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Review Article

Deterioration models for prediction of remaining useful life of timber and concrete bridges: A review

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HIGHLIGHTS

- A critical review on deterioration models for predicting the remaining service life of bridges is presented.
- Examples are illustrated to develop bridge element deterioration models by deterministic, stochastic and ANN-based methods.
- Recommendations are made for future research in the area of bridge deterioration modeling.

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ABSTRACT

Bridge deterioration models are used for prioritization and maintenance of bridges. These models can be broadly classified as deterministic and stochastic models. There are mechanistic models (or physical models) as well as Artificial Intelligence (AI)-based models, each of which can be stochastic or deterministic in nature. Even though there are several existing deterioration models, state-based stochastic Markov chain-based model is widely employed in bridge management programs. This paper presents a critical review of different bridge deterioration models highlighting the advantages and limitations of each model. The models are applied to some case studies of timber superstructure and concrete bridge decks. Examples are illustrated for arriving at bridge deterioration models using deterministic, stochastic and Artificial Neural Network (ANN)-based models based on National Bridge Inventory (NBI) data. The first example is based on deterministic model and the second on stochastic model. The deterministic model uses the NBI records for the years 1992–2012, while the stochastic model uses the NBI records for one year (2011–2012). The stochastic model is state-based Markov chain model developed using Transition Probability Matrix (TPM) obtained by Percentage Prediction Method (PPM). The two deterioration models (i.e., deterministic and stochastic models) are applied to timber highway bridge superstructure using NBI condition data for bridges in Florida, Georgia, South Carolina and North Carolina. The illustrated examples show that the deterministic model provides higher accuracy in the predicted condition value than the stochastic Markov chain-based model. If the model is developed based on average of transition probabilities considering the data for the period 1992 to 2012, the prediction accuracy of stochastic model will improve. Proper data filtering of condition records aids in improving the accuracy of the deterministic models. The third example illustrates the ANN-based deterioration model for reinforced concrete bridge decks in Florida based on the NBI condition

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data for the years 1992–2012. The training set accuracy and testing set accuracy in the ANN model are found to be 91% and 88% respectively. The trained model is utilized to generate missing condition data to fill the gaps due to irregular inspections of concrete bridges. This paper also discusses scope for future research on bridge deterioration modeling.

1. Introduction

Bridges form a major part of U.S. infrastructure, which has a total of 614,387 bridges. The structurally deficient bridges form 9.1% of the nation's bridge population (ASCE, 2017). Besides, almost 40% of the bridges are over 50 years old, which is the average design-life of a bridge. In order to prioritize and maintain the bridges, it is essential to arrive at bridge maintenance strategies based on deterioration models for bridge elements. These models have been developed using inspection records from National Bridge Inventory (NBI) for the bridges in the United States. The NBI database includes information on the: i) geometric and design parameters of the bridge like span length, skew angle, deck width, material type, superstructure design type and design load; ii) operational conditions such as Average Daily Traffic (ADT), age, and highway classification; and iii) structural condition of bridges in the states' inventory. NBI specifies a condition rating scale of 0–9 based on visual inspection, with 9 being excellent condition, and 4 indicating poor condition. A bridge qualifies as structurally deficient if the condition rating is 4 or below for the bridge deck, superstructure or substructure. Table 1 gives the descriptions of the condition ratings for the bridge deck based on NBI. Visual inspections are carried out either annually or biennially, and the inspection records are used to assist the maintenance of bridge inventory. The NBI records are used to develop bridge deterioration models. The NBI records have certain limitations such as: i) subjectivity of visual inspection process; ii) unbalanced, noisy and large amounts of data scatter; and iii) condition data availability for only a small window in time for many bridges. Winn (2011) analyzed these aspects of NBI database for concrete highway bridge decks in Michigan.

Typical condition ratings adopted across the world are presented in Table 2. The information is adapted from literature reported by Hearn et al. (2005), Jeong et al. (2017), Liao et al. (2017), Masahiro and Takashi (2013), Xie et al. (2014), and Yusuf and Hamid (2018).

Several researchers have attempted to improve the deterioration modeling for prediction of remaining useful service life of bridges. Imbsen et al. (1987) evaluated the strength of reinforced concrete bridges by considering the degree of deterioration in the structure, frequency of inspection, preventive maintenance, and ultimate resistance evaluation. A comprehensive Bridge Management System (BMS) for the Indiana Department of Highways (IDOH) using the Markov chain was developed by Jiang et al. (1988) and Jiang and Sinha (1989). Frangopol (2002), Frangopol and Maute (2003), Frangopol et al. (2004, 2010), and Barone and Frangopol (2014) contributed to the field of reliability-based deterioration prediction and lifetime maintenance cost optimization of infrastructure. Agrawal et al. (2008, 2010) presented the development of Markov chains and Weibull distribution based approaches for the calculation of deterioration rates of different bridge elements in New York State Department of Transportation (NYS DOT) considering the factors such as the material types, design types, etc. Morcous et al. (2002a, b) demonstrated a "proof of concept" application for modeling the deterioration of concrete bridge

Table 1 – NBI condition rating (Federal Highway Administration, 1995).

NBI scale	Condition	Description
9	Excellent	New condition, no noteworthy deficiencies
8	Very good	No repair needed
7	Good	Some minor problems, minor maintenance needed
6	Satisfactory	Some minor deterioration, major maintenance needed
5	Fair	Minor section loss, cracking, spalling, or scouring for minor rehabilitation; minor rehabilitation needed
4	Poor	Advanced section loss, deterioration, spalling or scouring; major rehabilitation needed
3	Serious	Section loss, deterioration, spalling or scouring that have seriously affected the primary structural components
2	Critical	Advanced deterioration of primary structural elements for urgent rehabilitation; bridge maybe closed until corrective action is taken
1	Imminent failure	Major deterioration or loss of section; bridge may be closed to traffic, but corrective action can put it back to light service
0	Failed	Out of service and beyond corrective action

Table 2 – Condition ratings in other countries.

Country	Bridge condition rating
Denmark	0 to 5 condition rating plus inspector's recommendation on repair urgency
Finland	0 to 4 condition rating scale plus importance in load path, severity, urgency of repair, condition of the bridge element
France	1 to 3 condition rating scale. 2E indicates urgent need for specialized maintenance, 3U indicates urgent need for repair, and S indicates a threat to user safety and an urgent need for action
Germany	0 (good) to 4 (very poor) severity condition rating scale and each bridge component is assigned three ratings; one each for structural damage, traffic safety, and bridge durability
Norway	1 to 4 severity rating scale plus a consequence code (impact on load capacity, traffic operations, maintenance cost or environment)
South Africa	Ratings in three categories: physical, functional and economic condition (related to extent of damage)
United Kingdom	1 to 5 severity rating plus A to E extent rating
Japan	Maintenance urgency ratings: A–no repairs needed, B–no immediate repairs needed, C–repair needed, E1–emergency action is necessary from the viewpoint of structural safety and stability, E2–emergency action is necessary because of other factors, M–repairs needed in the course of the regular maintenance work, S–further detailed investigations needed
China	Five condition states: CS I–good condition, whereas CS V–unacceptable condition
Malaysia	1 to 5 condition rating scale with 1–no damage found and no maintenance required as a result of inspection and 5–being heavily and critically damaged, and possibly affecting the safety or traffic
South Korea	A to E rating scale with A–perfect condition to E–failure condition

decks using Case-Based Reasoning (CBR). Morcous et al. (2003) proposed an approach to provide an effective decision support tool to identify the categories that best define the environmental and operational conditions specific to bridge structures with an ability to correlate the parameters such as highway class, region, ADT, and percentage of truck traffic. Morcous et al. (2010) presented an integrated system for bridge management using probabilistic and mechanistic deterioration models for bridge decks. Morcous (2011) developed deterioration models for Nebraska bridges using Markov chain-based method. Bu et al. (2011, 2012, 2014) proposed bridge deterioration modeling based on Backward Prediction Model (BPM) and Markovian-based deterioration procedure. Cavalline et al. (2015) and Goyal et al. (2017) developed proportional hazards regression-based methodology to identify the most critical factors affecting deterioration. Tolliver and Lu (2012) and Lu et al. (2016) analyzed bridge deterioration rates using multivariable regression analysis. Kosgodagan (2017), Rafiq et al. (2015), Straub (2009), Tabatabaee and Ziyadi (2013), Torre et al. (2017), and Wang et al. (2012) proposed a methodology to develop a deterioration model using Bayesian network which aids in updating the model as new data becomes available. She et al. (1999) described a framework for developing a Geographical Information System (GIS)-based Bridge Management System (BMS). Chun et al. (2010) proposed a bridge deterioration prediction method using Markov chain-based model, whose transition probabilities are expressed as a function of environmental conditions obtained from GIS. Though BMS have been developed and improved by many engineers and researchers, there are still challenges and scope for improvements in deterioration modeling. Present BMS are based on state-based Markov chain models. These models assume state-independence (i.e., the future condition state of the bridge is based only on the current state). The probability of the bridge condition changing from one state to another is determined using expert judgment and empirical observations, which are represented in a matrix form. This matrix is called the Transition Probability Matrix (TPM). Based on the current condition or initial condition state of a bridge element, the future condition can be predicted through the multiplication of the current condition vector and the TPM. Current Markov chain models in BMS assume time homogeneity (i.e., the transition probabilities remain the same over the service life). In addition, one of the main drawbacks is that current BMS are based on qualitative deterioration modeling in terms of condition states which are not essentially related to physical quantitative parameters such as deformations, stresses and cracking. In this paper, a critical literature review on bridge deterioration models is presented with illustrative examples, and scope for future research on deterioration modeling is discussed.

2. Bridge deterioration models

Reinforced and prestressed concrete and timber bridges together amount to about 67% of the total bridge inventory based on 2017 NBI records. The total number of bridges in the United States based on NBI 2017 data is shown in Fig. 1.

During the service life, concrete bridges are subjected to aggressive influences viz. variable loadings and vibrations, extreme weather conditions, presence of chlorides in de-icing salts and freeze and thaw cycles, plus air borne chlorides in marine environments. These factors lead to concrete bridge deterioration, predominantly due to reinforcement steel corrosion. Several authors have developed deterioration models for concrete bridge elements, which are discussed in the following sub-sections. However, there are only limited studies available on the deterioration prediction of timber bridge elements. Ranjith et al. (2011) developed stochastic Markov chain-based model for the prediction of timber bridge elements' condition using data obtained from the Roads Corporation of Victoria in Australia. The authors have applied Percentage Prediction Method (PPM), regression-based optimization method, and nonlinear optimization technique to predict transition probabilities from the

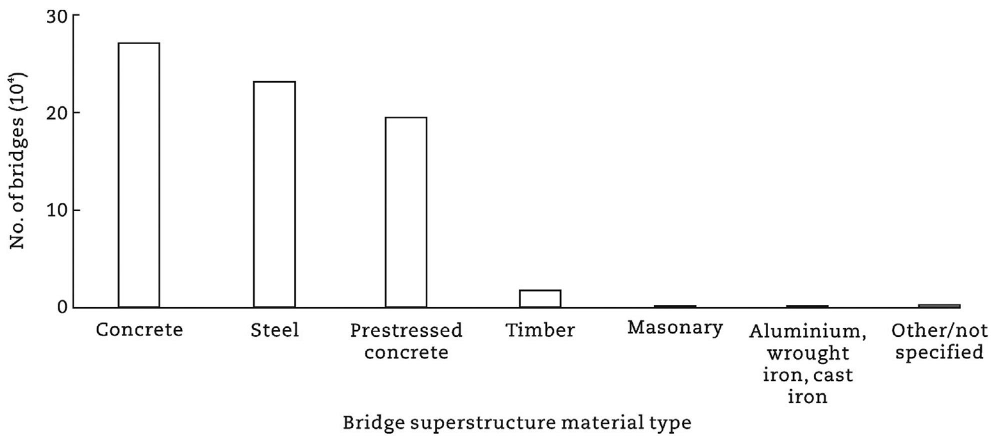


Fig. 1 – Bridge classification based on superstructure material type as per NBI record (2017).

condition data. The authors selected the most suitable deterioration model for timber bridge elements based on goodness-of-fit test. It has been concluded that the deterioration prediction of timber bridge elements based on the nonlinear optimization technique provides reasonable accuracy. An alternative approach to bridge degradation modeling has been proposed by Le and Andrews (2015) to model the deterioration of railway bridge elements using maintenance data. The deterioration process is modeled by a Weibull distribution that governs the time that a component deteriorates to a degraded condition state following a repair. The authors have mentioned that the rates for reaching different deteriorated conditions increase significantly with time for timber decks and that the timber deck is usually replaced once the material reaches a critical point with severe defects. The major limitation of this method is its dependence on significant amount of maintenance data for modeling the bridge element deterioration. An empirical method for predicting the remaining lifespan of timber bridges has been suggested by Abbott et al. (2019) using the Australian bridges' condition data. The authors have mentioned that further research is necessary to validate the accuracy of the model.

Bridge deterioration models can be broadly classified as deterministic and stochastic models. There are mechanistic models (or physical models) as well as Artificial Intelligence (AI)-based models, each of which can be stochastic or deterministic in nature.

2.1. *Deterministic models*

Deterministic models assume that tendency of bridge deterioration process is certain and are based on regression analysis of condition data. These models depend on an empirical relationship between two or more variables that affect the bridge condition with one dependent variable and one or more independent variables. Linear regression models do not provide enough accuracy for long-term performance of bridge and may underestimate or overestimate the bridge condition at a specific time unlike the non-linear regression models. Previous researchers have found that a polynomial curve for condition state as a function of age provides a good estimate for most of the concrete bridges (Bolukbasi et al., 2004; Tolliver and Lu, 2012). The following are the advantages and limitations of deterministic models.

Advantages: i) simplest approach to predict the future condition of bridges; and ii) practicality at the network level.

Limitations: i) neglects uncertainty due to the inherent stochastic nature of infrastructure deterioration; ii) computationally expensive to update deterministic models when new data is obtained; and iii) disregards the interaction between deterioration of different bridge components, such as the bridge deck and deck joints.

2.2. *Stochastic models*

Stochastic models consider the bridge deterioration process as one or more random variables (viz. time, condition state of bridge elements) and hence can capture the uncertainty and randomness of the deterioration process. Stochastic models can be classified as either state-based or time-based models.

In state-based models, the deterioration process is modeled through a probability of transition from one condition state to another in a discrete time interval. Markov chains have been extensively used in state-based models given that the deterioration process is dependent on a set of measurable variables such as age, Annual Average Daily Traffic (AADT), climate, material, etc.

In time-based models, the duration that a bridge element remains at a particular condition state is modeled as a random variable using probability distributions, such as Weibull distribution, Gamma distribution, etc., to describe the deterioration process (Kotze et al., 2015).

2.2.1. *State-based models*

Markov chain model is a state-based model which is based on discretization of the condition of the bridge elements/systems into a finite set of states and probabilities that the element or system will jump from one condition state to the next state within a unit time period. These probabilities are obtained from either expert opinions or from a combination of expert opinions and maintenance data when available (Betti, 2010). Markov chain theory is based on two assumptions: memoryless (i.e., the future states of the process depend only on the current state) and homogeneous (i.e., the rates of transition from one state to another remain constant throughout the service life). For example, the Markov chain for two states A and B can be represented as shown in Fig. 2 where the numbers represent the transition probabilities.

Cesare et al. (1992) described methods for utilizing Markov chains in the evaluation of highway bridge deterioration. Two methods that are frequently used for developing state-based Transition Probability Matrix (TPM) are Percentage Prediction Method (PPM) (Jiang and Sinha, 1989) and regression-based optimization (Butt et al., 1987). Since the latter method is affected significantly by any prior maintenance actions, whose records may not be readily available in many Bridge Management System (BMS) databases, the PPM is commonly used (Morcous, 2011). The advantages and limitations of Markov chain models are given below.

Advantages: i) Markov model provides a framework that accounts for the uncertainty; ii) it is compatible with existing qualitative/discrete bridge condition rating systems; and iii) these models are simple to use and are very practical at the network level.

Limitations: i) transition rates among condition states of a bridge element are time independent (homogeneous) (Betti, 2010); ii) the Markov chain models only provide a qualitative prediction of the future condition of the bridge element (e.g., excellent, good, fair, poor). The damage states are based on qualitative condition ratings of bridge systems that are not uniquely related to measurable physical quantities. Qualitative models are inadequate for severely damaged bridges for which safety may become an issue (Betti, 2010); and iii) Markov chain model cannot be used to assess the reliability of a structure in terms of strengths and stresses (Frangopol et al., 2004).

2.2.2. *Time-based models*

In time-based models, probability distributions such as Weibull distribution, Gamma distribution, etc., are used to describe the deterioration process. In these models, the duration that a bridge element remains at a particular condition state is modeled as a random variable. Mishalani and Madanat (2002) presented the development of a time-based discrete-state stochastic duration model. Sobanjo (2011) developed a semi-Markov model for Florida DOT, which incorporates Markov-Weibull model. In this model, Weibull survival function is used to model the probability of remaining in condition state (CS) 1, as a function of age, and Markov is used for remaining states. It was found that the onset of deterioration is age-dependent and that a Weibull survival probability model provided a relatively simple and useful way of describing the effect of bridge age. Fig. 3 shows the Probability Distribution Function (PDF) for different condition states for Cast In Place (CIP) concrete

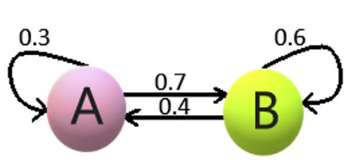


Fig. 2 – Markov chain representation.

deck. The condition states 1, 2, 3, and 4 in Fig. 3 correspond to NBI condition ratings 9, 8, 7 and 6, respectively. Mašović et al. (2015) presented an application of semi-Markov chain process in bridge management.

The advantages and limitations of time-based models are given below.

Advantages: i) Weibull models are found to be more realistic since the Weibull-based method utilizes actual scatter in duration data for a particular condition rating and considers this duration as a random variable (Agrawal et al., 2009); and ii) time-based models have been used to obtain an age-dependent probability of failure as an enhancement of the Markov model (Thompson et al., 2012).

Limitations: i) interaction between different elements in relation to the structural integrity is ignored (Ghodoosi et al., 2014); ii) complexity in the estimation of distribution parameters, especially in the lower condition states where there is a lack of condition data; and iii) time-based models are considered appropriate only if more than 20 years of inspection data are available, otherwise state-based models are considered more suitable (Mauch and Madanat, 2001).

2.3. *Mechanistic models*

Mechanistic models overcome the limitation of Markov chain model in terms of capability to relate the qualitative measurement of condition state to the quantitative physical parameters of the bridge such as material properties, stress conditions, structural behavior, etc. These parameters are critical data for assessing the structural capacity, and hence, the reliability of the bridge. Estes and Frangopol (1999) proposed a system reliability approach for optimizing the lifetime repair strategy for highway bridges which involves modeling the bridge as a series-parallel combination of failure modes, and the reliability of the overall bridge system is computed using time-dependent deterioration models. Van Noortwijk and Frangopol (2004) compared two maintenance models: condition-based and reliability-based models. The former model is condition-based and treats only one component, one failure mode and one uncertainty. The latter model is reliability-based and treats the multi-component, multi-failure mode and multi-uncertainty case. Roelfstra et al. (2004) suggested an approach to model the chloride-induced corrosion of steel reinforcement in which results from the simulation were mapped to condition states and Markov transition matrices were calibrated to fit the simulation results. Morcous et al. (2010) illustrated an example of a mechanistic model for reinforced concrete bridge deck based on probabilistic corrosion initiation and propagation model. Fig. 4(a) (shaded area between the arrows) shows 86% probability of corrosion initiation at 40 years. Fig. 4(b) shows the cumulative probability of percentage of remaining steel at different years. For example, the probability of losing 30% of steel (i.e., 70% remaining steel area) is estimated as 10% after 50 years, about 25% after 60 years and 50% after 75 years. The corrosion model was originally proposed by Tuutti (1982). Zonta et al. (2007) presented a reliability-based bridge management concept for Autonomous Province of Trento (APT) in Italy. Ghodoosi et al. (2014) evaluated the system

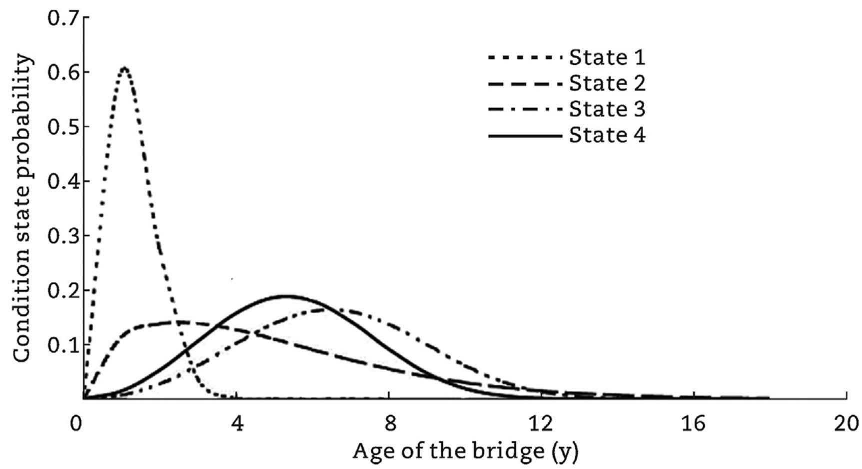


Fig. 3 — PDF for duration of condition ratings for bridge CIP concrete deck (Sobanjo, 2011).

reliability of existing conventional concrete bridge decks over time. The authors have applied system reliability analysis to simply supported concrete bridge superstructures designed according to the Canadian Highway Bridge Design Code (CHBDC-S6) and developed the deterioration pattern based on the reliability estimates. A reliability analysis of existing highway bridges in China based on SIE2011 was carried out by Xie et al. (2014). The authors have applied Monte Carlo sampling method to calculate the reliability indices of existing reinforced concrete simply supported T-beam highway bridges and predict the probability of failure of the existing highway bridges in each condition state and each age. Barone and Frangopol (2014) proposed a multi-objective optimization technique involving reliability, risk, hazard, and cost. Recently, Zambon et al. (2019) presented a detailed overview on carbonation-induced corrosion.

The following are the advantages and limitations of mechanistic models.

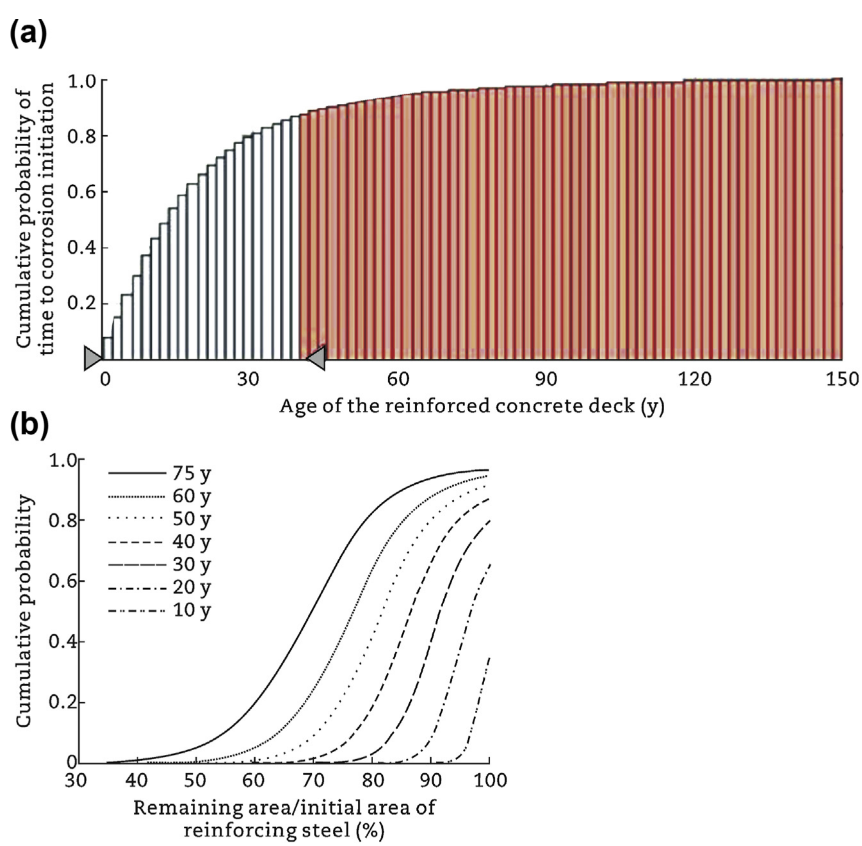


Fig. 4 — Probabilistic corrosion initiation and propagation model. (a) Cumulative probability of time to corrosion initiation. (b) Cumulative Distribution Function (CDF) of percentage of remaining reinforcing steel at different times (Morcous et al., 2010).

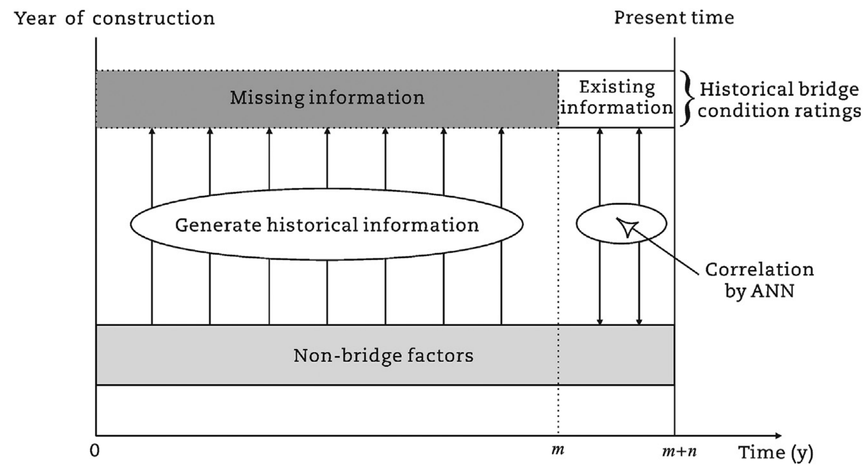


Fig. 5 – Backward Prediction Model (Lee et al., 2008).

Advantages: i) mechanistic models are suitable for project level analysis; and ii) the models provide reliability based quantitative deterioration prediction for bridge elements.

Limitations: i) this deterioration model is costly in terms of data requirements and modeling and therefore, will be inefficient for a large bridge network; and ii) these models cannot be directly integrated into a BMS due to the high cost associated with data collection by available on-site inspection techniques.

2.4. *Artificial-Intelligence (AI) based models*

AI-based models include expectation maximization (EM) approach (Mašović and Hajdin, 2014), Case-Based Reasoning (CBR) (Morcous et al., 2002a), evolutionary algorithms like genetic algorithms, shuffled frog leaping (Elbehairy et al., 2006), and particle swarm optimization (Elbehairy, 2007). AI based models also include Artificial Neural Network (ANN) models like Back Propagation method with Multi-Layer Perceptron classifier (BP-MLP) (Huang, 2010) and Backward Prediction Model (BPM) (Lee et al., 2011).

Mašović and Hajdin (2014) modeled the deterioration of bridges elements of concrete girder bridges in Serbia based on the Markov chain. The authors applied EM algorithm to condition data from the Serbian bridge information database to estimate the transition probabilities. It was highlighted that the EM algorithm provided reasonable deterioration model even if the inspection records were limited. Using an ANN-based BPM, it is possible to generate artificial historical bridge condition states (Lee et al., 2008; Son, 2010). Fig. 5 illustrates the BPM proposed by Lee et al. (2008). Bu et al. (2015) developed an integrated model that incorporated both time-based and state-based models with backward prediction approach for long-term deterioration prediction of bridge components. The state-based model was based on Markov chain and Elman Neural Networks (ENN) to calculate the transition probabilities and the time-based model was based on Kaplan and Meier (K-M) estimate to calculate the Probability Distribution Function of transition times.

CBR technique searches for previous cases where examples that are similar to the current problem are accessed from the case library to solve the current problem (Morcous et al., 2002b). Fig. 6 shows the CBR cycle originally proposed by Bergmann et al. (2009).

Huang (2010) developed ANN based model to predict the deterioration of concrete decks based on inspection records for Wisconsin bridges. The study identified 11 significant factors including age, design load, maintenance history, length, ADT, deck area, environment, number of spans, degree of skew, district and the previous condition to predict the condition rating of the bridge decks. It was found that the ANN model performs well when modeling deck deterioration in terms of pattern classification. It was claimed that the developed model had the capacity to accurately predict the condition of bridge decks and therefore provide pertinent information for maintenance planning and decision making at both the project level (a single bridge) and the network level (a group of bridges).

Artificial Neural Networks are computational models inspired by biological neural networks and used to approximate the unknown functions. There are different ANN

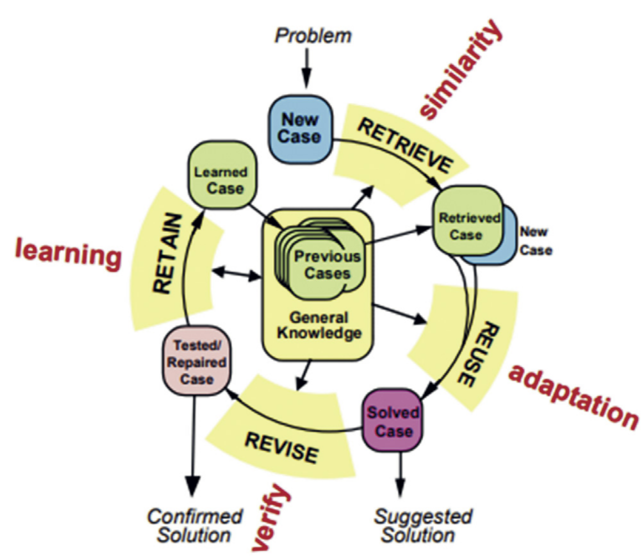


Fig. 6 – CBR cycle (Bergmann et al., 2009).

models, of which, Multi-Layer Perceptron (MLP) is widely used. MLP is a class of feedforward Artificial Neural Network. It consists of at least three layers of nodes: an input layer, a hidden layer and an output layer. Except for the input nodes, each node is a neuron that uses a nonlinear activation function. MLP utilizes a supervised learning technique called Back Propagation (BP) for training the neural network (Haykin, 2014; Winn, 2011).

MLP is a highly interconnected network of many simple linear or nonlinear processors (i.e., functions) distributed in parallel (Fig. 7). The network can learn from experience and then apply the knowledge to perform complex calculations to find the values for missing data. Each processing unit receives multiple inputs through weighted connections from neurons in the previous layer. It performs appropriate computations and transmits the output to other processing units. The network performs operations by propagating changes in activation (i.e., the state of a neuron which is passed through the activation function) through the weighted connections between the processors (Winn, 2011).

ANN obtains knowledge through training phase. In this phase, the network is established using a set of training data. During the learning phase, the system learns and identifies the relationship between the input and output parameters. The relationship is defined using the interconnection strengths between nodes known as synaptic weights. The weights are used to store the knowledge from the training. Once the weights are known and the knowledge is stored, the developed network can be used to solve the problems for an unknown dataset (Hasan, 2015).

Neural network derives its computing power through its massively parallel distributed structure and generalization. Generalization refers to the neural network's production of reasonable outputs for inputs not encountered during training (learning). These two information processing capabilities make it possible for neural networks to find good approximate solutions to complex and large-scale problems that are intractable (Haykin, 2014).

The following are the advantages and limitations of AI-based models.

Advantages: i) ANN-based technique can generate missing condition state data to fill the gaps due to irregular inspections; and ii) CBR technique can be used to perform “what if” analyses for different maintenance scenarios by changing maintenance decisions and retrieving cases with similar decisions based on available maintenance data.

Limitations: i) ANN is just an approach to artificially generate missing data and it needs complementary tools to utilize generated information for modeling bridge deterioration; and ii) the performance of the CBR approach depends on the size of the case library and the adequacy of case description, correct setting of the attribute weights which is subjective and the availability of knowledge for case adaptation.

3. Current state-of-the-art on criteria for remaining useful life of bridges

An asset is considered to have reached its life expectancy when it is either physically deteriorated or can no longer provide the intended service (Kumar et al., 2018). Expected bridge life can be defined as the time until the bridge is replaced or removed from service (Jeong et al., 2017). Taking into account that the theoretical design life of bridges is usually 50 years, a large proportion of the bridges in the United States are considered deficient (Crevello et al., 2015). Hence, it is critical for the highway agencies to estimate the remaining service life of bridges to implement suitable Maintenance, Repair and Rehabilitation (MR&R) measures at the appropriate time. Preventive maintenance will generally be more cost-effective than a reactive maintenance.

The life expectancy of bridges has been found to vary by condition threshold and maintenance/preservation intensity. The following are reported by Ford et al. (2011).

- Estes and Frangopol (1999) compiled bridge life expectancy estimates based on data and expert opinions and found that reinforced concrete decks survive between 24 and 48 years or 29–58 years if threshold NBI condition ratings of 4 and 3 are applied respectively; and reinforced concrete

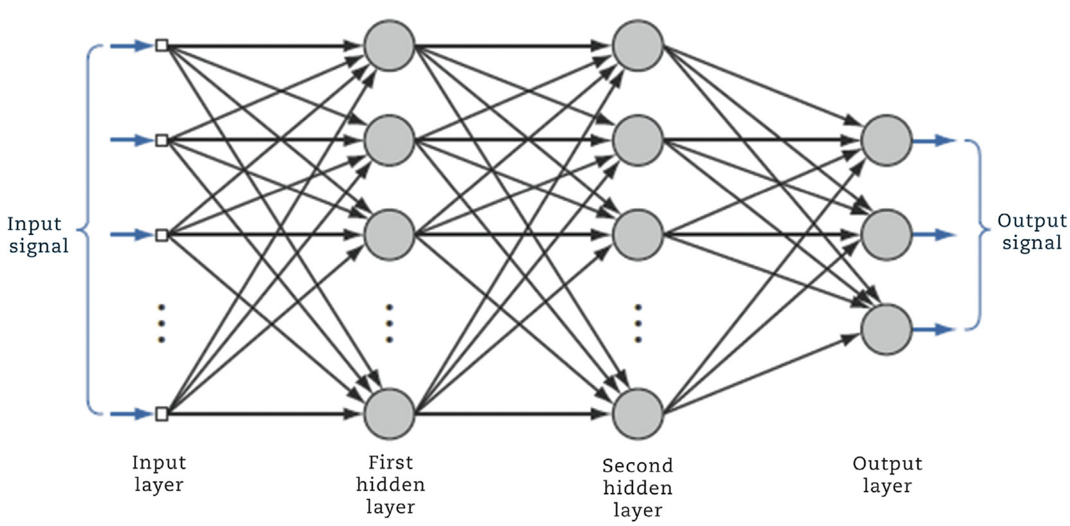


Fig. 7 – Multi-Layer Perceptron with two hidden layers (Haykin, 2014).

substructures survive 23–42 years (NBI rating 4 threshold) and 27–50 years (NBI rating 3 threshold).

- In Indiana, concrete bridge deck life is approximated at 50 years (NBI rating 4 threshold) to 60 years (NBI rating 3 thresholds) (Jiang and Sinha, 1989). In Indiana, it was further estimated that, assuming minor maintenance, concrete and steel bridges would survive 50 and 65 years, respectively (Gion et al., 1992). It was found that life can vary between 35 and 80 years depending on the maintenance/preservation activities performed (Cope, 2009; Sinha et al., 2009). For example, if a major repair (e.g., bridge rehabilitation) is done every 20–25 years, then a bridge life of 70–80 years can be expected in Indiana (Sinha et al., 2005).
- In Massachusetts, a typical bridge life, excluding major maintenance, of 60 years is reported (Massachusetts Infrastructure Investment Coalition, 2005). Bridges were predicted to last 90 years with a preservation activity at year 35, or 110 years if rehabilitated at year 50 (Massachusetts Infrastructure Investment Coalition, 2005).
- In Florida, concrete decks were found to survive a maximum of 146 years; reinforced concrete superstructures were found to survive 80 years (up to 335 years if prestressed) (Thompson and Sobanjo, 2010).
- In Colorado, median bridge life has been estimated at 56 years (mean life is 76 years) with the deck component surviving 19 years (Hearn and Xi, 2007).
- Bridges with less common designs may have different life estimates. For example, in Chicago, bascule bridges were found to have an estimated life of 75–100 years (Zhang et al., 2008). Bridge decks with stainless steel reinforcement can be expected to last for 75–120 years (NX Infrastructure, 2008).
- International estimates of bridge life are generally similar. In Sweden, bridges are predicted to survive 40–150 years with a typical minimum of 50 years assumed (Hallberg, 2005). Dutch bridges are typically designed to survive 80–100 years (Van Noortwijk and Klatter, 2004). In Canada, bridge decks have been found to survive 38–45 years (Morcous, 2006).

The following models have been applied to predict the service life of bridges (Ford et al., 2011).

- Mechanistic methods based on corrosion (Ford et al., 2011).
- Linear and non-linear regression (Ford et al., 2011; Rodriguez et al., 2005).
- Markov chains (Ertekin et al., 2008; Estes and Frangopol, 1999; Ford et al., 2011; Hallberg, 2005; Jiang and Sinha, 1989; Morcous, 2006; Zhang et al., 2003).
- Survival probability curves (Akgül and Frangopol, 2004; Biondini et al., 2006; Estes and Frangopol, 2001; Ford et al., 2011; Lin, 1997; Lounis, 2000; Oh et al., 2007; Saber et al., 2006; Strauss et al., 2008).
- Ordered probit models (Ford et al., 2011; Rodriguez et al., 2005).
- Neural networks (Ford et al., 2011; Narasinghe et al., 2006).

In general, bridge decks are predominantly studied among other bridge components due to the fact that bridge decks are directly exposed to harsh environment and traffic conditions. Bridge deck life corresponds to one half of the overall bridge life (Kumar et al., 2018). Caner et al. (2008) proposed a simple method to estimate the remaining service life of a bridge based on the relationship between its present condition rating and its age by assessing a set of bridges at different ages from which deterioration trend can be computed using least squares fit. The authors suggested this method for the agencies that either does not inspect their bridges periodically or do not inspect them at all. For example, Turkey performs bridge MR&R based on an as-needed basis (Caner et al., 2008). In a case study, 28 bridges were inspected for the first time to assess the average life expectancy. The average life of a bridge was predicted to be 80 years.

A condition-based approach using visual inspection data (e.g., NBI rating) is often used to forecast the bridge life expectancy. Based on the inspection data collected, deterioration models are generated. The deterioration models describe the likelihood of the change of an element condition from one condition to another over a given period. The most commonly used BMS is Pontis (now also known as AASTHOware Bridge Management (BrM) Software), which uses Markov chain deterioration modeling. According to Ford et al. (2011), bridge engineers use these models and pre-defined thresholds in order to estimate the time (in years) since the bridge physical condition reaches a given threshold for reconstruction or rehabilitation. In general, the NBI condition rating of 4 is used by bridge engineers and managers as the threshold for the rehabilitation and replacement purposes (Kumar et al., 2018).

4. Examples of deterministic, stochastic and ANN-based models

This section presents an illustration of bridge deterioration models based on deterministic, stochastic and ANN-based approaches. Examples 1 and 2 present timber bridge superstructure deterioration models based on deterministic and stochastic approaches respectively using NBI data. Only low volume traffic bridges (i.e., Average Daily Traffic (ADT) lower than 500) located in Florida, Georgia, South Carolina and North Carolina are considered in these two examples. The analysis considers only those bridges which have not undergone any reconstruction during their service life. This paper assumes that the maximum service life of timber bridges without reconstruction is approximately 60 years, based on NBI records and published literature (Lokuge et al., 2017). Example 3 shows an illustration of ANN-based BP-MLP approach for concrete bridge decks in Florida.

4.1. *Example 1: Deterministic model*

Fig. 8 shows the superstructure condition rating as a function of age for timber highway girder type bridge data from NBI records (1992–2012). Since the data is highly scattered, the average condition rating is calculated for discrete ages of the bridge superstructure. For example, corresponding to bridge age 10, there are 106 records for condition rating of the

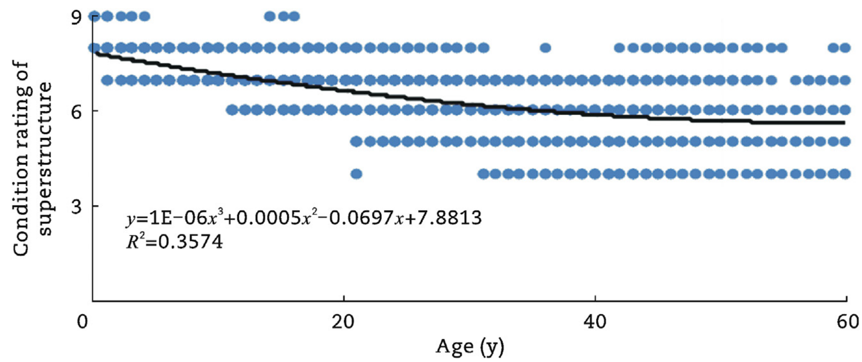


Fig. 8 – Polynomial regression curve for condition rating of timber bridge superstructure from unfiltered data.

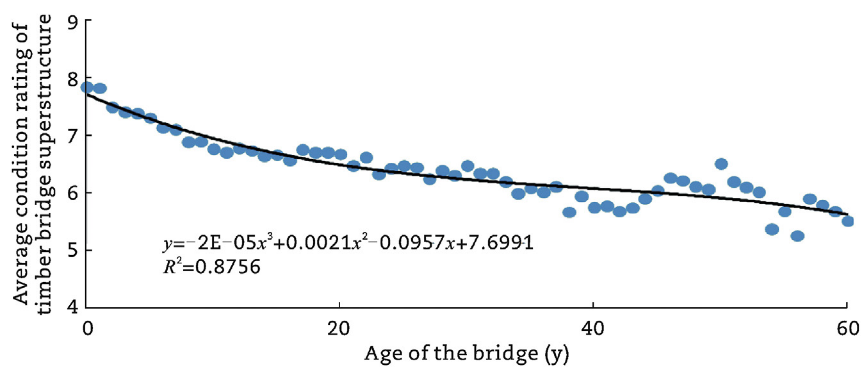


Fig. 9 – Polynomial regression curve for average condition rating of timber bridge superstructure (with ADT ≤ 500) from unfiltered data.

Table 3 – Condition rating considered for data filtering.

Age of the bridge (y)	Condition rating considered
0	9, 8
1	9, 8, 7
2 to 5	8, 7
6 to 20	8, 7, 6
21 and 22	7, 6
23 to 53	7, 6, 5
54 to 60	7, 6, 5, 4

bridge superstructure. The average condition rating for these records is calculated and obtained as 6.75. This procedure is followed to obtain the average condition rating as a function of age of the bridge as shown in Fig. 9.

In order to improve the accuracy of the polynomial regression model in Fig. 9, condition data is filtered based on Table 3 to reflect the practical scenario. The filtered dataset is obtained by considering only those condition records which lie within the range of mean ± 1 standard deviation. Then, average condition rating vs. age is obtained as shown in Fig. 10. The number of years from the current condition to the period for initiating maintenance can be predicted using

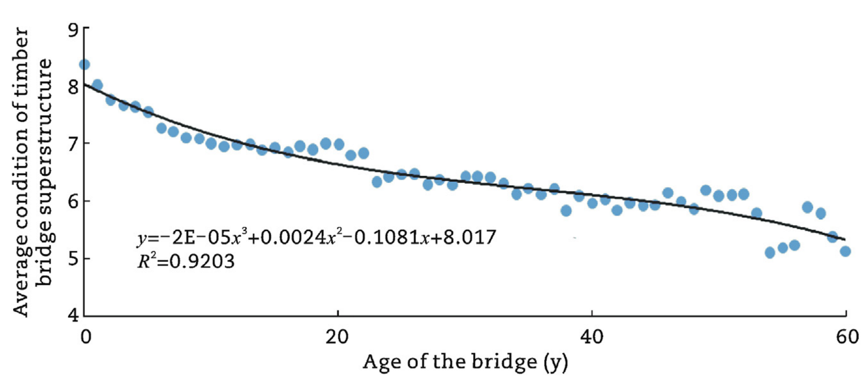


Fig. 10 – Polynomial regression curve for average condition rating of timber bridge superstructure (with ADT ≤ 500) from filtered data.

the deterioration curve shown in Fig. 10. For example, the expected average condition rating at 10 years is obtained as 7.17. The number of years it takes for the superstructure elements to deteriorate from condition rating of 7.17 to 6 (i.e., when the structural elements need major maintenance) can be seen as 29 years.

4.2. *Example 2: Stochastic model*

State-based Markov chain model (a stochastic model) is applied to obtain probabilistic deterioration model of timber highway bridge superstructure. For example, NBI records from 2011 to 2012 are considered to obtain the Transition Probability Matrix (TPM) using Percentage Prediction Method (PPM). The annual NBI inspection records are considered in developing the deterioration model.

The probability of the bridge condition changing from one state to another is determined using expert judgment and empirical observations, which are represented in a matrix form. Table 4 shows the TPM for this Example 2. Based on the current condition or initial condition state of a bridge, the future condition can be predicted through the matrix multiplication of the current condition vector and the TPM.

4.2.1. *Calculation basis for obtaining the elements in TPM*

In PPM method, the probability p_{ij} is estimated using Eq. (1).

$$p_{ij} = \frac{n_{ij}}{n_i} \tag{1}$$

where n_{ij} is the number of bridges transitioned from state i to state j within a given time period, n_i is the total number of bridges in state i before the transition.

For example, the probability of the bridge superstructure which started with condition state (CS) 8 in 2011 and remained in the same condition at the end of one year is calculated as follows.

- Number of bridges in state 8 which remained in state 8 within a given time period (i.e., 2011–2012), $n_{88} = 19$.
- Total number of bridges in state 8 in 2011, $n_8 = 25$.
- Therefore, the probability of bridge superstructure remaining in the state 8 during the given period is calculated as shown in Eq. (2).

Table 4 – TPM for Markov chain-based deterioration model for timber bridge superstructure.

CS	9	8	7	6	5	4
9	0.0000*	1.0000	0.0000	0.0000	0.0000	0.0000
8	0.0000	0.7600	0.2400	0.0000	0.0000	0.0000
7	0.0000	0.0000	0.9580	0.0420	0.0000	0.0000
6	0.0000	0.0000	0.0000	0.9667	0.0333	0.0000
5	0.0000	0.0000	0.0000	0.0000	1.0000	0.0000
4	0.0000	0.0000	0.0000	0.0000	0.0000	1.0000

Note: "*" means the probability of network of bridges starting with CS9 and remaining in the same state at the end of one inspection period based on 2011–2012 NBI records is obtained as 0.0000. This probability value could be different from zero if NBI records from other years are considered.

$$p_{88} = \frac{n_{88}}{n_8} = \frac{19}{25} = 0.76 \tag{2}$$

- The probability that the bridge superstructure transitioned from state 8 to state 7 is obtained as shown in Eq. (3).

$$p_{87} = 1 - p_{88} = 1 - 0.76 = 0.24 \tag{3}$$

In this way, all the other elements of the Transition Probability Matrix (P) are obtained.

4.2.2. *Calculation basis for obtaining condition rating as a function of age using Markov chain model*

Expected value of bridge condition (E(t)) at transition period t based on Markov chain is calculated using Eq. (4).

$$E(t) = P(0)[P^t]^T S \tag{4}$$

where P(0) is the initial condition vector (i.e., (1, 0, 0, 0, 0, 0) for a new bridge), $[P^t]^T$ is the transpose of TPM (P) at period t, and S is the vector of condition states (9, 8, ⋯, 4).

For example, the condition of the timber bridge superstructure at 10 years is obtained as follows.

The initial condition for a new bridge is given by the initial condition vector P(0) = (1, 0, 0, 0, 0, 0). This means that the bridge is 100% in CS9 and 0 in rest of the conditions states, i.e., CS8, ⋯, CS7, CS4. The vector of condition states (S) remains constant (9, 8, 7, 6, 5, 4). Then, the condition rating of the bridge superstructure at time period $t = 10$ years is obtained by using TPM (Table 4) and Eq. (4) as shown in Eq. (5).

$$E(10) = \begin{pmatrix} 1 \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \end{pmatrix} \times \left[\begin{bmatrix} 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0.76 & 0.24 & 0 & 0 & 0 \\ 0 & 0 & 0.958 & 0.042 & 0 & 0 \\ 0 & 0 & 0 & 0.9667 & 0.0333 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 \end{bmatrix}^{10} \right]^T \times (9,\ 8,\ 7,\ 6,\ 5,\ 4) = 6.87 \tag{5}$$

Similarly, the expected value of condition rating at any discrete time period can be obtained based on the initial condition and the TPM.

Thus, a probabilistic model using state-based Markov chain approach is obtained (Fig. 11). The number of years from the current condition to the period for initiating maintenance can be predicted using the deterioration curve shown in Fig. 11. For example, the expected average condition rating at 10 years is obtained as 6.87. The number of years it takes for the superstructure elements to deteriorate from condition rating of 6.87 to 6 (i.e., when the structural elements need major maintenance) can be seen to be 24 years.

Chi-square goodness of fit test is performed to compare the prediction accuracy of deterministic and stochastic models, and the results are shown below.

Fig. 11 – Markov chain-based deterioration model for timber bridge superstructure.

A chi-square goodness of fit test is performed to compare the performance of deterministic model and Markov chain-based stochastic model. NBI records for the year 2014 are considered for the purpose of testing the models. Both the models (i.e., deterministic and stochastic) have a chi-square value lesser than the critical chi-square value of 78 obtained for a level of significance of 5% and degrees of freedom of 59. The chi-square value for deterministic model is obtained as 2 whereas the value for stochastic model is 4.5. This shows that, based on the data considered for the analysis, the deterministic model gives better prediction when compared to the stochastic model. This is because the authors have considered only one set of inspection records (2011–2012) to obtain the stochastic model for illustration purposes only. However, in reality, the TPM should be developed based on the average of probabilities obtained for all the years from 1992 to 2012. Hence a number of transition probability matrices have to be developed for every set of inspection records (i.e., 1992–1993, 1993–1994, ⋯, 2011–2012), and the average probability values should be used to obtain the deterioration curve using Markov chain. The model developed using average of transition probabilities obtained from the data for the period 1992–2012 will improve the prediction accuracy of stochastic model.

4.3. *Example 3: ANN-based model*

This example illustrates the Back Propagation based Multi-Layer Perceptron (BP-MLP) approach to generate missing condition data, which could be used for developing deterioration curve through regression analysis (or other methods) for both project level and network level analyses of bridge element condition. Condition data for bridge decks of solid slab bridges in Florida are used for illustration. The data is obtained from NBI database for the years 1992–2012. The different steps involved in developing ANN model are represented in the flowchart (Fig. 12).

The following steps are performed to develop ANN-based deterioration model.

Step 1. Dataset preparation

This step is performed to obtain training dataset which is fed into the input layer of the MLP. In this step, duplicates and

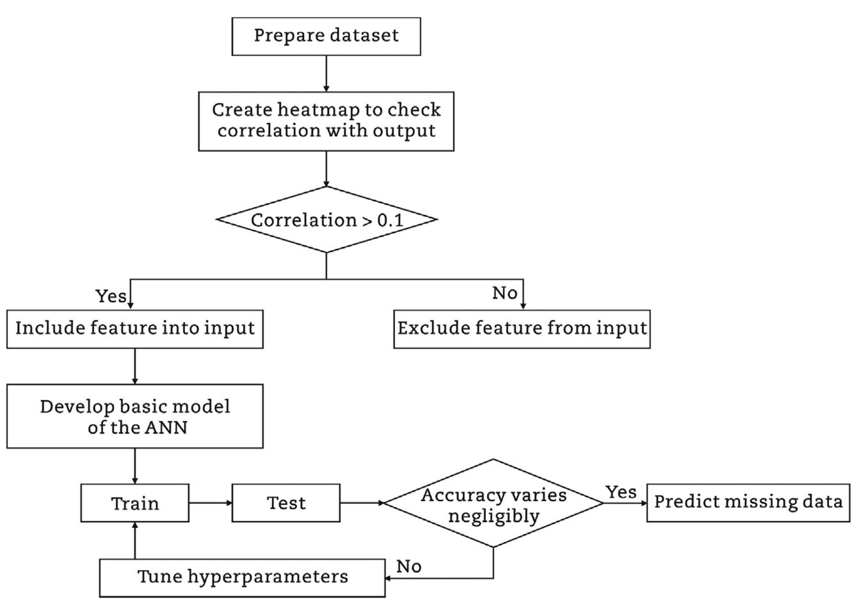


Fig. 12 – Flowchart of ANN-based model for finding missing data.

incomplete data are removed. The resulting data obtained is skewed with respect to available data points for each condition rating. Hence, oversampling of the least populated condition rating is performed (Simpson, 2015).

Totally 9398 bridge records from 1992 to 2012 are considered from NBI database after removing duplicates and incomplete data (Fig. 13). These records are further filtered by removing the outliers and oversampling the least represented condition ratings like 9, 5 and 4, to reflect the practical scenario. Finally, 8837 records are fed into the neural network for training and testing purposes as shown in Fig. 14.

Step 2. Choice of input features

Seaborn heatmap is used to decide on the choice of input features. Seaborn is a Python data visualization library based on matplotlib. It provides a high-level interface for drawing attractive and informative statistical graphics. The best thing about the heatmap is that it can show the Pearson correlation coefficient for each feature with respect to every other feature. The ANN model is built after selecting the features. The filtering is done using correlation matrix and it is most commonly done using Pearson correlation.

The correlation coefficient has values between −1 and 1.

i) A value closer to 0 implies weaker correlation (exact 0 implying no correlation).
ii) A value closer to 1 implies stronger positive correlation.
iii) A value closer to −1 implies stronger negative correlation.

Fig. 15 shows the heatmap for selected input variables like age, Average Daily Traffic (ADT), structure length, design load, skew angle, number of spans, maximum span length, roadway width and deck width. It is found that skew angle and structure length have minimum correlation with respect to deck condition. Variables having Pearson correlation coefficient greater than 0.1 (highlighted as blue boxes in Fig. 15) with respect to deck condition are chosen as input features for building the ANN-based model. As expected, age has a strong negative correlation of 0.78 with deck condition implying that the deck condition degrades as a function of age.

Step 3. Development of neural network

The neural network in this example is a multiclass classification Multi-Layer Perceptron using Back Propagation approach (BP-MLP) (Fig. 16). The chosen input variables for the input layer include age, ADT, design load, number of spans, maximum span length, roadway width and deck width. Using historical bridge maintenance data of reinforced concrete bridge decks in Florida, a neural network consisting of seven inputs in input layer, five hidden layers each containing 64 nodes and one output layer containing 6 labels (for ratings 9 to 4) is developed. Keras, an open-source neural network library written in Python, is utilized for

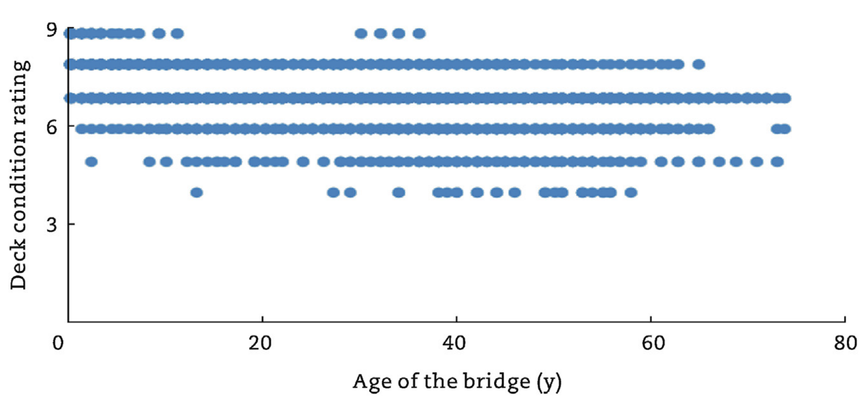


Fig. 13 – Deck condition rating vs. age for Florida RC bridges.

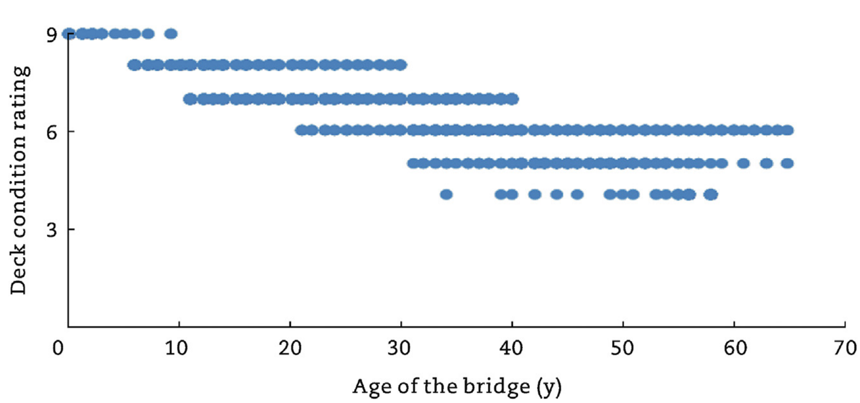


Fig. 14 – Deck condition rating vs. age for Florida RC bridges (data for neural network).

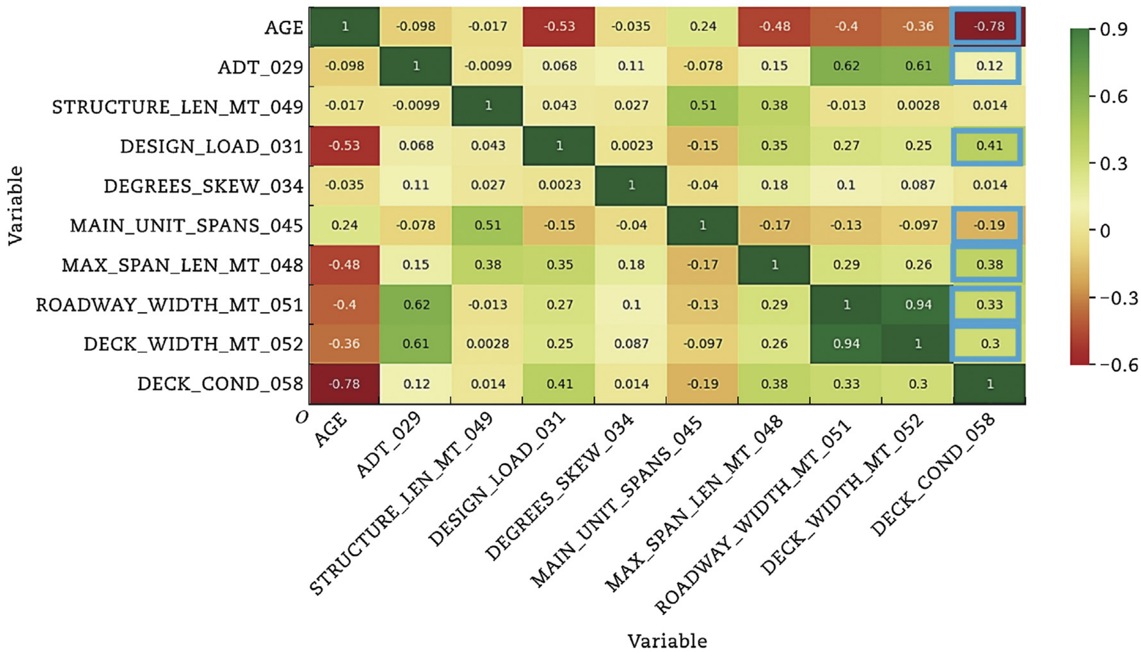
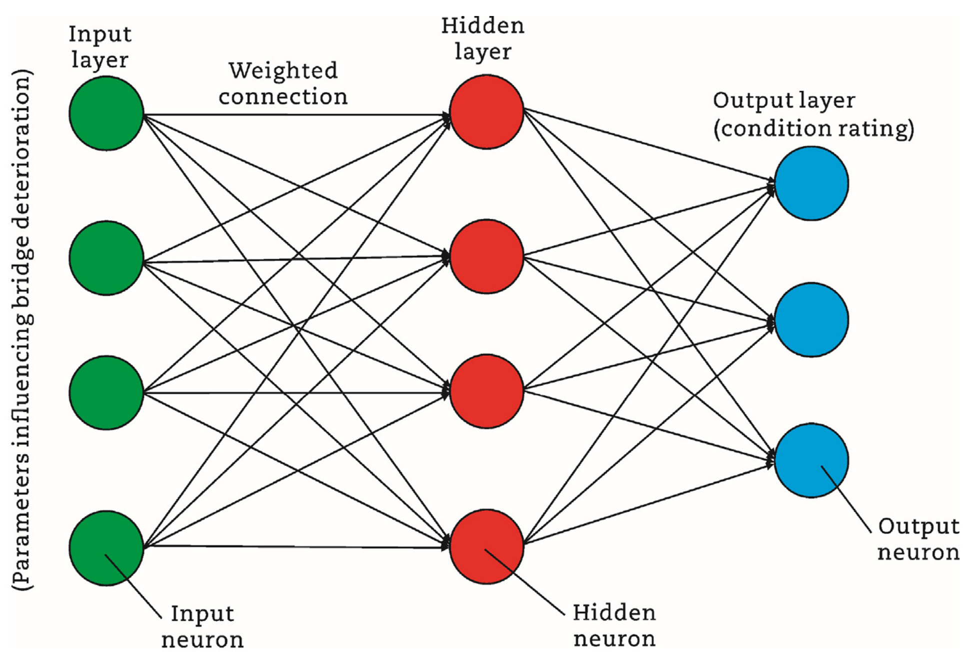


Fig. 15 – Heatmap for feature selection.

developing the model. The condition ratings are converted into a class vector 0 to 5 and is further converted into a binary class matrix using the Keras function to_categorical. Finally, the efficient Adam gradient descent optimization algorithm with a logarithmic loss function (categorical_crossentropy loss) is used to train the model.

Step 4. Training, testing and refining the parameters of neural network

The data is normalized and split into 80–20 ratio for training and testing respectively. After training for an arbitrary number of epochs, the testing set accuracy is calculated.



Note: the input parameters influencing bridge deterioration include age, ADT, design load, number of spans, maximum span length, roadway width and deck width.

Fig. 16 – Schematic diagram of MLP with single hidden layer.

Hyperparameter tuning (i.e., adjusting the variable parameters of the network like number of nodes, epochs, layers, etc.) is performed and the optimal configuration for the network is obtained by trial and error. The final network has 5 hidden layers, using scaled exponential linear unit (SELU) and rectified linear unit (RELU) activation functions for the first two hidden layers respectively and the hyperbolic tangent activation function for the remaining hidden layers. The output layer uses Softmax function. Softmax function, also called normalized exponential function, is a function that takes as input a vector of K real numbers and normalizes it into a probability distribution consisting of K probabilities. The data is trained for 100 epochs of batch size two. After training, the training set accuracy and testing set accuracy are found to be 91% and 88% respectively.

Step 5. Making predictions for missing data and development of deterioration curve

The model developed is used to predict missing condition ratings during different time periods for 3 bridge decks which have limited inspection records. The already available data and the predicted data for the missing years are plotted together and linear regression is performed to obtain the deterioration curve for the bridge deck.

The deck condition ratings are predicted for the missing years and also the NBI data for the available years are checked with the predicted values from the ANN model, for three sample reinforced concrete bridges in Florida—Bridge #110002, #260103 and #790155.

4.3.1. ANN-based deterioration curve for bridge deck for Bridge #110002

Bridge #110002 was built in 1956. Since the NBI condition records are available only from 1992, there are missing condition ratings until the first documented inspection record. The available NBI dataset is left censored and condition ratings are predicted for years 1–35 with two-year time interval. Fig. 17 shows the available and predicted deck condition ratings for Bridge #110002.

The condition ratings from ANN prediction model is checked with respect to available NBI data. In this particular bridge case, except for two data points, the predicted values show agreement with the NBI data. Fig. 18 shows the NBI data and the ANN generated data for the available years.

Fig. 19 shows the deterioration curve developed for the bridge deck with only available NBI data. It is evident that there is no information on the deterioration during the years 1–23 due to missing inspection data.

Fig. 20 shows the deterioration curve developed using both available NBI data and the ANN predicted condition data for the missing years. This curve gives a better estimate of deck condition for all the years until around 60 years.

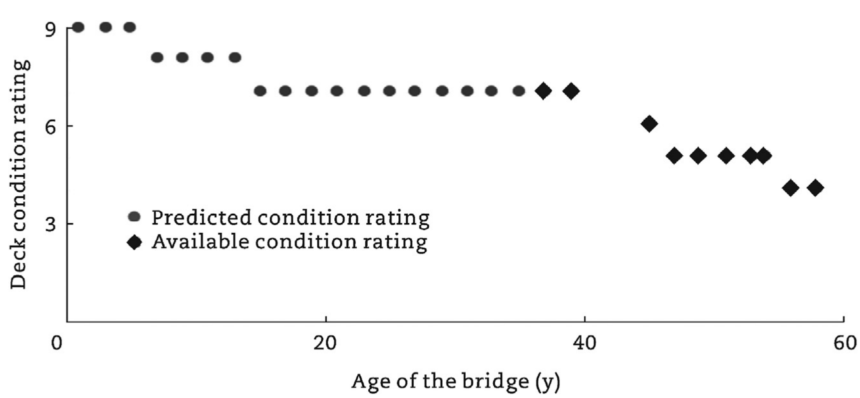


Fig. 17 – Available and predicted deck condition ratings for Bridge #110002.

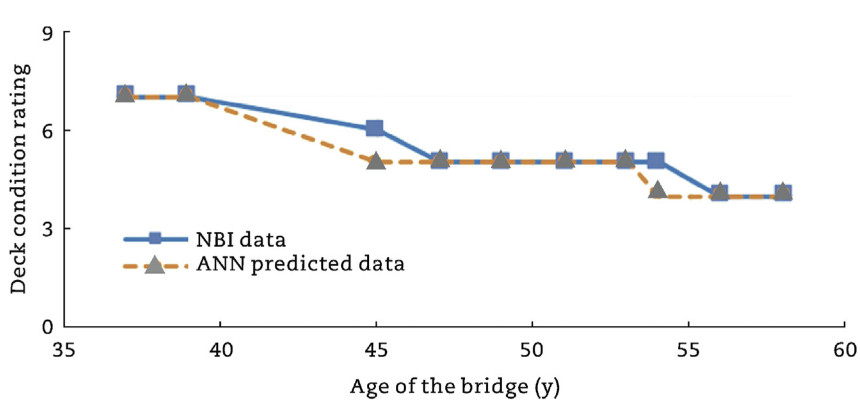


Fig. 18 – NBI data and ANN predicted data for Bridge #110002.

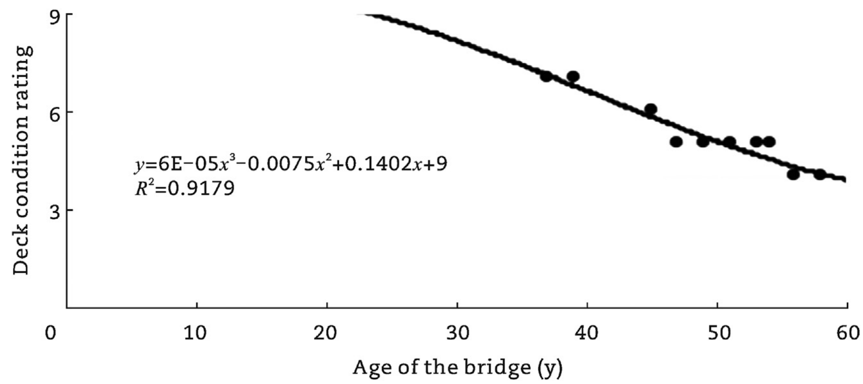


Fig. 19 – Deterioration curve for bridge deck with available data (Bridge #110002).

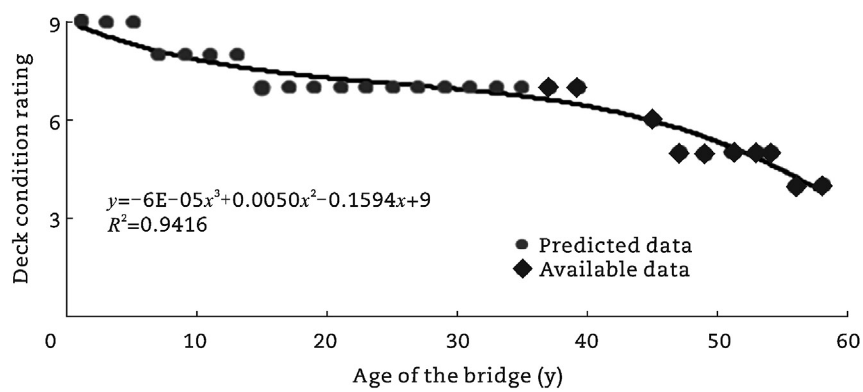


Fig. 20 – Deterioration curve for bridge deck with available and predicted data (Bridge#110002).

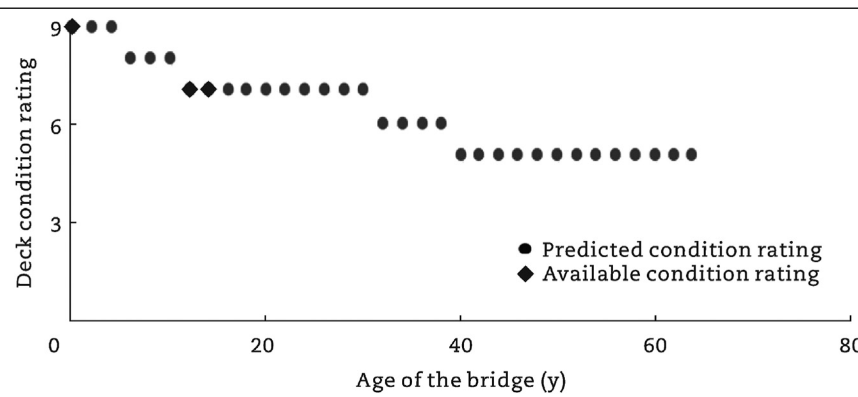


Fig. 21 – Available and predicted deck condition ratings for Bridge #260103.

4.3.2. *ANN-based deterioration curve for bridge deck for Bridge #260103*

Bridge #260103 was built in the year 2000. In this case, only limited condition records are available from NBI for deck condition. Fig. 21 shows the available and predicted deck condition ratings for Bridge #260103.

The condition ratings from ANN prediction model is checked with respect to available NBI data. In this case, all the predicted condition ratings show agreement with the NBI data. Fig. 22 shows the NBI data and the ANN generated data for the available years.

Fig. 23 shows the deterioration curve developed for the bridge deck with only available NBI data. It is seen that there is no information on the deterioration after 15 years of age due to missing inspection data.

Fig. 24 shows the deterioration curve developed using both available NBI data and the ANN predicted condition data for the missing years. This curve gives a better estimate of deck condition for all the years until around 65 years.

4.3.3. *ANN-based deterioration curve for bridge deck for Bridge #790155*

Bridge #790155 was also built in the year 2000. The available NBI dataset is right censored and condition ratings are predicted from 15 years of age with two-year time interval. Fig. 25

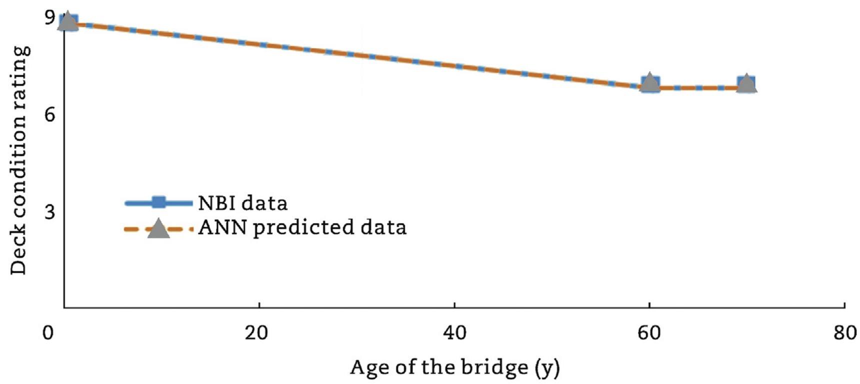


Fig. 22 – NBI data and ANN predicted data for Bridge #260103.

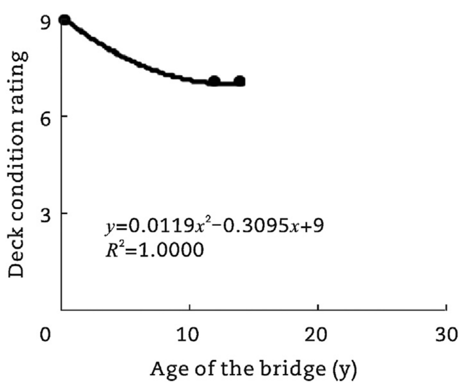


Fig. 23 – Deterioration curve for bridge deck with available data (Bridge #260103).

shows the available and predicted deck condition ratings for Bridge #790155.

The condition ratings from ANN prediction model is checked with respect to available NBI data. In this particular case, only three data points show agreement with the NBI data. This is due to faster deterioration rate of this particular bridge when compared to the other bridges. Fig. 26 shows the NBI data and the ANN generated data for the available years.

Fig. 27 shows the deterioration curve developed for the bridge deck with only available NBI data. It is evident that there is no information on the deterioration after 14 years.

Fig. 28 shows the deterioration curve developed using both available NBI data and the ANN predicted condition data for the missing years. This curve gives a better estimate of deck condition for all the years until around 65 years.

The above illustrated examples show the method to generate missing condition ratings for bridge elements for project level analysis. Similar procedure could be adopted to generate missing data for the analysis of a network of bridges.

5. Summary and conclusions

This paper presents a review of literature on deterioration modeling of bridges and the models are applied to some case studies of timber superstructure and concrete bridge decks. Current BMS uses Markov chain-based deterioration models for network level analysis and prioritization of bridges for maintenance activities. Several studies have been carried out by earlier researchers on improving deterioration models to obtain realistic bridge performance. Deterministic models are quick and easy to obtain based on regression analysis. However, it may not be very close to reality as infrastructure deterioration process is a random one. Stochastic processes are of two major types: state-based and time-based. State-based process is generally modeled using Markov chain and time-based process using probability distributions like Weibull, Gamma, etc. Markov chain-based models are very suitable for network-level analysis. However, they suffer from

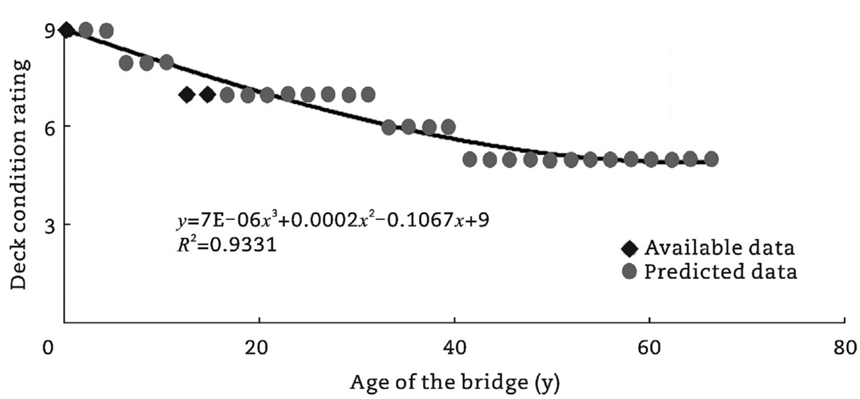


Fig. 24 – Deterioration curve for bridge deck with available and predicted data (Bridge #260103).

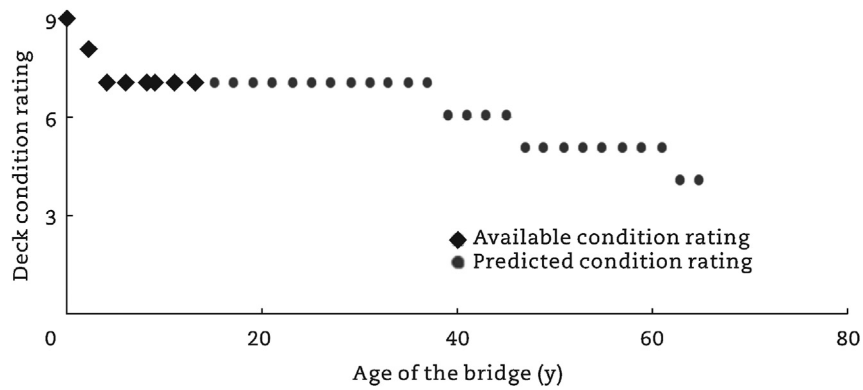


Fig. 25 – Available and predicted deck condition ratings for Bridge #790155.

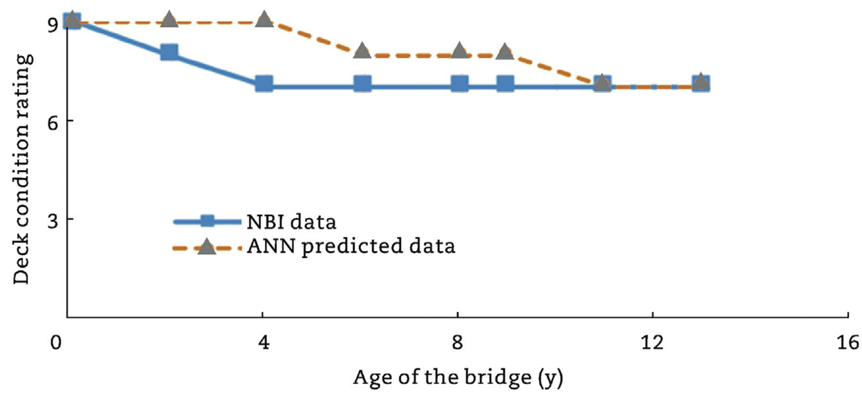


Fig. 26 – NBI data and ANN predicted data for Bridge #790155.

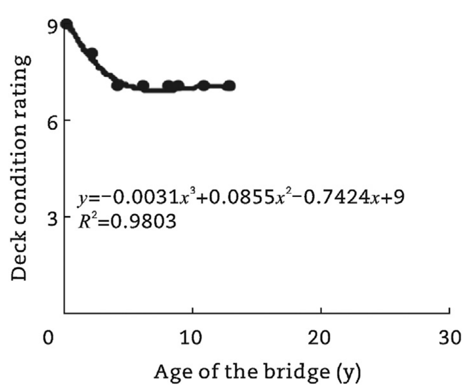


Fig. 27 – Deterioration curve for bridge deck with available data (Bridge#790155).

limitation of being memoryless and homogeneous. Time-based models utilize probability distributions such as Weibull distribution, Gamma distribution, etc., considering time as a random variable, to describe the deterioration process, however, it requires enormous amount of data to obtain reasonable prediction. Mechanistic models are used for project level analysis, but it requires a lot of computation time and data, which makes it nearly impossible to integrate it with current BMS for regular maintenance activities. AI-based models have great potential to overcome some of the above limitations of the other models. However, it is still in the nascent stage of development for its use in BMS.

Two examples are illustrated to show the application of a deterministic model and stochastic Markov chain model based on timber highway bridge data from NBI. It is observed from the illustrated examples that deterministic model provides higher accuracy than stochastic Markov chain-based model to predict the deterioration of timber bridge superstructure. However, if the model is developed using average of transition probabilities obtained for the years 1992–2012, the average transition probabilities will improve the prediction accuracy of the stochastic model. It is also evident that proper data filtering of condition records aids in improving accuracy of the deterministic models. The third example is on ANN-based models for reinforced concrete bridge decks in Florida. BP-MLP is used to predict missing condition data. In the illustrated ANN model, the training set accuracy and testing set accuracy are found to be 91% and 88% respectively. The trained model is utilized to generate missing condition state data to fill the gaps due to irregular inspections.

6. Recommendations for future research

There is scope for future research in bridge deterioration modeling which includes but not limited to the following aspects.

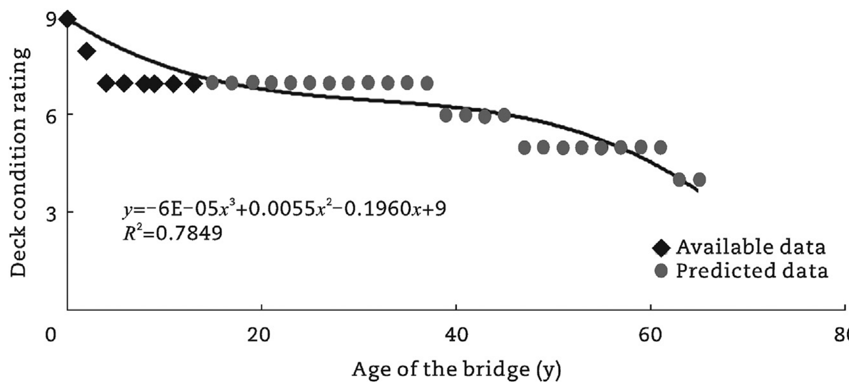


Fig. 28 – Deterioration curve for bridge deck with available and predicted data (Bridge #790155)

i) Quantitative deterioration modeling which considers the physical parameters like stresses, deflections, in addition to the condition data from visual inspection.
ii) Development of non-homogeneous Markov chain-based deterioration model.
iii) Improved AI-based models for prediction of bridge element deterioration.
iv) Computation of the remaining useful life of bridges using system reliability.
v) Application of Geographical Information System (GIS) for bridge deterioration modeling.
iv) Development of deterioration models for timber railroad bridges.

The above suggestions may improve the existing techniques to provide more robust and accurate prediction of bridge deterioration process, thereby aiding in the efficient use of resources in bridge management.

Conflict of interest

The authors do not have any conflict of interest with other entities or researchers.

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