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An Integrated System for Bridge Management Using Probabilistic and Mechanistic Deterioration Models: Application to Bridge Decks

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Abstract

This paper presents a system for the maintenance management of aging highway bridges that integrates two different approaches for deterioration modeling. Probabilistic state-based/time-based models are used to predict the macro-response of bridge components for network level analysis, while reliability-based mechanistic models are used to predict the micro-response of bridge components for project level analysis. Probabilistic state-based/time-based models are developed using qualitative performance indicators (condition ratings) that are determined through visual inspections to identify the overall condition of damaged components in a bridge network. Reliability-based mechanistic models are developed using quantitative performance indicators (physical parameters) that are determined through detailed condition surveys, analytical assessments, and empirical investigations to identify the extent and severity of specific deterioration mechanisms for safety critical structures and/or highly damaged components. The condition rating data obtained from the Ministére des Transports du Québec database and the condition assessment of the Dickson Bridge in Montreal, Canada were used to demonstrate the two approaches for predicting the deterioration of concrete bridge decks at the two levels of management of the integrated system.

Keywords: *bridge deck, condition rating, deterioration model, Markov chain, maintenance management, mechanistic models, probabilistic models*

1. Introduction

Bridge Management Systems (BMSs) have been developed to assist decision makers in maximizing the safety, serviceability and functionality of bridge networks within the available budget by making cost-effective maintenance, rehabilitation, and replacement (MR&R) decisions (Hudson, 1987). The quality of these decisions depends primarily on the accuracy and efficiency of the deterioration models used to predict the time-dependent performance and remaining service life of highway bridges (AASHTO, 1993). By definition a deterioration model is a link between a measure of infrastructure condition that assesses the extent and severity of damages, and a vector of explanatory variables that represent the factors affecting infrastructure deterioration such as age, material properties, applied loads, environmental conditions, etc. (Ben-Akiva and Gopinath, 1995). The inherit random nature of these variables, existence of other variables that are not typically observed or measured, and use of simplified physical models and statistical assumptions lead to a wide variation in the condition of bridge components. This variation necessitates the use of probabilistic models to capture the stochastic nature of the deterioration process and the uncertainty associated with predicting future conditions.

In general, the deterioration of infrastructure facilities is a continuous and cumulative process that may span over several decades. Discrete ratings or states are commonly used to represent facility condition as they simplify facility inspection, deterioration modeling, and maintenance optimization. An example is the ordinal condition rating system adopted by the Federal Highway Administration (FHWA) since 1970s to evaluate the condition of primary bridge components (i.e., substructure, superstructure, and deck) (FHWA, 1995). A condition rating from 0 to 9 is assigned to each bridge component during the biannual visual inspections and the ratings accumulated over the years in the National Bridge Inventory (NBI) database are used for developing deterioration models. Other examples are the condition states used by several BMSs in North America and Europe, such as Pontis, Ontario BMS, Quebec BMS, and KUBA-MS (Pontis, 2005; Thompson *et al.*, 2003; Ellis *et al.*, 2008; Roelfstra *et al.*, 2004).

Discrete condition ratings are used to develop probabilistic deterioration models for bridge components. Although these

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models are easy to develop/update, simple to use, and efficient when applied to large-size networks, they have some limitations when applied to the analysis of safety-critical components and for detailed analysis at the project level (Lounis, 2000). The most important limitation is the reliability and consistency of the condition ratings, which rely heavily on the subjective judgment of bridge inspectors rather than being explicitly linked to quantitative physical parameters, such as material properties, stress conditions, structural behavior, etc. In that regard, the FHWA has initiated an investigation to evaluate the reliability and accuracy of visual inspections of highway bridges in the United States (Moore *et al.*, 2001). This investigation has concluded that 95% of condition ratings of primary bridge components vary within plus or minus two rating points on the 0-to-9 scale from the average condition rating, while only 68% of condition ratings vary within plus or minus one rating point from the average (Phares *et al.*, 2004). This significant variability indicates the subjective nature of visual inspections and inaccuracy of the resulting condition ratings. In addition, the lack of information about the type of material damages, their location within the component, their rate of propagation, and most importantly, their consequence hinder the use of these qualitative performance indicators (i.e., condition ratings) for modeling the deterioration of safety-critical components and project-level decision making. Although the use of conditions states in recent BMSs to quantify the severity and extent of damage for each bridge element has resulted in improved accuracy, these condition states still inherit the subjective nature of visual inspections and lack of information on the initiation and propagation of damage.

On the other hand, quantitative performance indicators that are explicitly linked to the physical parameters of the damaged components can be used to develop reliability-based mechanistic deterioration models. These models can accurately predict the initiation, propagation, and failure induced by different damage mechanisms, such as corrosion, fatigue, overstress, for safety-critical structures and project-level analysis. However, reliability-based mechanistic models can be quite costly in terms of data needs and modeling. Hence, despite their improved accuracy, these models can be quite inefficient when applied to every bridge component in a network that may consist of hundreds or thousands of bridge structures with several failure modes and different consequences of failure.

Therefore, a bridge management system that integrates state-based/time-based probabilistic deterioration models with reliability-based mechanistic models represents a balanced solution to the problem at hand. A simple architecture of such a system that achieves the desired practicality of probabilistic models and the accuracy of mechanistic models was proposed by Lounis and Madanat (2002) to improve the effectiveness of the bridge management process. This paper presents a refined version of that architecture along with its application to the modeling of the deterioration of Reinforced Concrete (RC) bridge decks. State-based and time-based probabilistic models in addition to reliability-based mechanistic models will be developed for RC decks using visual inspection and condition survey field data. RC decks were selected because they are the most deteriorated components in bridge systems due to their direct exposure to traffic loads, deicing salts used in winter, and frequent freezing and thawing cycles. However, the same procedures can be followed to develop deterioration models for other bridge components and other infrastructure facilities as well. It should be noted that the system architecture proposed in Fig. 1 is only a concept; no prototype was developed at the meantime.

2. An Integrated System for Bridge Maintenance Management

The architecture of a typical BMS consists of four modules: 1) a database module, 2) deterioration prediction module, 3) life-cycle cost module, and 4) maintenance optimization module. The database module stores inventory, condition, and appraisal data. The deterioration prediction module estimates the future condition of bridge components. The life-cycle cost module calculates agency and user costs for various maintenance alternatives. The maintenance optimization module determines the most cost-effective maintenance strategies for a given planning horizon. The main problem of this typical architecture is that it relies on only one type of deterioration models, usually condition rating-based models, to predict the future condition of bridges for both network level and project level analyses. These models provide acceptable reliability for network level analysis, where bridges are prioritized according to eligibility to maintenance funds for management purposes. However, these models become quite inappropriate for the detailed analysis of specific components, such as critical structures with severe consequences of failure (e.g., fracture-critical structures) and advanced levels of deterioration. Mechanistic models, on the other hand, can provide reliable and quantitative prediction of damage progress but cannot be efficiently applied to every structure in a large network.

Fig. 1 shows the proposed architecture of an integrated bridge management system that overcomes the limitations of existing BMS. This new system consists of the same four main modules but it combines two different approaches for network level and project level analyses. The first approach, shown on the left side of Fig. 1, is based on the qualitative (i.e., subjective) performance indicators, i.e., condition ratings, obtained from the routine visual inspections that are performed on every structure at a fixed inspection period (i.e., 2 years in the case of NBI inspections). These condition ratings are used to develop state-based/time-based probabilistic deterioration models that can predict the macro-response of a large network of bridges over a given planning horizon. These models are simple, computationally efficient, and easy to update (e.g., Bayesian updating) when new condition ratings are obtained. Based on the predicted conditions, the life-cycle costs of different maintenance alternatives are estimated using the unit cost data stored in the life-cycle cost module. This process is repeated by the maintenance optimization module for a large number of bridges to generate the list of projects that maximize the network condition under given budget constraints. This list includes the bridges that have higher priority for funding and the proposed maintenance decisions. The actual maintenance actions are often determined later by bridge engineers based on their judgments and the actions recommended by the second approach, which is discussed in the next section.

The second approach, shown on the right side of Fig. 1, is based on quantitative performance indicators (i.e., stress, deformation, resistance) obtained from detailed condition surveys, analytical assessments, and/or empirical investigations that are performed on the following subset of components:

1. Bridge components that are candidates for MR&R funds in the coming year, which are determined using the priority list obtained from the first approach and based on the overall condition (Arrow # 1).
2. Fracture-critical components that are eligible for more frequent, and mostly special inspections (Arrow # 2).
3. Bridge components that cannot be assessed with adequate accuracy using visual inspections due to the existence of physical barrier, such as bridge decks covered with asphalt layer (Arrow # 3).

Several non-destructive and partially destructive evaluation (NDE) techniques, such as coring, half-cell potential, ground penetrating radar, and impact echo, can be utilized to quantitatively assess the physical parameters that represent different damage mechanisms. The information obtained using these techniques is interpreted and analyzed to accurately determine the values of the governing deterioration parameters (e.g., cover thickness, chloride content, corrosion rate, and crack width). These values are then used to develop reliability-based mechanistic deterioration models that predict the micro response of the component to each damage mechanism (project-level analysis). This analysis is performed for the selected subset of components and the most cost-effective maintenance strategies for each component is determined by the maintenance optimization module based on the life-cycle cost assessment of several maintenance alternatives. This assessment considers both agency cost and user cost calculated via the life-cycle cost module based on historical records of similar projects.

For those components that are not included in the priority list and are not classified as fracture-critical components, condition survey data are aggregated and converted back into the corresponding condition state for network-level analysis (Arrow # 4). This conversion is performed by matching the extent and severity of different distresses with the definition of condition states (Hearn and Shim, 1998). It should be noted that the purpose of converting NDE results into condition ratings (e.g., 0 to 9 scale of FHWA or 5-state scale of Pontis) is to allow the use of the deterioration models, cost, and optimization modules of

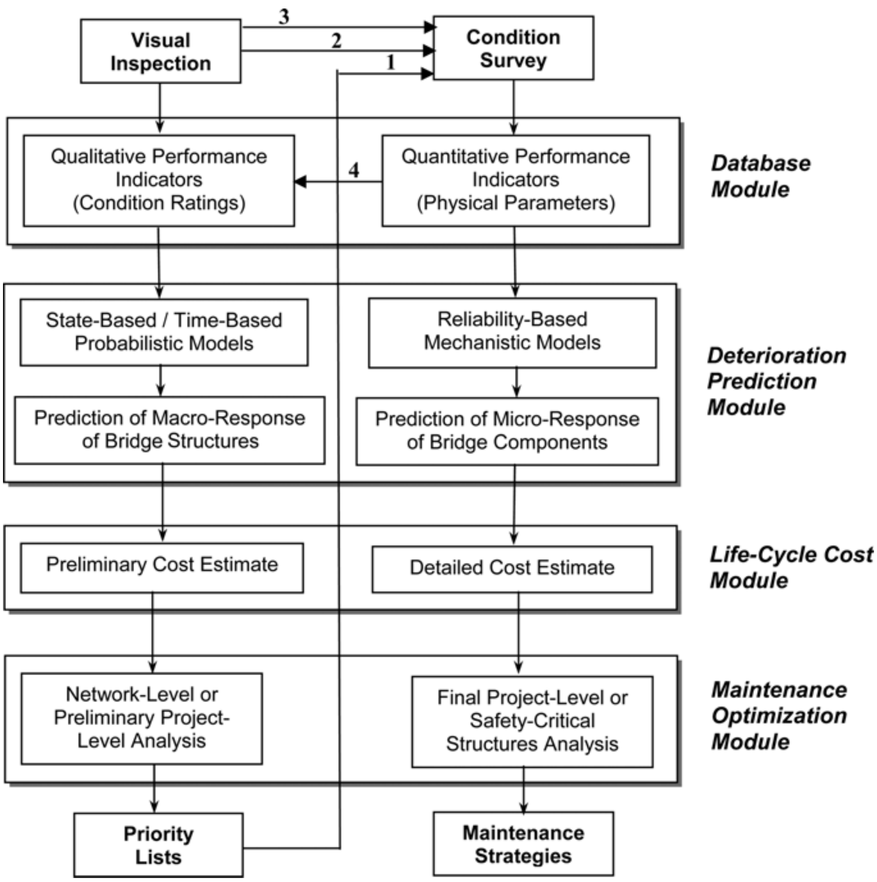

Fig. 1. Architecture of Integrated BMS

the first approach. This conversion is not recommended for fracture-critical components or project-level analysis because it limits the benefits from NDE data and may result in losing the information captured in their original form.

The integrated BMS presented in Fig. 1 addresses the needs of bridge managers for a decision support tool that is both practical and reliable. The application of this system to safety-critical infrastructure facilities, such as bridges, dams, and nuclear plants is crucial to achieve the cost-effectiveness and consistency of MR&R decisions. The application of this integrated system will be demonstrated in the following sections by developing illustrative examples for modeling the deterioration of RC bridge decks using the data obtained from routine visual inspection and detailed condition surveys.

3. Deterioration Models for Network-Level Analysis

3.1 Condition Rating Data

The condition rating data used in developing these models were obtained from the Ministére des Transports du Québec (MTQ) database, which is part of a comprehensive system for managing 57 different types of highway structures in Québec, Canada. Reinforced Concrete (RC) slab-on-girder bridges are selected for model development because they are the most dominant type of structures, since they represent about 60% of the 9678 provincially-owned highway structures. The condition rating data of RC decks represent the results of the detailed visual inspections carried out approximately every three years. These data comprise two condition ratings (MTQ, 1995): (i) Material Condition Rating (MCR), which represents the condition of a deck based on the severity and extent of observed defects; and (ii) Performance Condition Rating (PCR), which describes the condition of a deck based on its ability to perform the intended function in the structure. Both the MCR and PCR are represented in an ordinal rating scale that ranges from 1 to 6, where 6 represents the condition of a new and undamaged deck. Because MCR is the governing parameter in most of MTQ maintenance decisions, deterioration models will be developed for MCR only. Fig. 2 shows how the MCR of any element is determined given the type of element (i.e., primary, secondary, or auxiliary), percentage of the material defects in the element cross-section, surface area, or length, and the severity of these defects (i.e., very low, low, medium, severe, and very severe). It should be noted that since 2007, MTQ has been using a different inventory and inspection database as part of the newly developed BMS (Ellis *et al.*, 2008). In this system, the element condition is recorded as severity and extent separately. Quantities of defects in each of the four condition states are determined for each bridge element, which is significantly different from the MCR used in this study (Ellis *et al.*, 2008).

RC decks with Asphalt Concrete (AC) overlay as a wearing surface are selected for model development because they represent 93% of the RC decks in Québec. Deterioration parameters, other than wearing surface, that affect the performance of RC decks, such as climatic region, highway class, average daily traffic, and percentage of trucks, were not taken into account in this study to simplify the development of state-based/time-based probabilistic deterioration models. For more information on the effect of these parameters, refer to Morcous *et al.* (2003).

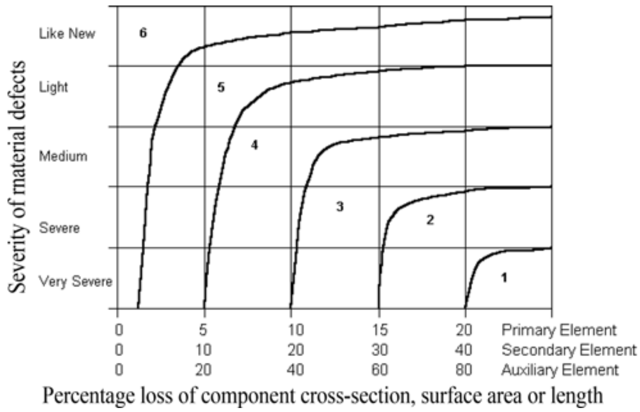

Fig. 2. Material Condition Rating System Used by MTQ (MTQ, 1995)

3.2 State-Based Probabilistic Deterioration Models

State-based models are those used to predict the probability of transition from one condition state to another over multiple discrete time intervals (Bogdanoff, 1978). Markov chain models are the most common example of state-based models, which are extensively used for modeling the deterioration of pavements, bridges, and sewer/water pipes (Micevski *et al.*, 2002). These models (sometimes called Markovian cumulative damage models) predict the macro-response of a facility or a network in terms of a qualitative global indicator of performance or damage (e.g., condition rating) using transition probability matrices. These matrices consist of transition probabilities for all possible condition changes over a specific time period conditional on the values of governing deterioration parameters, such as design and construction attributes, environmental and operating conditions, and maintenance practices. Conventional first-order Markov-chain models use constant transition probabilities assuming that the future condition of a facility depends only on its initial condition and not on the past condition (i.e., state independence assumption) or even the time elapsed in the initial condition (i.e., stationary process) for simplicity purposes (Lounis, 2000).

More realistic models have been developed to account for the effect of the time spent in the initial condition on the transition probabilities (i.e., semi-Markov or non-stationary process) and to relax the state independence assumption by accounting for the past condition among other explanatory variables (DeStefano and Grivas, 1998; Madanat *et al.*, 1997). Several methods have been adopted to accurately estimate transition probabilities from accumulated condition data, which include percentage prediction method, expected-value method, ordered probit model, and Poisson regression (Mauch and Madanat, 2001). These methods are used when a statistically significant number of consistent and complete sets of condition data are available, otherwise expert judgment elicitation procedure is used. These elicitation procedures require the participation of several experienced engineers to generate initial transition probability matrices, which are then statistically updated using the Bayesian approach when condition data are accumulated over the years (Thompson and Shepard, 1994).

Stationary first-order Markov-chain models are developed as an application example of state-based probabilistic deterioration models using the expected-value method. In this method, the bridge deck data are plotted on a two dimensional chart as shown in Fig. 3, where the horizontal axis represents the age in years, and the vertical axis represents the MCR. The regression model that best fits the plotted data points is obtained. Then, transition probabilities are estimated by solving the non-linear optimization problem that minimizes the sum of absolute differences between the deck condition $Y(t)$ predicted using the regression model and the deck condition $E(t)$ predicted using the Markov-chain model over N number of years. The objective function and the constraints of this optimization problem are formulated as follows:

$$\text{Minimize } \sum_{t=1}^{N} |Y(t) - E(t)| \tag{1a}$$

$$\text{Where } E(t) = P(0) \times P^t \times S \tag{1b}$$

$$\text{Subject to : } 0 \le p_{ij} \le 1 \qquad \text{for} \qquad i, j = 1, 2, ..., n \tag{1c}$$

$$\sum_{i=1}^{n} p_{ij} = 1$$

The expected value $E(t)$ at age (t) is obtained from the multiplication of the initial condition vector $P(0)$, the transition probability matrix (P) raised to the power (t), and the vector of condition states (S). Assuming a unit jump in the condition rating during a one-year period, the elements of the transition probability matrix (p_{ij}) are assumed to be zeros except for the diagonal line and the line above it. The matrix obtained by solving the above optimization problem is then raised to the power three to calculate the three-year transition probability matrix shown below. This matrix, shown in Eq. (2), can be used for modeling the deterioration of MTQ bridge decks with AC overlay when no maintenance actions are taken.

$$\boldsymbol{P} = \begin{array}{c} \begin{array}{cccccc} \mathbf{6} & \mathbf{5} & \mathbf{4} & \mathbf{3} & \mathbf{2} & \mathbf{1} \end{array} \\ \begin{bmatrix} 0.839 & 0.159 & 0.002 & 0 & 0 & 0 \\ 0 & 0.958 & 0.040 & 0.002 & 0 & 0 \\ 0 & 0 & 0.890 & 0.101 & 0.008 & 0 \\ 0 & 0 & 0 & 0.792 & 0.178 & 0.030 \\ 0 & 0 & 0 & 0 & 0.625 & 0.375 \\ 0 & 0 & 0 & 0 & 0 & 1 \end{bmatrix} \end{array} \begin{array}{c} \\ \mathbf{6} \\ \mathbf{5} \\ \mathbf{4} \\ \mathbf{3} \\ \mathbf{2} \\ \mathbf{1} \end{array} \tag{2}$$

3.3 Time-Based Probabilistic Deterioration Models

Time-based models (sometimes called duration models) are those used to predict the probabilistic distributions of facility transition times given the values of governing deterioration parameters, such as design and construction attributes, environmental and operation conditions, and maintenance practices. The transition time is defined as the time needed for a facility to change from an initial condition state to the next lower state in the condition rating scale. The length of the transition time varies significantly from one facility to another due to inherent stochastic nature of the deterioration process and the existence of unobserved/unmeasured explanatory variables. State transition events recorded in the BMS database are used to perform the life data analysis required to study the characteristics of facility deterioration and develop cumulative distribution functions of transition time for different condition states. Examples of time-based deterioration models developed using life data analysis are the model developed for structural deck systems using the *New York State Thruway Authority* (NYSTA) database (DeStefano and Grivas, 1998), and the models developed for RC bridge decks using Indiana Bridge Inventory (IBI) database (Mauch and Madanat, 2001; Mishalani and Madanat, 2002).

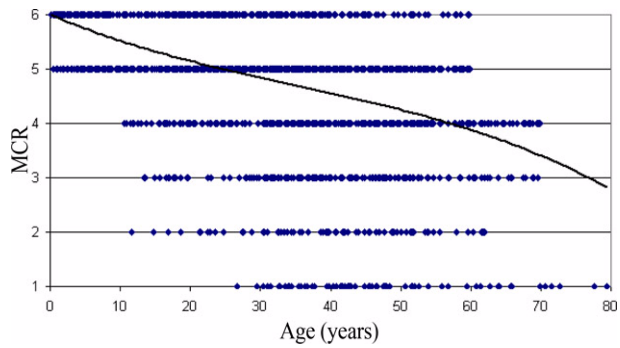

Fig. 3. Regression Model that Best Fits Bridge Deck Data

The information required for developing time-based probabilistic models consists of condition state transition events and the corresponding time data, which are obtained from the MTQ database. Condition state transition events are identified using sequential changes in MCR of RC decks. The actual time of these changes cannot be easily identified because visual inspections are performed only every three years, in addition, the condition data available to the authors cover only the period from 1993 to 2000. Therefore, adequate sequential condition data can be obtained for only the most common condition states (state 5 and state 4), and their related time data are considered "multiply censored". Censored data means that the observed event (state transition in this study) does not take place during the observation period, however, it is known that the event takes place after a specific time (right censored), before specific time (left censored), or both (interval censored) (Nelson, 1982). If this specific time is constant for all data records, it is referred to as "singly censored", otherwise it is referred to as "multiply censored", which is the case of MTQ data.

Life data analysis of the multiply censored data is performed using Kaplan and Meier methods to estimate the non-parametric survival and hazard functions of RC bridge decks. The survival function $S(t)$, sometimes called reliability function $R(t)$, represents the probability that a bridge deck remains in its condition state for at least time (t). This function can be expressed as follows:

$$S(t) = 1 - F(t) = 1 - \int_0^t f(t)dt \tag{3}$$

where t is the random variable that represents the transition time (sometimes referred to as time-in-state), $f(t)$ is the probability density function of the transition time (t), and $F(t)$ is the corresponding cumulative distribution function. The hazard function $h(t)$ represents the instantaneous probability that a bridge deck will change its condition state to the next lower condition state at time t. This function can be expressed as follows:

$$h(t) = \frac{f(t)}{S(t)} \tag{4}$$

Survival and hazard functions developed in this study are considered non-parametric because they do not relate the random variable to any deterioration parameters. Parametric and semi-parametric functions have been developed by other researchers for several infrastructure facilities (Prozzi and Madanat, 2000; Mauch and Madanat, 2001). Figs. 4 and 5 show the survival and hazard functions developed for times-in-state 5 and 4 using the MCR data of RC bridge decks in Quebec. These data contain the sequential condition states (past i, current j, and future k) needed to define transition events. Table 1 lists the different possible condition sequences for a given current condition state j and the corresponding method used to calculate the time-in-state (T_j). It should be noted that if the transition event is observed between two consecutive condition states, the transition event is assumed to occur at the middle of the inspection period for simplicity. The data type in this case only is considered complete (not censored), which represents 15% of the data used for estimating the time-in-state 5 and 20% of the data used to estimate the time-in-state 4. The high percentage of multiply censored data (i.e., 85% and 80%) justifies the development of non-parametric models and the use of Kaplan-Meier Method (DeStefano and Grivas, 1998). Using the survival functions in Figs. 4 and 5, the probability of having the time-in-state 5 equals to 3 years is estimated at 96%, while the probability of having the time-in-state 4 equals to 3 years is 88%.

It should be noted that state-based models and time-based models are related, so that information on a state-based model can be used to develop the corresponding time-based model and vice versa (Mauch and Madanat, 2001). For example, if the probability distribution of the transition time from condition state 5 to condition state 4 is known, the transition probability from condition state 5 to condition state 4 over a given time interval can be easily calculated. Also, if several transition probabilities between two specific condition states are available for different transition periods, the probability density function of the transition time can be estimated. It should also be noted that the decision of which type of models is more appropriate for deterioration prediction is highly dependent on the nature of the available condition data (Mishalani and Madanat, 2002). Frequent inspections over a long observation period are required for developing time-based models, while infrequent inspections over a relatively short observation period can be used for developing state-based models.

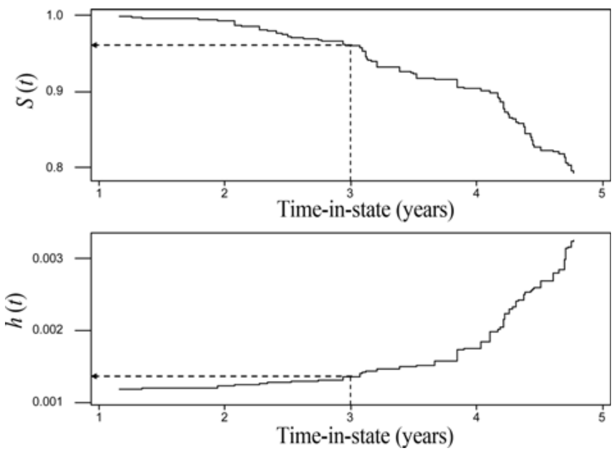

Fig. 4. Survival and Hazard Functions for Time-in-state 5

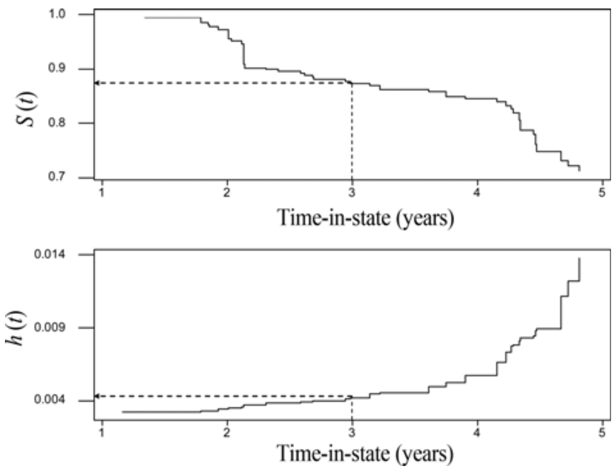

Fig. 5. Survival and Hazard Functions for Time-in-state 4

Table 1. Sequential Condition States and the Corresponding Time-in-state

Time-in-state			Condition States	Data Type
i	j	k	T_j	
j+1	j	j-1	$D_{ij}/2+D_{jk}/2$	Complete
j+1	j	j	$D_{ij}/2 + D_{jk}$	Censored
j	j	j-1	$D_{ij} + D_{jk}/2$	Censored
j	j	j	$D_{ij}+D_{jk}$	Censored

4. Deterioration Models for Project-Level Analysis

Mechanistic models predict the micro-response of the structure to the action of applied loads and in-service environment. This micro-response includes onset of damage, damage growth, and damage impact on the safety and serviceability of the structure.

These models are used for project level analysis and the analysis of safety-critical structures, where the damage of structures is described by quantitative performance indicators such as resistance, stress, deflection, etc.

Damage mechanisms of bridge structures may be divided into three broad categories: (i) overstress damages such as those due to total or partial collapse (brittle or ductile mode), yielding, buckling, cracking, large deformations; (ii) wear-out failures such as those due to material wear, fatigue, corrosion; and (iii) combination of overstress and wear-out failures. These mechanisms result in a complex process that varies with the applied loading, in-service environment, initial design and construction, structural system behavior, material, and application of systematic inspection and maintenance procedures. Most of these parameters are time-dependent and random in nature, with considerable levels of uncertainty. As a result, the response of the structure is also random with large fluctuations from the mean value identified by high coefficients of variation or low signal-to-noise ratios. The sources of uncertainty in the structure response can be classified into:

- *Physical or inherent uncertainty*: identified with the inherent random nature of a basic variable such as: (i) variability of the structure geometry (e.g., concrete cover thickness, member depth, etc.); (ii) variability of the material properties (strength, diffusivity, etc.); (iii) variability of the micro-environment (e.g., surface chloride concentration on the deck); (iv) variability of the applied loads (e.g., traffic load); and (v) variability of the condition rating.
- *Statistical uncertainty*: arising from modeling the parameters and/or performance indicators using simplified stochastic processes or random variables by using lower order of stochastic correlation of stochastic processes or assuming independence of random variables. This uncertainty arises also from the use of a limited sample size to estimate the statistical parameters that describe the probabilistic model of the parameters and performance indicators.
- *Model uncertainty*: resulting from the use of simplified physical models to describe the damage initiation or damage growth mechanisms, such as corrosion, cracking, spalling, collapse, etc.
- *Decision uncertainty*: associated with the definition of the acceptable level of damage or limit state or acceptable probability of failure for both serviceability and ultimate limit states. This is quite a complex problem due to its dependence on the risk of loss of life and injury, cost of repair and replacement, redundancy of the structure, and failure mode considered.

Therefore, given the considerable uncertainty that affects the structure micro-response, a probabilistic modeling of damage mechanisms of bridge structures has much to offer with regard to practicality and reliability as compared with attempts of formulating purely deterministic models (Ditlevsen, 1984). Several researchers have developed reliability-based mechanistic deterioration models for deteriorating bridge structures that are subject to the action of aggressive environment and to the combined action of the environment and mechanical loads (Frangopol *et al.*, 1997; Stewart and Rosowsky, 1998). In North America, the deterioration of RC bridge structures is mostly due to the corrosion of reinforcing steel from the use of deicing salts in winter. This corrosion leads to delamination and spalling of the concrete surface, reduction of concrete and reinforcement cross sectional areas, loss of bond between the reinforcement and concrete, reduction in strength (flexural, shear, etc.), and eventually failure.

The condition data used in developing reliability-based mechanistic models for bridge deck degradation due to corrosion were obtained from the Dickson Bridge in Montreal, Canada. This bridge was constructed in 1959, and had a total length of 366 m and width of 27 m. The superstructure of this bridge consisted of reinforced concrete T-girders in the end sections and a concrete deck on steel girders in the central section. The deck was severely deteriorated because of the inadequate quality control in construction and the aggressive environment resulting from the frequent use of de-icing salts in winter. A detailed condition assessment was carried out in 1999 (i.e., after 40 years) on the bridge deck prior to its demolition (Amleh, 2000; Fazio, 1999). This assessment resulted in hundreds of data points that indicated a considerable variation in the parameters affecting the chloride contamination of the deck and corrosion of the top mat of reinforcing steel throughout the deck.

Tuutti (1982) proposed a model that describes the performance of concrete structures exposed to chlorides as a two-stage process: (i) *Initiation stage*, which is defined as the time period from the initial exposure to chlorides until the onset of corrosion; and (ii) *Propagation stage*, which is the post-corrosion stage that corresponds to damage initiation (cracking, delamination, spalling, etc.) and damage accumulation until failure. The following subsections demonstrate the development of a probabilistic model for predicting the duration of each stage considering the uncertainty in the governing parameters.

4.1 Probabilistic Corrosion Initiation Model

During corrosion initiation stage, the chlorides from deicing salts used during winter penetrate the concrete slab, reach the top layer of reinforcement and accumulate until they reach a critical concentration referred to in the literature as “chloride threshold level” at which the reinforcing steel starts to corrode. The reinforcing steel in concrete is protected by a passivating iron oxide film on its surface in the highly alkaline concrete pore water solution. The chlorides trigger the dissolution of the iron oxide layer followed by the dissolution of steel. The ingress of chlorides into concrete is a complex process that combines several transport mechanisms such as diffusion, capillary sorption (or convection), and permeation, which is influenced by several factors such as concrete mix, nonlinear chloride binding of the cement, temperature, curing, etc. The mechanistic model used to predict the time to corrosion initiation is based on the assumption that diffusion is the key governing mechanism of chloride ingress in concrete decks especially those subjected to periodic salt applications. Crank's closed-form solution of Fick's second law of diffusion for a semi-infinite medium is used to obtain the distribution of chloride concentration $C(x,t)$ at depth (x) and time (t) as follows:

$$C(x,t) = C_S\left[1 - erf\left(\frac{x}{2\sqrt{Dt}}\right)\right] \tag{5}$$

where: C_s : surface chloride concentration; D : diffusion coefficient of chlorides; and erf : error function (which is equal to twice the cumulative distribution of the normal distribution with a mean of zero and a variance of 1/2). The time to corrosion initiation (T_i) of the top reinforcing steel in a reinforced concrete deck slab can be determined by substituting the depth (x) with the depth of the concrete cover (d_c) to the top steel and the chloride concentration (C) with the threshold chloride concentration (C_{th}) in Eq. 5, which leads to the following equation:

$$T_i = \frac{d_c^2}{4D\left[erf^{-1}\left(1 - \frac{C_{th}}{C_S}\right)\right]^2} \tag{6}$$

The statistical information of the random variables required for reliability analysis were derived from the data collected during the field survey using non-destructive evaluation techniques and coring as shown in Table 2 (Lounis and Mirza, 2001; Amleh, 2000). The concrete cover depth (d_c) was measured at 137 locations using a covermeter and was found to have a normal distribution with a mean of 36.6 mm and a coefficient of variation of 0.45. The "apparent" values of the diffusion coefficient and surface chloride concentration were obtained by regression analysis to best fit the solution given by Eq. (5) to the chloride profiles obtained from field data. The chloride content of powdered concrete samples was measured at 35 locations on the deck using the SHRP chloride analysis method known as the specific ion electrode technique (Amleh, 2000; Fazio, 1999). The "near surface" chloride concentration (C_s) was found to have a lognormal distribution with a mean of 4.57 kg/m^3 and a coefficient of variation of 0.4. The apparent diffusion coefficient (D) also had a lognormal distribution with a mean of 51.2 mm^2/year and a coefficient of variation of 0.3.

The chloride threshold level is determined by correlating chloride content measurements with electrochemical measurements of the steel embedded in concrete using changes in either half-cell potential or corrosion rate. The half-cell potential was measured at 137 locations using the conventional copper-copper sulfate half-cell and ASTM C876 criteria. The corrosion rate measurements were done with two different probes: 3-electrode linear polarization (3LP technique) and linear polarization device with controlled guard ring. The electrical resistivity was measured at 137 locations using the Wenner four probe apparatus. The detection of delamination was investigated at 140 sites using a hammer. Another method used was the direct measurement of the weight loss from which the corrosion initiation time and, consequently, the threshold level can be estimated by using the corrosion rate data. Other methods included visual inspection for rust stains, cracking and spalling, and the sounding technique using a hammer for delamination detection and correlating the results with the measured chloride contents. A combination of all these results yielded a lognormal distribution of the threshold chloride concentrations (C_{th}) with a mean of 1.35 kg/m^3 and a coefficient of variation of 0.1.

The Monte Carlo simulation technique was used to generate the probability density function and cumulative distribution function of the time to corrosion initiation as shown in Fig. 6. The initiation time was found to have a skewed distribution with a mean of 21.2 years and a coefficient of variation of 1.14. The probability of corrosion initiation in the RC decks at the age of 40 years (time of deck investigation) was found to be 86% (refer to the shaded area in Fig. 6), which is very close to the actual percentage of the damaged area of the bridge deck at that time.

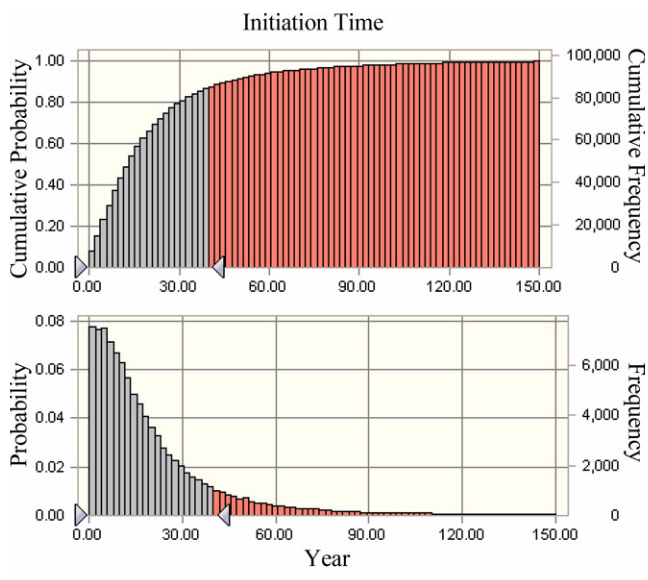

Fig. 6. Probability Density and Cumulative Distribution Functions of the Time to Corrosion Initiation

Table 2. Parameters Affecting Initiation Time for Corrosion in RC Bridge Decks

Parameter	Description	Unit	μ	COV	σ	Distribution
d_c	Cover Depth	mm	36.60	0.45	16.47	Normal
C_s	Surface Cl Concentration	kg/m^3	4.57	0.40	1.83	Lognormal
D	Diffusion Coefficient	mm^2/year	51.10	0.31	15.84	Lognormal
C_{th}	Threshold Cl Concentration	kg/m^3	1.35	0.10	0.14	Lognormal

This confirms the capabilities and accuracy of reliability-based mechanistic models in predicting the micro-response of bridge components. Also, a sensitivity analysis was carried out to determine the sensitivity of the time to corrosion initiation to each of the governing parameters. The results of this analysis, as shown in Fig. 7, strongly agrees with the literature where the cover depth and surface chloride concentration have been identified as major contributors to the corrosion of concrete bridge decks with the cover depth considered more critical.

4.2 Probabilistic Corrosion Propagation Model

The propagation stage starts once the passive film is broken down by the chloride ions reaching a concentration above threshold level at the steel surface (assuming that both oxygen and moisture are present for corrosion to proceed), and then activate the electrochemical reactions that generate corrosion products, or rust (Bentur *et al.*, 1997). The corrosion products absorb water, increase considerably in volume, and induce stresses on the surrounding concrete, which causes concrete cracking, spalling or delamination of the concrete surface, and loss of bond between the reinforcement and the concrete, and may ultimately lead to failure of the concrete structure due to reduction in bond, strength, and ductility.

For simplification, the reinforcing steel bars in a concrete bridge deck were assumed to have equal initial diameter (D_i), and the reduction of that diameter due to corrosion is assumed to be uniform. Then, the time variant diameter of reinforcing steel $D(t)$ at any time (t) is calculated as follows:

$$D(t) = \begin{cases} D_i & \text{for } t \le T_i \quad \text{(7a)} \\ D_i - r_{corr}(t-T_i) & \text{for } T_i < t < T_i + \dfrac{D_i}{r_{corr}} \quad \text{(7b)} \\ 0 & \text{for } t \ge T_i + \dfrac{D_i}{r_{corr}} \quad \text{(7c)} \end{cases}$$

Where (T_i) is the time to corrosion initiation and (r_{corr}) is the corrosion rate. For reliability analysis, initial bar diameter, initiation time, and corrosion rate are assumed to be random variables with lognormal distributions that have the parameters shown in Table 3. The bar diameter was assumed to have an initial value of 25 mm. The distribution parameters of corrosion initiation time were calculated as shown in the previous section, while the distribution parameters of corrosion rate were obtained from Enright and Frangopol (1998), which are common values in the literature.

Since the flexural capacity of corroded reinforced concrete members, in general, is a function of the cross-sectional area of reinforcing bars and not the diameter, the time-variant cross-section area $A(t)$ is calculated based on $D(t)$ calculated in Eq. (7). The ratio of time-variant cross-sectional $A(t)$ to initial cross-section area (A_i) is used to characterize corrosion propagation because this ratio does not depend on the number of steel bars used. Monte Carlo simulations were performed to estimate the distributions of this ratio as percentages at different points in time including 10, 20, 30, 40, 50, 60, and 75 years. Figs. 8 and 9 show the quartiles and cumulative distribution functions of the percentage of remaining steel area at different points in time, while Table 4 lists the parameters of these distributions. These figures can be effectively used to provide quantitative information regarding the damage accumulation and propagation with time. For example, using the cumulative distribution curves in Fig. 9, the probability of losing 20% of the steel cross-section area (i.e., 80% remaining area) is estimated at 20% after 40 years, 43% after 50 years, and 64% after 60 years. Fig. 8 also indicates that the mean value of the percentage of remaining steel area decreases linearly with time, while the variation increases with time. Table 4 lists the mean, coefficient of variation, and standard deviation at different points in time. These values clearly indicate that the uncertainty in predicting corrosion propagation increases with time in an almost linear fashion. This

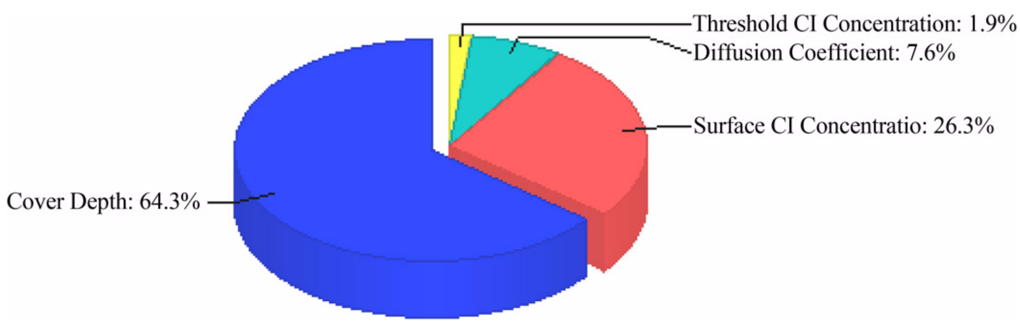

Fig. 7. Sensitivity of Corrosion Initiation Time to the Governing Parameters

Table 3. Parameters Affection Corrosion Propagation in RC Bridge Decks

Parameter	Description	Unit	μ	COV	σ	Distribution
T_i	Initiation Time	year	21.2	1.14	24.13	Lognormal
D_i	Initial Diameter	mm	25	0.020	0.500	Lognormal
r_{corr}	Corrosion Rate	mm/year	0.076	0.300	0.023	Lognormal

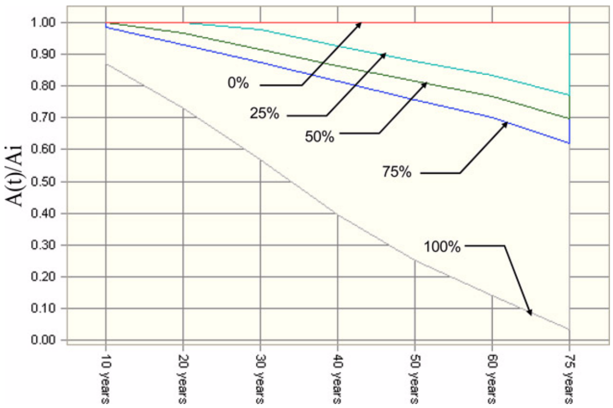

Fig. 8. Quartiles of the Percentage of Remaining Steel Area at Different Times

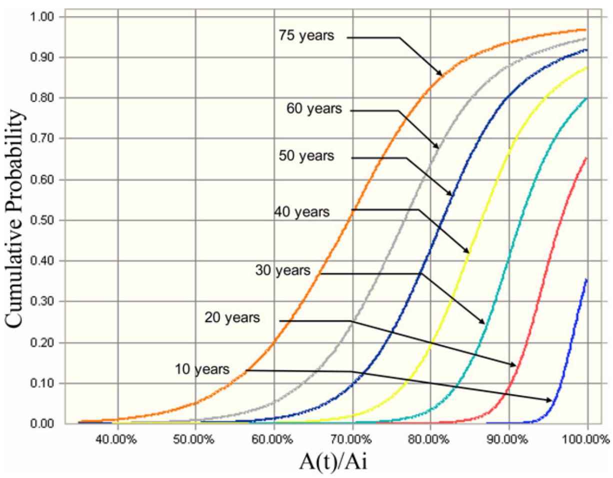

Fig. 9. Cumulative Distribution of the Percentage of Remaining Steel Area at Different Times

Table 4. Distribution Parameters of the Percentage of Remaining Steel Area at Different Times

Time (years)	Nominal	μ	COV	σ
10	100.0%	99.1%	0.015	1.5%
20	100.0%	96.0%	0.042	4.1%
30	94.8%	91.7%	0.069	6.3%
40	89.1%	87.0%	0.093	8.1%
50	83.5%	82.1%	0.118	9.7%
60	78.1%	77.1%	0.142	10.9%
70	70.4%	69.8%	0.178	12.5%

quantitative information is valuable for making cost-effective maintenance decisions at the project-level and for maintaining the safety and serviceability of critical structures.

5. Conclusions

The main goal of a BMS is to provide bridge managers with the necessary information for making decisions regarding maintenance, rehabilitation and replacement of a large bridge network in a reliable and efficient manner. This paper presents the architecture of a two-level BMS that integrates two different approaches for modeling bridge deterioration. The first approach uses state-based/time-based probabilistic models to predict the macro-response of bridge components for network-level analysis. The second approach uses reliability-based mechanistic models to predict the micro-response of bridge components for project-level analysis. The two approaches are probabilistic in order to capture the stochastic nature of the deterioration process and the uncertainty due to the existence of unobserved variables, and the use of simplified models and statistical assumptions.

At the first level, Markov-chain models were developed as an example of state-based probabilistic models using the Material Condition Rating (MCR) that was used by the Ministére des Transports du Québec. The expected value method was used to generate the transition probabilities. Life data analysis was used to estimate non-parametric survival and hazard functions required for developing time-based probabilistic models. Kaplan-Meier method was adopted for this analysis because of the high percentage of multiply censored records in the available condition data. The probability distribution of time-in-state 5 and 4 can be easily calculated using the developed functions. The developed state-based and time-based models can predict the probability that the future condition of a bridge component changes from its current condition after a certain number of years and given the maintenance action taken (including "do-nothing"). This probability can be efficiently calculated for every bridge in a large network and for different combinations of maintenance actions to determine the most eligible bridges for maintenance funds in the short-term. This eligibility is determined through the optimization of the network performance over a specific time period and under budget constraints.

At the second level, field data obtained from the condition survey of a severely deteriorated bridge deck was used to develop reliability-based mechanistic models for the initiation and propagation of chloride-induced corrosion in reinforced concrete decks. The probability distributions of the governing parameters and Monte Carlo simulation technique were utilized to generate the probability density and cumulative distribution functions of the time to corrosion initiation and percentage of remaining steel area. This quantitative information is valuable for the accurate estimate of damage propagation, and consequently, the determination of the most cost-effective maintenance action and its timing.

Although the proposed integration of the two approaches achieved the balance between the accuracy and efficiency, it has several implementation challenges. First, the detailed condition survey required for the second approach might be onerous for some transportation agencies due to the time and cost required to perform these surveys on hundreds or thousands of bridges. Second, the available Non-Destructive Evaluation (NDE) techniques might not be applicable and/or reliable for various bridge components and construction materials. Third, several years of condition data are needed in order to perform long-term analysis and determine optimal MR&R actions. Future efforts will be devoted towards developing a prototype of the proposed integrated system to demonstrate its applicability, reliability and efficiency.

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