ever-increasing and changing traffic loading effects, and bridge aging all make accurate prediction difficult.

The existing models for condition prediction can be categorized into three main groups, namely, deterministic models [2], stochastic process models [2-4] and artificial intelligence models [5-7]. Among them, one of the most commonly used discrete time stochastic process models is the Markov chain (MC) model. Now it has been largely applied in the state-of-art BMS, such as Pontis [8] and BRIDGT [9]. However, it has limitations, such as indirect incorporation of observed data and "state space explosion" [7]. Bayesian Networks (BNs) are such an effective approach that can inherit the advantages of MC while overcoming its limitations. With inference ability, BNs can update and integrate newly obtained data directly. The latent nature of bridge deterioration can be modelled by BNs as well by means of observation variables. BNs can model a complex system in a compact representation of all the variables through localized network clusters, thereby avoiding the "state space explosion" problem of MC. They have been widely used in many areas such as risk assessment and reliability assessment [10-12].

This paper proposes a novel model using Dynamic Bayesian Networks (DBNs) for condition deterioration prediction of bridge elements. The proposed model improves prediction results by being able to handle, deterioration dependencies among different bridge elements, the lack of full inspection histories, and joint considerations of both maintenance actions and environmental effects. Based on the Bayesian updating ability, different types of data can be adopted. Expert knowledge can be used for prediction in case historical condition data are insufficient. The implementation of this model in software facilitates integrated bridge management for the purpose of maintenance optimization. In addition, this model will pave the way for bridge systems deterioration modelling using other Bayesian approaches.

The rest of this paper is organised as follows. Section 2 provides a brief introduction of BN theory and its dynamic representation. In the next section, the DBNs based model is formulated in detail, and consists of conceptual model development and parameters estimation. Furthermore, this model is validated through a steel main girder in Section 4, where its condition ratings over 100 years are predicted. Finally, Section 5 provides the conclusions and future work.

II. BN Theory

According to Jensen and Nielsen [13], a 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. Fig.1 gives a simple example of BN. Each node represents a probability distribution of a variable, which may in principle be continuous states or discrete states. Nodes X_2 and X_3 with arrows directed from other nodes are called child nodes, and they have a common parent node X_1. Nodes without any arrows directed into them are called root nodes. An arrow between two nodes X_1 and X_2 indicates conditional dependence between the two variables that are represented by the two nodes. The dependence relationships are represented by a set of conditional probability tables (CPTs). For instance, the probability of a dependent variable X_2 being in a particular state given for each state of variable X_1 is expressed as $P(X_2|X_1)$. Prior probability tables or functions are held by root nodes.

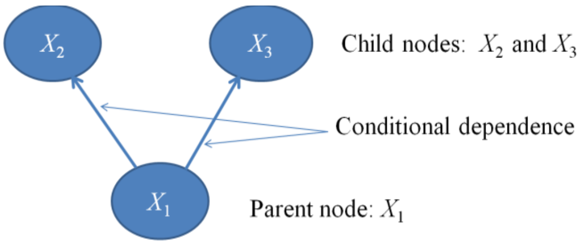

Figure 1. A simple BN consisting of three variables

As the probability of each variable is defined conditional on its parents, the joint probability of this network $p\{X_1, X_2, X_3\}$ is specified as a product of these conditional probabilities

$$P\{X_1, X_2, X_3\} = P\{X_1\}P\{X_2|X_1\}P\{X_3|X_1\} \qquad (1)$$

where $P\{X_2|X_1\}$ and $P\{X_3|X_1\}$ are conditional probabilities given X_1, respectively, and $P\{X_1\}$ is prior probability. Moreover, with the assumptions of the Markov property and conditional independence (d-separation[14]), the joint probability for any BN is given as

$$p(\boldsymbol{X}) = p\{X_1, \cdots, X_n\} = \prod_{i=1}^{n} p(X_i|Pa(X_i)) \qquad (2)$$

where $Pa(Xi)$ is the set of parents of node X_i. One distinctive advantage of BN is its inference ability in calculating beliefs of events based on new observed evidence. The beliefs (probabilities) are updated in accordance with observation using Bayesian updating. Assume an evidence e is observed, we can then have

$$p(\boldsymbol{X}|e) = \frac{p(\boldsymbol{X},e)}{p(e)} = \frac{p(\boldsymbol{X},e)}{\sum_{X} p(\boldsymbol{X},e)} \qquad (3)$$

Dynamic Bayesian Networks (DBNs) is a special class of BNs which includes a temporal dimension. A DBN is also referred to as a more general state space model, of which the two most common kinds are Hidden Markov Models (HMMs) and Kalman Filter Models (KFMs) [15]. An example is shown in Fig 2. The DBN consists of a sequence of time slices (t, t+1, … , t+n). In each slice, there are one or more BN nodes. Two adjacent time slices are connected by direct links between them. These direct links represent temporal probabilistic dependence, which leads to the definition of CPTs. Normally, the Markov property is held by DBNs. If the model structure and the CPTs are identical all the time except for the initial time, DBNs are homogenous. A introduction about DBNs in details which includes representation, exact and approximate inference, and learning algorithms was provided by Murphy [15].

III. DBNs Based Model for Condition Deterioration Prediction

A. Conceptual model development

Generally, the deterioration processes of bridge elements are normally modelled by stochastic processes, such as Markovian [2] or semi-Markovian stochastic processes [3], and Gamma [4] and Gaussian processes. In principle, both discrete-time and continuous-time stochastic processes are applicable. For simplicity, a discrete-time Markov process is employed to model the deterioration of bridge elements in this study. Additionally, the process can be homogeneous or non-homogeneous. If one bridge element E is defined with H exclusive condition ratings, Fig. 3 describes an DBN model representing the temporal deterioration of bridge element E between time t-1 and t by means of discrete-time Markov process defined by CPT of variable $E(t)$.

To ensure modelling consistency with regard to actual deterioration of bridge elements, deterioration factors related to

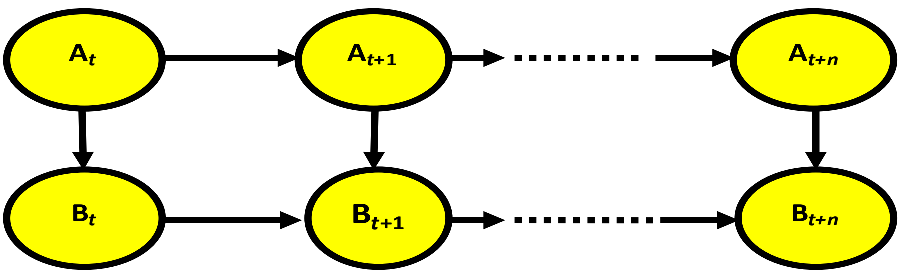

Figure 2. A simplified BN class and its instantiation

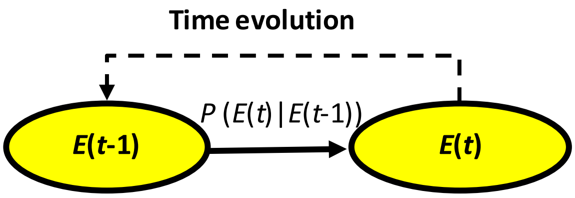

Figure 3. A DBN model for bridge element *E*

maintenance actions, environmental effects and observed information should be considered jointly. As these factors are independent of the past, a set of variables **X**(t), **Y**(t) and **Z**(t) related to maintenance actions, environment levels and observation, respectively, can be individually added to the DBN model in each time slice (Fig. 4). The maintenance variables **X**(t) are defined for each bridge element with several states according to available maintenance actions. Different maintenance actions have different impacts on the deterioration of bridge elements. For one bridge element, the probabilities over all the possible condition ratings can be used to express imperfect maintenance actions. The environmental variables **Y**(t) account for environmental effects, such as, traffic volumes, traffic loads, temperature, moisture and humidity. Four environmental states in the PONTIS BMS [16]: benign, low, moderate and severe are adopted. If a common environmental variable is considered, the environmental variable of each bridge element can be connected to one common environmental variable. The observation variables **Z**(t) facilitate Bayesian updating when newly observed condition ratings data are available. Observations from visual inspection can directly reflect true condition ratings of bridge elements, while Non-Destructive Technology (NDT) and monitoring techniques only provide indirect information about bridge deterioration. All this information can be characterized by either a probability of detection (PoD) or measurement accuracy.

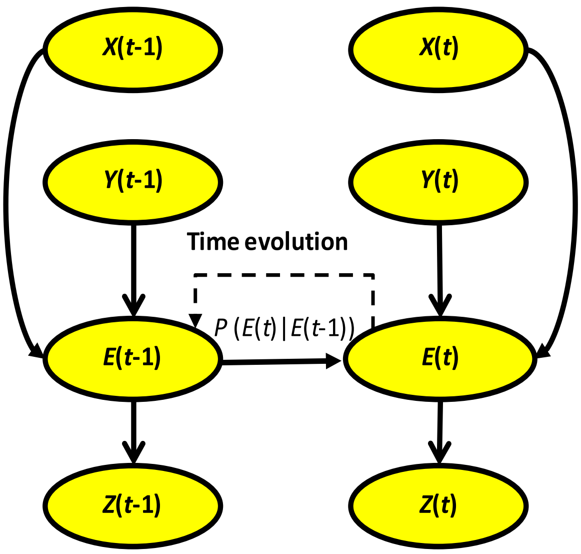

Figure 4. DBNs model for a generic bridge element *E* considering deterioration factors

B. Parameters estimation

- Bridge condition data

A BMS may have a bridge database including inventory data, condition ratings data (inspection data), appraisal data and maintenance data as well as monitoring data. By means of learning algorithms, all the CPTs related to bridge elements can be estimated based on the database. To date, a number of learning algorithms available have been listed by Murphy [15]. In practice, it is more realistic to estimate CPTs from condition ratings data for bridge elements modelled in Fig. 3. Normally, reliable CPTs estimation requires that at least two consecutive historical condition ratings data without maintenance intervenes are available. In this study, for simplicity, the bridge elements deterioration is assumed to follow a discrete-time Markov process. Two commonly used methods are the non-linear least square optimization method and the maximum likelihood estimation (MLE) method. In addition, if the available data are not completed, the Expectation-maximization (EM) algorithm will be more appropriate for CPTs estimation.

- Expert knowledge

Bridge practitioners with long-term working experience can acquire comprehensive bridge deterioration knowledge from their practice. The knowledge is referred to expert knowledge and can be used to estimate CPTs directly. Since these expert judgments have been verified in practice, it is straightforward to derive parameters based on them. The elicitation process normally consists of five steps [17]: experts selection, experts training, questions preparation, expert judgement elicitation and results verification. Several bridge maintenance engineers need to be selected according to their expertise and working experience. Since most of these engineers would more than likely, not be constant probability assessment, training courses should be provided. Additionally, the elicitation questions must be carefully designed to avoid subjective judgments. For instance, "What is the probability of a bridge element *E* being in condition rating *K* given all the information *X*?" or as "How likely is a bridge element *E* in condition rating *K* given all the information *X*?" Then the elicitor would present these bridge maintenance engineers the prepared questions and answers so derived. The obtained answers should be checked carefully by the elicitor in order to exclude any incorrect answer. The answers can be converted into conditional probabilities directly or indirectly. If the bridge maintenance engineers cannot indicate exact numbers but only a few words for his/her degree of beliefs on a scale, for instance, certain (100%-90%), probable (90%-75%), likely (75%-50%), unlikely (50%-25%), improbable (25%-10%), impossible (10%-0), the average number of each scale can be seen as the estimated probabilities. Other issues related to probability elicitation from expert knowledge can be found from [17].

Basically, some CPTs can be filled in by the developer based on miscellaneous knowledge. For instance, maintenance variables have a dominant influence on bridge element deterioration compared with other variables. By defining the impacts of different maintenance activities, CPT of a bridge element can be identified partially. CPTs of observation nodes can be estimated based on the nature of inspection methods. For instance, if observed information is obtained through visual inspection, the CPT of this observation associated to a bridge element is set to be 1. Moreover, if observations are obtained from NDT or monitoring techniques, CPTs can be estimated from a probability of detection (PoD) model or measurement accuracy, respectively.

Overall, parameters estimation could be undertaken according to the data availability. In this paper, because of lack of condition data, expert knowledge is chosen.

IV. Case Study

A. DBNs model construction

In this study, the proposed model was applied to a bridge element for condition prediction. A bridge main girder was selected from the "Albert Bridge", a railway bridge located in Brisbane, Queensland. In this paper, we predict the condition evolution over 100 years. Environmental effects and maintenance actions as well as simulated observations were all considered. Four environmental levels [16]: Benign, Low, Moderate and Severe, were used, and the maintenance actions were assumed to be perfect. The conceptual DBNs model for the bridge main girder is presented in Fig.5.

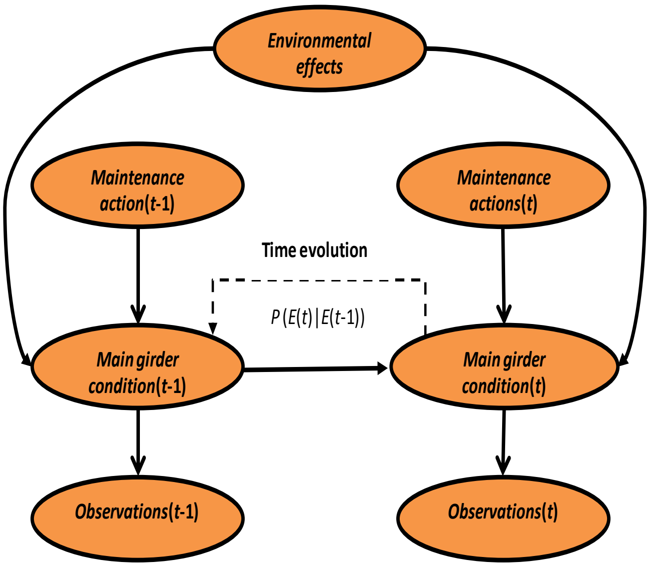

Figure 5. DBNs model for a steel bridge main girder

According to data availability, the CPTs were essentially estimated from expert knowledge. Bridge practitioners were able to provide their estimation about relative percentages of each condition rating under different environmental levels over a period of time. The least squares method as shown in (1) were employed so that the differences between expert estimation and the expected percentages predicted from transition probabilities were minimized.

$$min \sum_{m=1}^{M}\sum_{n=1}^{N}\left(P_{m,n} - (P_0\boldsymbol{T}^n)_m\right)^2 K(n)$$

Subject to $0 \leq T_{i,j} \leq 1 \quad i, j = 1,2,\ldots,M$

$$\sum_{j=1}^{M} T_{i,j} = 1 \tag{1}$$

where P_0 is a vector of the initial condition rating of a bridge element which is always assumed to be in good condition; $P_{m,n}$ is the actual relative percentage in condition m at age n (Here it is estimated from bridge experts); $\boldsymbol{T}$ is the estimated transition probabilities matrix defined over a certain transition period; M is the number of condition states; N is the number of years of condition data available; $K(n)$ is the number of bridge elements at age n for weighting each term.

The CPTs were derived using the Optimization Toolbox in MATLAB. Table I presents the estimated CPT associated with the bridge main girder under the environmental level of "low". It describes the discrete-time Markov process that models the deterioration of a bridge main girder with the considerations of environmental effects and maintenance actions.

B. Prediction Results

The DBNs model is supported by the software GeNIe [18], which actually runs the inference algorithm for the condition prediction. The bridge element is initialized with the condition rating showing no damage at all. To demonstrate the Bayesian updating ability, a perfect maintenance action was simulated to the bridge main girder at its 50th year. This maintenance action renewed the main girder into the condition "Sound paint". Moreover, four visual inspection records in Table II were simulated over 20 years. With a five-year interval, visual inspection was implemented to rate the conditions of bridge main girders. The percentages over all the conditions were listed in Table II.

TABLE I. The CPT of a main girder under the environmental level of "Low"

Environmental condition levels	Low							
Maintenance action	**No maintenance**				**Maintenance**			
Main girder self (t-1)	**Sound paint**	**Paint distress**	**Active corrosion**	**Strength loss**	**Sound paint**	**Paint distress**	**Active corrosion**	**Strength loss**
Sound paint	*0.9802*	*0*	*0*	*0*	*1*	*1*	*1*	*1*
Paint distress	*0.0198*	*0.9019*	*0*	*0*	*0*	*0*	*0*	*0*
Active condition	*0*	*0.0981*	*0.9445*	*0*	*0*	*0*	*0*	*0*
Strength loss	*0*	*0*	*0.0555*	*1*	*0*	*0*	*0*	*0*

The condition predictions of the bridge element in the next 100 years under different environmental conditions were generated. In the first scenario, Fig. 6 presents the evolution curve under the environmental level of "moderate" over 100 years. At the 50th year, the condition rating was renewed because of a maintenance activity. In the second scenario, the observed information in Table II was used to update the prediction. The original and updated evolution curves under the condition level of "Low" over 100 years are presented in Fig. 7 and Fig. 8, respectively. By comparison, we can see that the condition evolution curves have been updated dramatically. The Bayesian updating ability has been demonstrated through these two scenarios.

TABLE II. VISUAL INSPECTION RESULTS OF THE BRIDGE MAIN GIRDER

Inspection time (year)	5	10	15	20
Sound paint (%)	*100*	*50*	*0*	*0*
Paint distress (%)	*0*	*50*	*50*	*0*
Active condition (%)	*0*	*0*	*50*	*5*
Strength loss (%)	*0*	*0*	*0*	*95*
Total (%)	*100*	*100*	*100*	*100*

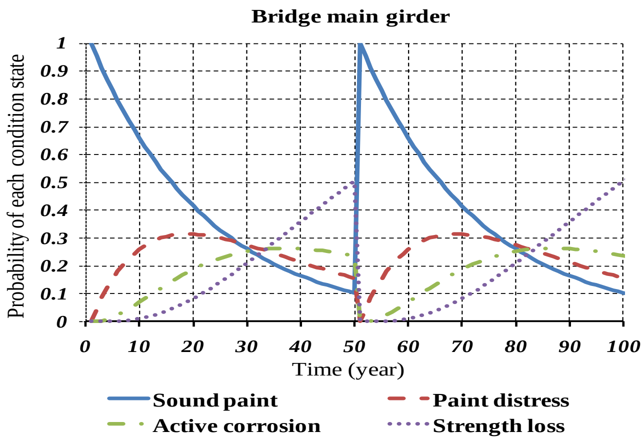

Figure 6. Condition prediction of the bridge main girder over the next 100 years under the environmental level of "Moderate" and a perfect maintenance action at 50th year

V. CONCLUSIONS AND FUTURE WORK

A DBNs based model has been proposed in this paper to predict condition deterioration of bridge elements. The model includes DBNs formulation and parameters estimation. A steel bridge main girder was selected to validate the applicability of the proposed model. It has been demonstrated that the model, possessing Bayesian updating, has the ability to consider multiple deterioration factors jointly. Two scenarios have been conducted to show the Bayesian updating ability. The potential application includes bridge health prediction and integrated management for bridge maintenance optimization. The applicability of the proposed model will be further investigated with a focus on other types of bridge elements. We believe the proposed model can be extended to the prediction of condition prediction of the whole bridge systems.

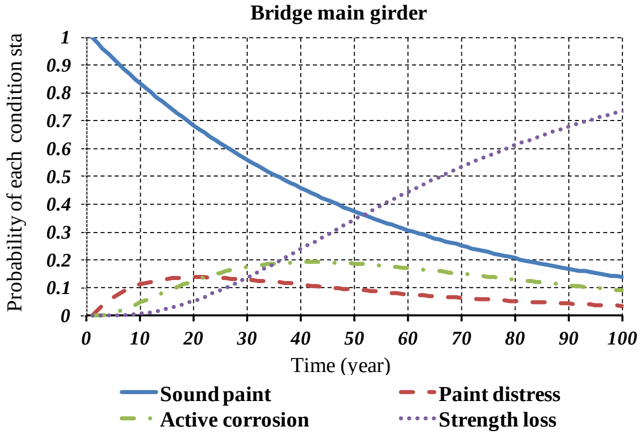

Figure 7. Original condition prediction of the bridge main girder over the next 100 years under the environmental level of "Low"

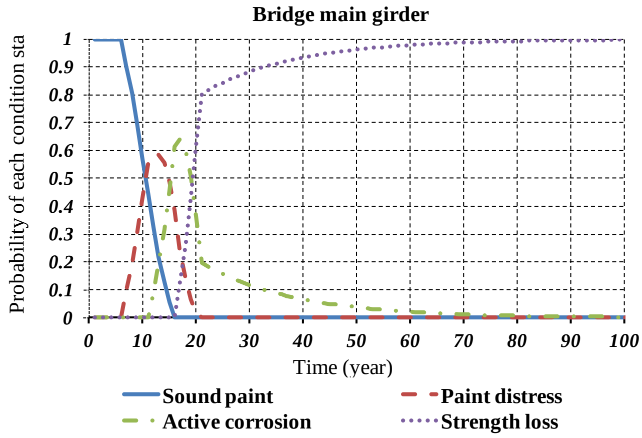

Figure 8. Updated condition prediction of the bridge main girder with visual inspection

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