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Prediction of Onset of Corrosion in Concrete Bridge Decks

Using Neural Networks and Case-Based Reasoning

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Abstract: This paper proposes a methodology for predicting the time to onset of corrosion of reinforcing steel in concrete bridge decks while incorporating parameter uncertainty. It is based on the integration of artificial neural network (ANN), case-based reasoning (CBR), mechanistic model, and Monte Carlo simulation (MCS). A probabilistic mechanistic model is used to generate the distribution of the time to corrosion initiation based on statistical models of the governing parameters obtained from field data. The proposed ANN and CBR models act as universal functional mapping tools to approximate the relationship between the input and output of the mechanistic model. These tools are integrated with the MCS technique to generate the distribution of the corrosion initiation time using the distributions of the governing parameters. The proposed methodology is applied to predict the time to corrosion initiation of the top reinforcing steel in the concrete deck of the Dickson Bridge in Montreal. This study demonstrates the feasibility, adequate reliability and computational efficiency of the proposed integrated ANN-MCS and CBR-MCS approaches for preliminary project–level and also network-level analyses.

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1. INTRODUCTION

Highway bridges are critical links in the transportation network and should be kept safe and functional to accommodate the traffic that supports commerce, economic growth and personal mobility. Reinforced concrete (RC) deck slabs are aging and are identified as the most deteriorated elements in the provincial/state bridge networks. RC deck slabs may require replacement after 15 to 20 years only, while other bridge components (girders, piers) may last for 50 years or more (FHWA-NDEVC 2001). It is estimated that about one-third to one-half of the projected bridge rehabilitation costs in the U.S are related to the maintenance of decks (Cady and Weyers 1983). The main causes of deterioration of RC deck slabs are chloride-induced corrosion of the reinforcement, traffic overload, and freeze-thaw cycling. This deterioration impairs the safety and serviceability of the bridge and leads to shortened service life and high life cycle cost due to frequent inspections, repairs and rehabilitation.

In the last two decades, highway agencies developed and implemented bridge management systems (BMS) for planning the inspection and maintenance of their bridges in order to ensure their reliability and minimize their life cycle costs. The effectiveness of a BMS, however, is highly dependent on the reliability of the deterioration models used. In the current BMS, such as *Pontis* (Thompson and Shepard 1994) and *BRIDGIT* (Hawk 1995), stochastic deterioration models based on Markov chains were developed to predict the deterioration of different bridge components, including concrete deck slabs (Madanat et al.1997).

An evaluation of the current Markovian deterioration models identified some limitations, including: (i) they are qualitative prediction models, based on subjective condition ratings as opposed to quantitative models; (ii) do not consider all parameters that govern the component deterioration; (iii) assume constant rate of deterioration; and (iv) do not consider the historical performance of component (Lounis 2000; Morcous et al. 2002b). These limitations may be acceptable for network-level analysis in which bridges are prioritized only for eligibility to maintenance funds. These models, however, have serious shortcomings for project-level analysis in which detailed and quantitative assessment of the levels of chloride contamination, corrosion, cracking, spalling, loss of bond and strength are critical for the identification of the appropriate and cost-effective rehabilitation strategy.

A more appropriate model for concrete deck slabs exposed to chlorides from deicing salts is the mechanistic model based on Fick's law of diffusion of chlorides and the concept of the "chloride threshold level" for corrosion initiation (Tuutti 1982; Kropp and Hilsdorf 1995; Liang et al. 2002). This model is able to predict the time and space variations of chloride contamination of concrete and the time to onset of corrosion of the reinforcing steel. Several other models, including empirical, analytical, numerical and statistical, have been developed to predict the levels of chloride contamination of concrete, times to onset of corrosion, cracking, spalling and failure. The practicality and reliability of these predictive models, however, is limited because they are not able to effectively account for the uncertainty in the governing variables, model, and condition assessment methods. These models can predict the chloride ingress, steel corrosion and concrete cracking, provided that the parameters are certain and the underlying assumptions are satisfied. Intuitively, given the considerable uncertainty in the governing parameters of the model, there is a considerable uncertainty in the response parameter. In the case of chloride contamination of concrete or corrosion of the reinforcing steel, this uncertainty is due to the heterogeneity of concrete, temporal and spatial variability of its properties, variability of the environment, concrete cover depth, chloride transport model and chloride threshold level, and measurement errors. Some of these shortcomings have been overcome through the use of probabilistic modeling of the chloride transport and corrosion initiation and solving the problem using reliability-based methods, such as Monte Carlo simulation, first-order or second-order reliability methods, or crossing theory (Enright and Frangopol 1998; Stewart and Rosowsky 1998; Lounis and Mirza 2001). Because the use of these methods with mechanistic models is often computationally prohibitive, functional mapping tools that accurately replace the mechanistic model are required to improve the computational efficiency of the uncertainty analysis.

Over the last two decades, artificial intelligence (AI) techniques have been developed and applied by many researchers to solve different engineering problems. They provide efficient solutions to complex problems because of their non-traditional heuristic problem-solving capabilities. These techniques have been widely used in transforming the row data of several domains into usable knowledge that can be applied to solve planning, prediction, classification, and design problems (Boussabaine 1996; Watson 1997). The ANN technique is very powerful as it can enable to map any complicated functional relationship between independent and dependent variables, thus providing better prediction capabilities than traditional curve fitting methods (Zou et al. 2002). The case base of a CBR model can be seen from the functional viewpoint as a representation of a mapping between input and output values (Anthony et al. 1995).

In this paper, a procedure that integrates the ANN and CBR techniques with Monte Carlo simulation is proposed to predict the onset of corrosion in concrete bridge decks taking into account parameter uncertainty. It is applied to a case study of the Dickson bridge in Montreal. The first section of the paper provides a brief description of the performance of concrete bridge decks exposed to chlorides. The second section describes the development of the ANN and CBR models and their applications to a case study. The capabilities of the proposed models are evaluated by comparing their predictions to actual field data of the deck condition, as well as to the predictions obtained using the traditional mechanistic model.

2. PERFORMANCE OF CONCRETE BRIDGE DECKS EXPOSED TO CHLORIDES

2.1 Mechanism of chloride-induced corrosion of reinforcement in concrete structures

The main cause of deterioration of concrete bridge deck slabs in North America is the chloride-induced corrosion of the reinforcing steel. 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 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. Hence, the corrosion of the reinforcement 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 (Rosenberg et al. 1989; Neville 1995; 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, 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.

2.2 Mechanistic predictive models of chloride ingress and corrosion initiation

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 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.

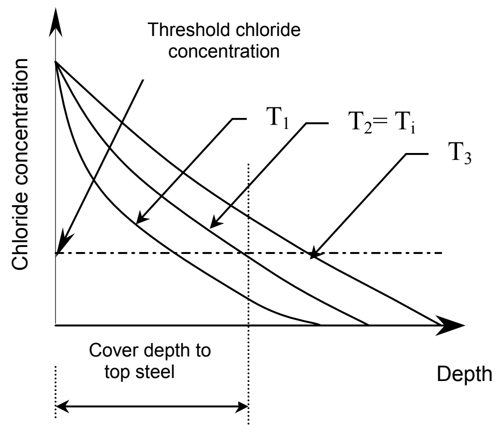
For the initial condition C(x,0)=0, boundary condition C(0,t)=C_s, and assuming that both C_s and D are constant in time and space, Crank's closed-form solution of Fick's second law of diffusion for a semi-infinite medium is as follows:

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

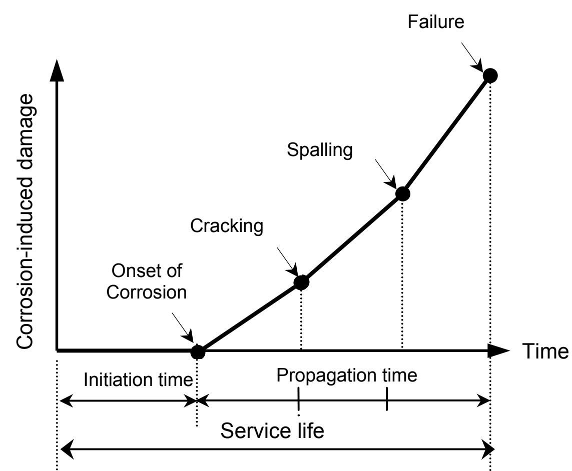
where : C(x,t): chloride concentration at depth (x) and time (t); C_s : surface chloride concentration; D : diffusion coefficient of chlorides; and erf: error function (which is equal to twice the cumulative distribution of the normal distribution with a mean of zero and a variance of ½). Figure 1(a) illustrates some typical chloride concentration profiles at different times obtained using Eq. 1. The penetration of chlorides into concrete is a time-dependent process driven by the chloride concentration gradients. 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. 1, which leads to the following equation:

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

From Eq.(2), the time to onset of corrosion (or duration of the initiation stage) is governed by the depth of the concrete cover, amount of chlorides at the surface (proportional to the amount of de-icing salts used), and rate of chloride ingress into concrete or diffusivity of concrete, and the value of threshold chloride concentration level. Figure 1(b) shows a modified damage accumulation model first introduced by Tuutti (1982). Despite its simplicity and extensive use, this model has some serious shortcomings, such as the assumptions of (i) diffusion process for chloride ingress into concrete; (ii) constant and independent threshold chloride concentration; and (iii) constant values of the governing variable despite the heterogeneity of concrete and the spatial and temporal variability of its properties.



(a) Chloride concentration profiles at different times



(b) Service life of corrosion-damaged concrete structures

Fig. 1. Performance of concrete structures exposed to chlorides

To overcome some of the shortcomings of Fick's law-based chloride ingress into concrete, an approach that combines the use of Fick's law of diffusion and in-situ evaluation of concrete structures has been widely adopted for the prediction of chloride concentration in concrete structures (Tuutti 1982; Cady and Weyers 1983; Andrade et al. 1993; Kropp and Hilsdorf 1995; Bentur et al. 1997). It is based on using the so-called "apparent" values of the diffusion and surface chloride concentration that are obtained by regression analysis to best fit the solution given by Eq. (1) to the chloride profiles obtained from field data.

The introduction of the apparent values of governing parameters addressed to some extent the uncertainty associated with the diffusion model for chloride transport, however, the model does not consider the considerable uncertainty associated with the values of the governing parameters that vary considerably within the deck and with time. A brief description of the governing parameters is given below.

Diffusion coefficient

It is not a constant but rather depends on time, temperature, and depth because of the heterogeneous nature and aging of concrete (Cady and Weyers 1982; Neville 1995)

Surface chloride concentration

As a bridge deck is subjected to a continually changing chloride exposure, the surface chloride concentration is not constant but time-dependent. Using field data, it has been shown that the surface chloride concentration increases with age (square root law). This increase is relatively fast and reaches a quasi-constant concentration in about 5 years (Weyers 1998). Given the fact that the service life of a bridge deck varies between 20 to 40 years, it is therefore practical and reasonable to assume a constant surface chloride concentration.

Threshold chloride concentration

The value of the threshold chloride concentration depends on several parameters, including: (a) concrete type (cements with high contents of tricalcium aluminate-C_3A have a great capacity to bind chlorides, resulting in increased chloride threshold level); (b) source of chlorides, temperature and moisture content (higher temperature and moisture contents will decrease the threshold level); (c) type of reinforcing steel (conventional black, carbon steel, epoxy-coated steel, galvanized steel, or stainless steel); (d) concrete cover depth (thicker covers increase the threshold level by reducing the moisture and oxygen variations at the steel surface); (e) water-to-binder ratio (a lower ratio helps to stabilize the micro-environment at the steel level as the moisture permeability is decreased); (f) carbonation of concrete; and (g) presence of macro-cracks (reduces the threshold value).

Despite the fact that only the free chlorides induce steel corrosion, for practical purposes, the threshold content is given in terms of total chlorides (free and bound), as it is difficult to measure the free chlorides (Glass and Buenfeld 1995). In the literature, there is a considerable uncertainty associated with the value of the threshold concentration level "C_{th}" obtained from laboratory and field studies where C_{th} was found to vary between 0.17% and 2.5% in terms of total chlorides by weight of cement for conventional black steel (Glass and Buenfeld 1995). Many highway agencies, however, use a total chloride threshold level of 0.2% by weight of cement (or 0.03% by weight of concrete or 0.7 kg/m^3).

Concrete cover depth

It is not constant throughout the deck but varies depending on the quality control practices during construction.

2.3 Incorporation of Parameter Uncertainty in Mechanistic Model

To overcome some of the shortcomings of the above corrosion initiation model based on Fick's law and apparent values of parameters and improve its prediction capability, a probabilistic modeling of the mechanistic model is proposed to incorporate the considerable uncertainty associated with the governing parameters. All governing parameters are modelled as independent random variables that are obtained by fitting the best statistical model to the data obtained from the field survey for each parameter. The solution of the probabilistic problem is then obtained using Monte Carlo simulation (MCS), which is used to generate the distributions of the chloride concentrations and time to onset of corrosion of the top layer of reinforcement. The following section presents how the artificial intelligence models (ANN and CBR) are developed as functional mapping tools to be used in the numerical realizations of the MCS analysis.

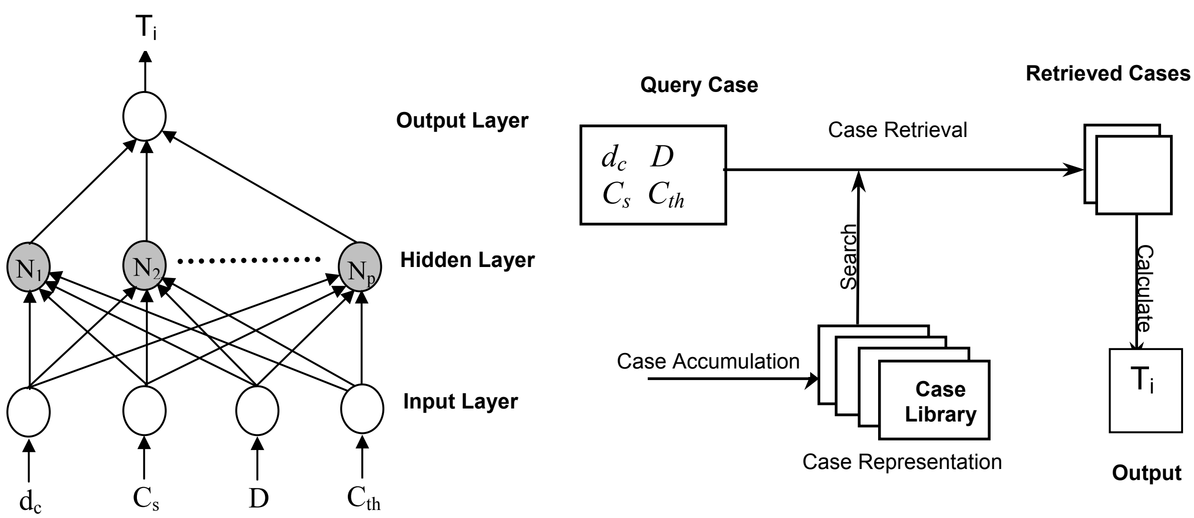
3. CORROSION TIME PREDICTION USING ARTIFICIAL INTELLIGNCE MODELS

3.1 Integrated Neural Network-Monte Carlo Simulation Model

An artificial neural network (ANN) is a data processing system consisting of a large number of simple, interconnected computational elements referred to as "*neurons*" in an architecture inspired by the structure of the cerebral cortex of the brain (Fausett 1994). The ANN technique uses very simple computational operations (e.g. addition, multiplication, and logic operations) to solve complex problems that are ill-defined and possess high degrees of nonlinearity. The use of the ANN technique in predicting bridge deterioration was first proposed by Sobanjo (1997). A more elaborate ANN model was developed by Tokdemir et al. (2000), which incorporated additional governing factors, such as highway class, design type, material type, and traffic volume. A time-series based ANN model was developed by Lou et al. (2001) to predict the future condition of pavements given past condition records.

In this study, a back-propagation neural network (BPNN) is used to approximate the relationship between the corrosion initiation time of the top layer of reinforcing steel in concrete bridge decks and its governing parameters. Although other neural network architectures, such as the generalized regression neural network (GRNN) and genetic adaptive nets (GAN), could provide faster training, BPNN was selected because of its proven mapping capabilities and widespread application in civil engineering (Moselhi et al. 1991).

The design of the ANN model requires identifying the network architecture (i.e. number of input neurons, output neurons, hidden layers, and neurons in each hidden layer) and the network settings (activation function and learning rate). The adopted network architecture consists of four neurons in the input layer, which represent the values of the governing parameters (d_c, D, C_s, and C_{th}) for concrete bridge decks, and one neuron in the output layer, which represents the value of the corresponding corrosion initiation time (T_i) as shown in Figure 2(a). The optimal number of hidden layers was determined by considering the trade off between generalization and mapping capabilities of the neural network. Basically, the choice is limited to one or two hidden layers because of the ability of these networks to approximate any nonlinear function and map any unknown relationships between the input and output variables (Hornik et al. 1989). Four-layer ANN’s (i.e. two hidden layers) have superior fitting capabilities over three-layer ANN’s (i.e. one hidden layer), however, three-layer ANN’s are computationally faster and have better generalization capabilities (Tamura and Tateishi 1997). Also, it was reported that 95% of the working applications were based on three-layer networks with only few exceptions (Simpson 1996). That is why a three-layer ANN was selected for the present application.



(a) Architecture of proposed ANN model

(b) Architecture of proposed CBR model

Fig. 2. Architectures of proposed ANN and CBR models

The neural network simulator "*BrainMaker*" (California Scientific Software 1996) was used in developing a three-layer BPNN model for this application. This model needs to be trained and validated before it is used to represent the input-output relationship between the input parameters and the corrosion initiation time. The Monte Carlo simulation (MCS) technique was adopted to generate the training and testing sets according to the statistical distributions of the governing parameters derived from the field data. The input values of the ANN model were randomly generated and fed into the mechanistic model to obtain the corresponding output values for training and validating the neural network. A total of 200 cases were created and divided into three sets: (i) training set (60% of the cases); (ii) testing set (20% of the cases); and (iii) validation set (20% of the cases). The training set was used to refine network weights. The testing set was used to measure the network performance while training in order to optimize the network design. The validation set was used to evaluate the overall performance of the trained network.

The optimal number of neurons in the hidden layer that yields reliable results is determined through a trial-and-error procedure as the use of few neurons will not enable the network to "*learn*" the problem, while the use of several neurons would make the network "memorize" and not "*learn*". The optimal number of hidden neurons that achieves an adequate trade-off between the above requirements and ensures satisfactory results cannot be determined in advance, however, a rule of thumb known as the Baum-Haussler rule (Baum and Haussler1988), was used to provide a preliminary estimate of this number as follows:

$$N_{hidden} \leqslant \frac{N_{train} E_{tolerance}}{N_{pts} + N_{output}} \tag{3}$$

where N_{hidden}: number of hidden neurons; N_{train}: number of training examples; $N_{tolerance}$: error tolerance; N_{pts}: number of data points per training example, and N_{output}: number of output neurons. Higher and lower numbers of hidden neurons were used in the trial-and-error procedure and the network performance corresponding to each number was evaluated by the root mean square error (RMSE) and mean absolute error (MAE) of the testing set. The optimal number of hidden neurons that minimizes both error measures was found to be 10.

For the network settings, activation functions are applied to bind the network input and output of the different layers to a specific range that the network can efficiently handle. This range is usually scaled between 0 and 1 or −1 and 1. Different activation functions are provided by the used simulator, such as sigmoid, threshold, step, linear, and Gaussian functions. The selection of the most appropriate function is also a matter of trial-and-error. A scaling range between 0 and 1 with the logistic sigmoid activation function were found to be the best settings for the present application. The learning rate, which identifies the amount of adjustments to connection weights during training, was determined based on the network performance. The learning rate was set to change from 1.0 to 0.1 according to the percentage of correct predictions (from 100% to 0%) in each training cycle. This set up is efficient since it results in high learning rates in the early training cycles, and low learning rates in advanced training cycles, which is required to fine tune network weights and achieve network stability.

3.2 Integrated Case-Based Reasoning- Monte Carlo Simulation Model

The case-based reasoning (CBR) technique is a machine learning approach that solves a problem by reusing the solution of previous and similar problems (sometimes called query case). Each of these cases consists of the problem definition and its corresponding solution and is stored in the so-called case library (Kolodner 1993). The use of CBR in modeling bridge deterioration was first proposed by Morcous et al. (2002b) to predict the future condition of bridge decks by reusing the recorded condition of other decks that are similar in their physical features, environmental and operational conditions, and inspection and maintenance records. This investigation demonstrated the success of the CBR technique over traditional prediction approaches (i.e. regression analysis) in predicting the service life of bridge decks at the network level. Another investigation was carried out by Melhem and Cheng (2003) to compare the capabilities of using instance-based learning and inductive learning in predicting the remaining service life of concrete bridge decks.

A typical CBR model consists of four aspects: case representation, case accumulation, case retrieval, and case adaptation. The need for case adaptation depends on three factors:

- *Task of CBR system*: In synthesis tasks, such as design and planning, adaptation is much more needed than for decision support tasks, such as classification, diagnosis, mapping, and prediction (Bergmann 1998).
- *Nature of retrieved cases*: Case adaptation is more required for composite and knowledge-intensive cases than cases with simple structures (Kolodner 1993).
- *Size of case library*: The larger the case library, the less likely the possibility of having a novel case that requires too much adaptation (Leake 1996).

Since the purpose of the proposed system is functional mapping, cases are simple in structure, and the case library contains adequate number of cases, no adaptation capabilities are required in the present model. In the proposed CBR model, the case for which the time to corrosion initiation needs to be predicted is presented as the query case, while all other cases for which the time to corrosion initiation is known are presented as stored cases in the case library. A retrieval algorithm searches the case library for the most similar stored case(s) to the query case based on the values of the four governing parameters (d_c, D, C_s, and C_{th}) in each case as shown in Figure 2(b). The overall similarity between the query case and each stored case is assessed using the nearest-neighbour approach (Melhem and Cheng 2003). In this approach, the degrees of similarity between the parameter values in the query case and retrieved case are evaluated using the so-called similarity measures, which is based on their difference (Morcous et al. 2002a). In this study, a linear function that represents how close the values of each parameter in a scale from 0 to 1 (where 1 is totally similar and 0 is completely dissimilar) is used as the similarity measure. Then, the weighted average of these degrees of similarity is calculated using parameter weights, which represent the contribution of each parameter to the time to corrosion initiation. The weights of the parameters are obtained through a trial-and-error procedure until the performance of the model becomes satisfactory.

The output of the CBR model is estimated based on the solution of the retrieved case(s) that has the highest similarity with the query case. The CBR development tool called "*Case-Based Reasoning for Modeling Infrastructure Deterioration –CBRMID"* is used in developing the CBR model because of its generic design and suitability to generating CBR applications for modeling infrastructure deterioration (Morcous et al. 2002a). In this study, the CBR technique is integrated with Monte Carlo simulation, as the proposed case library of the CBR model is populated with the same cases used in training the ANN model.

4. CASE STUDY

4.1 Bridge Description

The proposed ANN and CBR techniques are applied to the prediction of the time to onset of corrosion of 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. This superstructure 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 superstructure prior to its demolition (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. The statistical distributions of the governing parameters were derived from the data collected during the field survey using non-destructive evaluation techniques and coring (Fazio 1999)

4.2 Field Survey

Concrete cover depth: The concrete cover depth was measured at 137 locations using a covermeter. The concrete cover depth (d_c) was found to be normally distributed ranging from 10 mm to 89 mm with an average of 36.6 mm and a standard deviation of 16.5 mm.

Diffusion coefficient and surface chloride concentration: As mentioned earlier, the "apparent" values of the diffusion coefficient and surface chloride concentration were obtained by regression analysis to best fit the solution given by Eq. (1) 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 (Fazio 1999). The "near surface" chloride concentration (C_s) was found to have a lognormal distribution with an average of 4.57 kg/m^3 and a standard deviation of 1.84 kg/m^3. The apparent diffusion coefficient (D) also had a lognormal distribution with an average of 51.2 mm^2/year and a standard deviation of 15.8 mm^2/year.

Threshold chloride level: 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 an average of 1.35 kg/m^3 and a standard deviation of 1.84 kg/m^3.

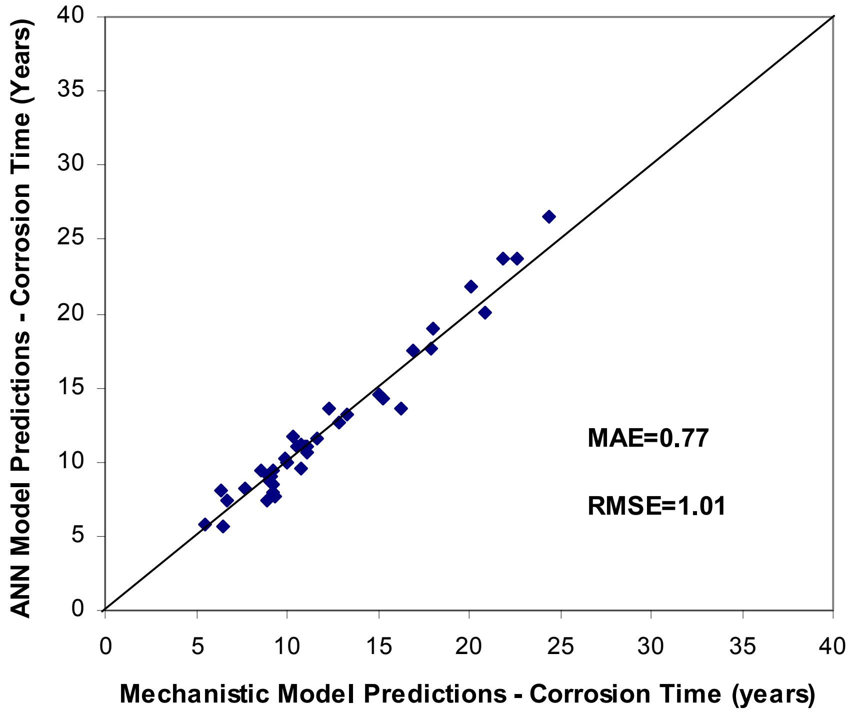
4.3 Prediction of Corrosion Time using ANN and CBR Models

Before using the developed ANN and CBR models in predicting the corrosion time, the ability of these models to accurately map the input-output relationship of the mechanistic models was validated. Figure 3a presents the validation of the trained ANN model by comparing its prediction with the prediction of the mechanistic model for each case in the validation set. This figure and the values of RMSE and MAE indicate that the ANN model provides a good approximation of the mechanistic model and it can be used in the numerical realizations of the Monte Carlo simulation. The sensitivity of the ANN model was also analyzed to determine the importance of each parameter on the time to corrosion initiation. It was found that the concrete cover depth had the greatest impact followed by the diffusion coefficient, surface chloride concentration and chloride threshold level.

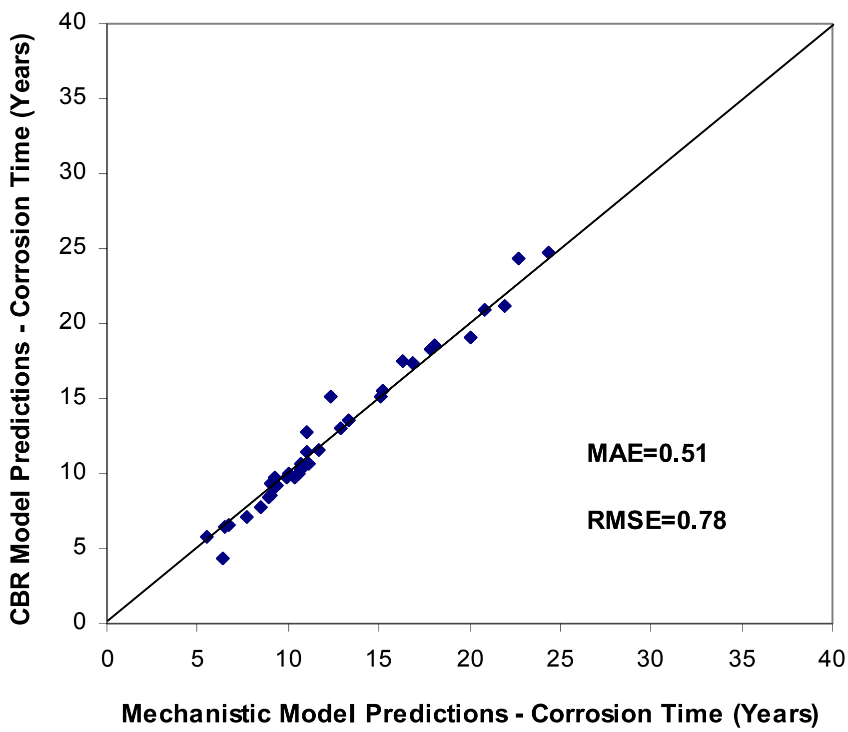
Figure 3b presents the validation of the developed CBR model by comparing its prediction with the prediction of the probabilistic mechanistic model for each case in the validation set. This figure and the values of RMSE and MAE indicate that the CBR model is a good approximation of the mechanistic model and it can be used in the numerical realizations of the MCS technique. For the CBR model, initially, all the parameter weights were assigned the same numeric value (equals 1.0). These weights were subsequently refined in several iterations until the results obtained from the testing set were satisfactory. The final values of the weights were 0.55 for the concrete cover depth, 0.25 for the apparent diffusion coefficient, 0.15 for the surface chloride concentration, and 0.05 for the threshold chloride concentration. These values confirm the results of the sensitivity analysis carried out on the ANN model, where the concrete cover depth was found to be the most important parameter in the corrosion initiation time, while the threshold chloride concentration is the least important one.

These results can be deduced by observing Eq. (2), which shows that the concrete cover depth has a great impact on the corrosion time, given the quadratic relationship between T_i and d_c. It is inversely proportional to the diffusion coefficient, and depends to a lesser extent on the surface chloride concentration and threshold chloride content. As the diffusion coefficient decreases, the corrosion time increases and the increase can be very considerable, especially for very low values of D (i.e. no diffusion is taking place). The surface chloride concentration is the driving force of the diffusion process. The larger the concentration gradient, the faster the diffusion process, and the smaller the corrosion time. However, as the surface chloride concentration approaches a value similar to the value in the concrete mix, the diffusion will slow down and eventually stop at the limit case. It should be pointed out that these variables are not entirely independent and that there is high level of correlation between them.

To use the developed and validated ANN and CBR models in predicting the time to onset of reinforcement corrosion in concrete bridge decks, 1000 cases were randomly generated based on the probabilistic distributions of the four governing parameters of the mechanistic model of Eq. (2). These cases were applied to the ANN and CBR models and resulted in 1000 values of T_i.



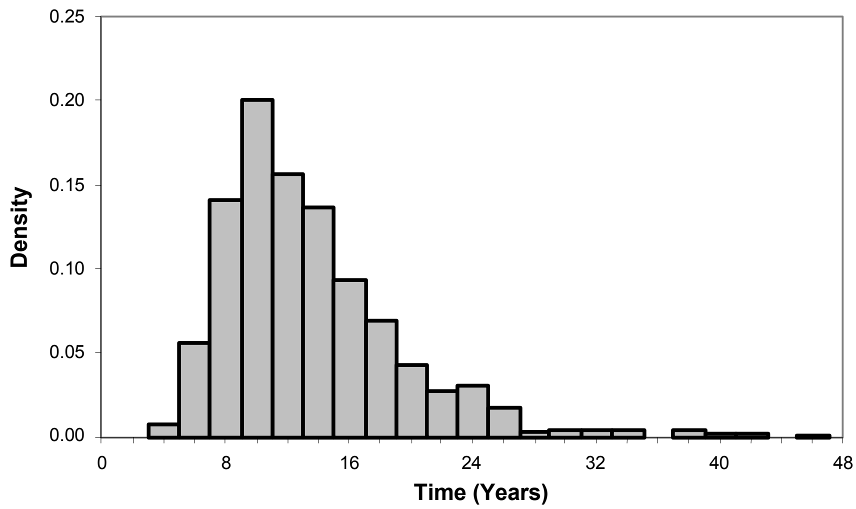
(a)



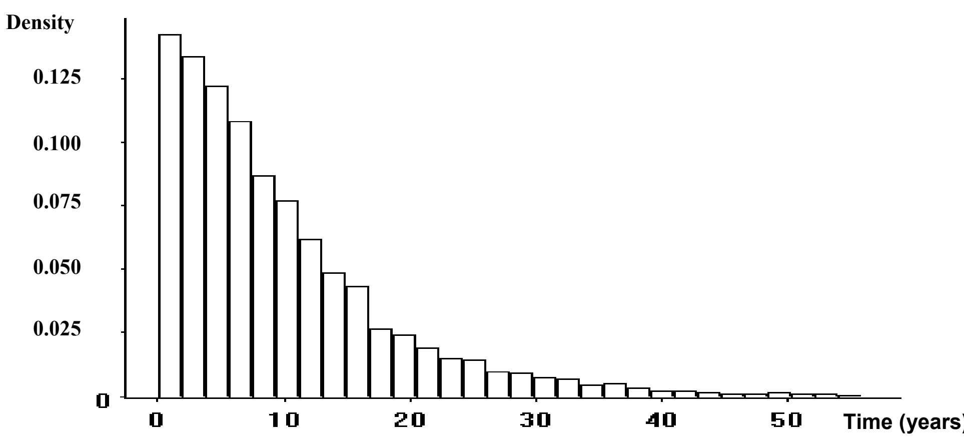
(b)

Fig. 3. Comparison of ANN and CBR predictions with the mechanistic model predictions of time to corrosion initiation

These values were classified into 20 classes of equal width of 2.5 years each and the frequency of each class was calculated. Figure 4a is a plot of the histogram of the time to corrosion initiation obtained using the proposed ANN model. A quasi-similar histogram was obtained using the proposed CBR model. This histogram (or the corresponding cumulative distribution curve) can be used by bridge engineers and managers to estimate the probability of corrosion in the concrete bridge deck at different ages.



(a) Integrated ANN-Monte Carlo simulation approach



(b) Reliability-based mechanistic model

Figure 4. Distribution of time to corrosion initiation in RC bridge decks

To validate the predictive capability of the developed models, a similar histogram was developed using the mechanistic model of Eq. (2) and plotted as shown in Figure 4b. The probability of corrosion after 40 years was obtained from Figures 4a and 4b, and compared with the results of the exhaustive condition survey undertaken on the Dickson Bridge at the age of 40 years. These probabilities were found to be 99% for the ANN/CBR models and 82% for the reliability-based mechanistic model, which are fairly close to the 85% estimated by different condition assessment techniques (Lounis and Mirza 2001). It should also be noted that running 1000 numerical realizations using ANN, CBR, and mechanistic models indicates that the ANN model is the most computationally efficient technique in predicting the time to corrosion initiation with uncertainty using Monte-Carol Simulations. The CBR model was not as efficient as the ANN model but still more computationally efficient than the mechanistic model. In addition, the ANN and CBR models have the potential to handle more complicated mechanistic models without a significant increase in the running time due to their functional mapping capabilities.

5. CONCLUSIONS

This article investigated the use of artificial neural networks (ANN) and case-based reasoning (CBR) techniques in conjunction with Monte Carlo simulation (MCS) for modeling bridge deterioration. In this investigation, two integrated ANN-MCS and CBR-MCS models were developed to act as functional mapping tools between the input and output of the mechanistic model used to predict the time to corrosion initiation of reinforcing steel embedded in concrete bridge decks. The data obtained from the field survey of the Dickson bridge in Montreal were used as a case study. The results of this study can be summarized as follows:

- The ANN and CBR models provide a good mapping of the relationship between the governing parameters (concrete cover depth, surface chloride concentration, apparent diffusion coefficient, and threshold chloride concentration) and time to onset of corrosion.
- The ANN and CBR models have potential for computationally efficient uncertainty analysis of the mechanistic model used in predicting the onset of corrosion.
- The results of the case study showed that the integration of ANN and CBR techniques and Monte Carlo simulation provide good predictions when compared to the field data.

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REFERENCES

Andrade, C., Alonso, C., and Molina, F. J. (1993). "Cover cracking as a function of rebar corrosion: Part I – Experimental test." *Materials & Structures*, Paris, 26, 453-464.

Anthony D. Griffiths and Derek G. Bridge. (1995) "Inductive bias in case-based reasoning systems". Technical Report YCS 95/259, Department of Computer Science, University of York.

Baum E. B. & Haussler D. (1988). "What size net gives valid generalization?" *Neural Computation*, 1, pp. 151-160.

Bentur, A. Diamond, S., and Berke, N.S. (1997). *Steel corrosion in concrete*. E & FN SPON.

Bergmann, R. (1998). "On the Use of Taxonomies for Representing Case Features and Local Similarity Measures." *Proc. 6th German Workshop on Case-Based Reasoning*, Berlin,Germany, March, pp. 23-32.

Boussabaine, A. H. (1996). "The use of artificial neural networks in construction management: A review." *Construction Management and Economics*, E&FN Spon, 14, 427-436.

Cady, P. D. and Weyers R. E. (1983). "Deterioration rates of concrete bridge decks." *J. Transportation Engrg., ASCE*, 110 (1), 34-44.

California Scientific Software (1996). "*BrainMaker -Neural network software*." USA.

Enright, M. P., and Frangopol, D. M. (1998). "Service-life prediction of deteriorating concrete Bridges." *J. Structural Engrg., ASCE*, 124 (3), 309-317

Fausett, L. (1994). *Fundamentals of neural networks: architectures, and applications*. Prentice Hall, Upper Saddle River, NJ, USA.

Fazio, R. (1999). "The assessment and prediction of reinforcing steel corrosion on the Dickson Bridge." *M.Eng. Thesis*, McGill University, Montreal, Canada.

Federal Highway Administration -Non-Destructive Evaluation Validation Center (2001). "The problem of deteriorating bridge decks." *www.tfhrc.gov/hnr20/nde/problem.htm*.

Glass, K., and Buenfeld, N.R. (1995). "Chloride threshold levels for corrosion-induced deterioration of steel in concrete." In *Chloride Penetration into Concrete*, L.O. Nilsson and J.P. Ollivier (eds.), RILEM Publications, France, pp. 429-440.

Hawk, H. (1995). "*BRIDGIT* Deterioration Models." *Transportation Research Record*, TRB, 1490, pp. 19-22.

Hornik, K., Strathcombe, M., and White, H. (1989). "Multilayer feed forward are universal Approximators." *Neural Networks 2*, Pergamon 2 (4), 359-366.

Kolodner, J. (1993). *Case-Based Reasoning*. Morgan Kaufmann Publishers, Inc.

Kropp, J., and Hilsdorf, H.K., eds. (1995). *Performance Criteria for Concrete Durability*. E&FN SPON, London.

Leake, D. B. (1996), (ed.) *Case-Based Reasoning: Experiences, Lessons, and Future Directions*. American Association for Artificial Intelligence Press, Menlo Park, CA.

Liang, M., Lin, L., and Liang, C. (2002). "Service life prediction of existing reinforced concrete bridges exposed to chloride environment." *J. Infrastructure Systems, ASCE*, 8(3), 76-85

Lou, Z., Gunaratne, M., and Dietrich, B., (2001). "Application of neural network model to forecast short-term pavement crack condition: Florida case study." *J. Infrastructure Systems, ASCE*, 7 (4), 166-171.

Lounis, Z. (2000). "Reliability-Based Life Prediction of Aging Concrete Bridge Decks." In *Life Prediction and Aging Management of Concrete Structures*, D. Naus (ed.), RILEM Publications, France, pp. 229-238.

Lounis, Z., and Mirza, M. S. (2001) "Reliability-based service life prediction of deteriorating concrete structures", *Proc. 3rd Int. Conf. on Concrete Under Severe Conditions*, Vancouver, Canada, Vol.2, pp. 965-972.

Madanat, S., Karlaftis, M. G., and McCarthy, P. S. (1997). "Probabilistic infrastructure deterioration models with panel data." *J. Infrastructure Systems, ASCE*, 3(1), 4-9

Melhem, H. G. and Cheng, Y. (2003). "Prediction of remaining service life of bridge decks using machine learning." *J. Computing in Civil Engrg., ASCE*, 17(1), 1-9.

Morcous, G., Rivard, H., and Hanna, A. M. (2002a). "Case-based reasoning system for modeling infrastructure deterioration." *J. Computing in Civil Engineering, ASCE*, 16 (2), 104-114.

Morcous, G., Rivard, H., and Hanna, A. M. (2002b). "Modeling bridge deterioration using case-based reasoning." *J. Infrastructure Systems*, ASCE, 8(3), 86-95.

Moselhi, O., Hegazy, T., and Fazio, P. (1991). "Neural networks as tools in construction." *J. Construction Engrg. & Management*, ASCE, 117(4), 606-625.

Neville, A. (1995). "Chloride attack of reinforced concrete: an overview." *Materials & Structures*, 28, 63-70.

Rosenberg, A., Hanson, C. M., and Andrade, C. (1989). "Mechanisms of corrosion of steel in concrete." *Material Science of Concrete I*, J. Skalny, ed., American Ceramic Society, Westerville, Ohio, 285-313.

Simpson, P. (1996). "Neural Networks Theory, Technology, and Applications." *IEEE*, NY.

Sobanjo, J. O. (1997) "A neural network approach to modeling bridge deterioration." *Proc. 4th Congress on Computing in Civil Engrg.*, ASCE, Philadelphia, PA, 623-626.

Stewart, M., and Rosowsky, D.V. (1998). "Structural safety and serviceability of concrete bridges subject to corrosion." *J. Infrastructure Systems, ASCE*, 4(4), 146-155.

Tamura, S., and Tateishi, M. (1997). "Capabilities of four-layered feed-forward neural networks: four layers versus three." *IEEE Trans. on Neural Networks*, 8(2), 251-255.

Thompson, P. D. and Shepard, R. W. (1994). "*Pontis.*" Transportation Research Circular, TRB, Vol. 324, pp. 35-42.

Tokdemir, O. B., Ayvalik, C., and Mohammadi, J. (2000). "Prediction of highway bridge performance by artificial neural networks and genetic algorithms." *Proc. 17th Int. Symp. Automation and Robotics in Construction*, ISARC, Taipei, Taiwan, 1091-1098.

Tuutti, K. (1982). "Corrosion of steel in concrete." Swedish Cement and Concrete Research Institute, Stockholm.

Watson, I. (1997). *Applying case-based reasoning: techniques for enterprise systems*. Morgan Kaufmann Publisher, San Mateo, CA, USA.

Weyers, R.E. (1998). "Service life model for concrete structures in chloride-laden environments." *J. ACI Materials*, 95(5), pp. 546-557.

Zou, R., Lung, W., and Guo, H. (2002). "Neural network embedded Monte Carlo approach for water quality modeling under input information uncertainty." *J. Computing in Civil Engrg., ACE*, 16 (2), 135-142.