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Title

Comparison of forecasting models to predict concrete bridge decks performance

Running Head

Comparison of forecasting models for concrete bridge decks

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Abstract

The accuracy of forecasting models for the prediction of an infrastructure's deterioration process plays a significant role in the estimation of optimal maintenance, rehabilitation, and replacement strategies. Numerous approaches have been developed to overcome the limitations of existing forecasting models. In this paper, a direct comparison is made between different models using the same input data to derive conclusions of their distinct performance. The models selected for the comparison were Markov, Semi Markov and Hidden Markov models together with Artificial Neural Networks (ANN), which have been reported in literature as reliable deterioration prediction models. A quality of fit was performed to measure how well the observed data corresponded to the predicted values, and therefore objectively compare the performance of each model. The results demonstrated that the most accurate prediction was accomplished by the ANN model. Nevertheless, all models presented differences with respect to typical values of concrete decks life expectancy, which is attributed to the inherent difficulties of the database. Additionally, the problem of the visual inspection subjectivity was also regarded as one of the potential causes for the found deviations. Therefore, this article also discusses the shortcomings of current condition assessment practices and encourages future Bridge Management Systems to replace the classical methods by more sophisticated and objective tools.

1. Introduction

Bridge owners encounter great challenges to efficiently allocate funds to preserve and maintain their aging bridges. The ultimate goal of asset management programs consists on defining strategic and systematic processes to identify the sequence of maintenance, preservation, repair, rehabilitation and replacement actions/interventions to ensure the safety, serviceability, and functionality of bridges within available budgets over their service life [1]. Many Bridge Management Systems (BMS) have been developed in the last decades. Typically, the architecture of a BMS consists of a database and modules dealing with condition and structural assessment, deterioration prediction, lifecycle cost, and maintenance optimization [2]. Even though all modules are equally important, a reliable bridge condition assessment is needed as input for the deterioration prediction modules, which accuracy is a key element for the subsequent maintenance optimization strategies.

Different condition assessment tools have been developed over the years such as visual surveys, probing, non-destructive techniques (NDT) and structural health monitoring (SHM) [3]. Based on these assessment tools, the damage is estimated and expressed through performance indicators (PIs), which are metrics that define qualitatively and/or quantitatively the condition state of the bridge elements [3]. Faleschini et al [3] classified the PIs in two main categories: operational and research indicators. Operational indicators are based on qualitative condition ratings, i.e. an adopted discrete scale where one value is defined as the as-built condition, and the remaining values represent the deviation from the as-built condition [4]. On the other hand, research indicators are based on a quantitative evaluation of the structural safety of the assets, i.e. computing the probability of failure for a given limit state [3].

Due to the distinction between the PIs, different forecasting models have been developed to predict the deterioration over time and the remaining service life of bridge elements. For instance, a lot of research has been conducted on analytical deterioration models to describe common phenomena affecting reinforced concrete structures such as chloride-induced corrosion [5]–[8], carbonation-induced corrosion [8], [9], alkali-aggregate reaction and freeze/thaw attack [10], [11], among others. Another approach has proposed using the reliability index as an indicator of the bridge performance and constructing a reliability profile, defined as the variation of the reliability index with time at a deterioration rate after the deterioration initiation time [12], [13].

Even though research PIs and their related forecasting models represent a more quantitative measure of the deterioration phenomena, their practical application on BMS is still limited due to the large amount of assets that transportation agencies must manage. Therefore, operational PIs, i.e. condition ratings, have been predominantly the input parameters for deterioration models in existing BMS [2]. Literature on deterioration modelling approaches based on condition ratings is extensive and include, but is not limited to: deterministic models (multiple linear regression [14], polynomial regressions [14]–[16], ordinal logistic regression [17]), stochastic models (Markov models [18]–[21], Semi-Markov models [20]–[22], Hidden Markov models [20], [23]), Artificial Intelligent (AI) techniques (Artificial Neural Networks (ANNs) [24]–[26], fuzzy logic [26], [27], Case-based Reasoning (CBR) [28]), Bayesian networks [29] and Petri-Nets [30].

Deterministic and stochastic Markov-chain models are the prevalent deterioration models currently used by most BMS [31], [32]. The main advantage of Markov-chains over the deterministic models is their capability to reflect the uncertainty of the deterioration process while being computationally efficient and simple to manipulate networks with large number of assets [19]. Nevertheless, it has been broadly discussed that some of the Markov-chains assumptions significantly affect the prediction accuracy [18], [21], [28]. Therefore, the aim of this study is to objectively analyse the impact of those assumptions through a direct comparison of the prediction accuracy obtained by the Markov-chains model with other deterioration modelling approaches, namely Semi Markov models, Hidden Markov models and Artificial Neural Networks. These models were selected as they have arisen as an enhancement/alternative to the Markov-chains model, while fulfilling desired characteristics for BMS. Furthermore, the implementation complexity of each model and the associated computational cost are also compared to provide recommendations for practice. To this end, a database containing inspections records from 766 different bridges with approximately 14 inspections (time window of approximately 26 years) is employed to predict the evolution of concrete bridge decks condition over time through each adopted model.

The present work is organized as follows: Section 2 provides a description of the employed database and the conducted filtering procedure. The following sections present a brief conceptual description of the selected deterioration models and their application to the database. For a more detailed explanation of the theory of the models the reader is referred to [20], [33]–[35]. Consequently, Section 7 compares the different degradation patterns predicted by each model and uses some metrics to measure how well the observed data corresponds to the predicted values. Section 8 presents a discussion on the prediction capabilities of the models compared to that reported on literature, and the drawbacks encountered for the individual and general development of the models. Finally, concluding remarks together with recommendations for future directions are provided.

2. Database Pre-processing

The models were implemented using inspection records of bridges retrieved from the National Bridge Inventory (NBI) database managed by the U.S. Department of Transportation, Federal Highway Administration (FHWA) [36]. According to the last ASCE's Report Card for America's Infrastructure [37], by 2016 there were 614.387 bridges in the USA , 9.1% of which had been declared as structurally deficient. Even though from a national perspective the condition of the nation's bridges has improved over the last 10 years, the highest percentage of structurally deficient bridges reached until 24.9% for the state of Rhode Island

[37]. The inspection records corresponding to Rhode Island were selected for the implementation of the deterioration models in the present work, granting that the records from any other state would similarly accomplish the aim of the work.

The visual inspection (VI) method is the predominant non-destructive evaluation (NDE) technique used for bridge inspections which are carried out biennially by certified inspectors [38]. The VI method examines the bridge members to identify deficiencies; for instance, detect concrete deck defects such as cracking, scaling, spalling, leaching, delamination, and full or partial depth failures. The bridge inspector is responsible for assigning a condition rating that properly characterizes the general condition of the entire component being rated based on the severity and extent of the deterioration [39]. The NBI specifies a condition rating ordinal scale from 0 to 9 (Table 1), where 0 represents a failed condition and 9 represents an excellent condition. Condition rating of 4 is generally considered as the threshold rating where rehabilitation or replacement measures have to be done (structurally deficient) [1]. A separately condition rating is assigned for the three major bridge components namely substructure, superstructure and deck. Herein, the deck ratings were selected to develop the models.

Table 1

The database comprises inspections records from 766 different bridges by the year 2017. The earliest inspections date from 1990, covering a span of approximately 26 years. However, some bridges were built after that period (see Figure 1) or were not inspected biennially, resulting in a lower number of available inspections. Consequently, only bridges with the maximum possible number of records, i.e. 14 inspections, were used to build the models. It can be observed from Figure 1 that the predominant deck structure type corresponds to concrete cast-in-place and concrete precast panels. Hence, the database was refined to contain only concrete bridge decks.

Figure 1

Further filtering was applied to the NBI database to remove inconsistencies before its implementation in the models. For instance, records without condition deck rating were removed, along with inspection records on bridges with reconstruction history which do not characterise a natural degradation trend. Additionally, there were cases where an improvement in the condition rating was observed. This effect can be attributed to non-recorded maintenance actions or visual inspection inaccuracy due to its inherent subjectivity. Both cases were herein studied, so a “Dataset 1” discarded the complete sequence of observations where improved transition were present; while a “Dataset 2” included the transitions towards better conditions up to two ratings assuming to represent the variability between inspectors [38]. All models implemented in the present work except the Hidden Markov model used Dataset 1.

Finally, bridge decks with a condition rating of “2” or lower are posted for reduced load or closed to traffic [26], so they were removed because they are not in a normal operation condition. It was also observed that following the filtering there was no records on bridge decks with a condition rating of “9”. Thus, the developed models were built to predict the deterioration from condition rating “8” to condition rating “3”. Table 2 presents information on the distribution of bridges according to their main structure type, functional class and recorded condition ratings for both considered datasets. It can be seen that there is a low number of very high and very low condition ratings in comparison with the number of available mid-condition ratings.

Table 2

3. Discrete Markov Models

Discrete Markov models are stochastic processes that describe physical systems where the probability that a system will be in a given state j at time t_2, may be obtained from a known state *i* at an earlier time t_I, but is independent on its history before time t_I (i.e. Markov property) [40]. The probability of a transition between state *i* and *j* per unit of time is expressed as [20]:

$$P_{ij} = Pr\{X_{t+1} = j|\, X_t = i_0\} = Pr\{X_1 = j|X_0 = i\}, \quad (1)$$

The probability of transitioning from all possible pairs (*i,j*) during a single period of time, may be assembled in the transition probability matrix (TPM) of order (*n* x *n*), where *n* is the total number of condition states [20]:

$$P = \begin{bmatrix} P_{11} & P_{12} & \cdots & P_{1n} \\ P_{21} & P_{22} & \cdots & P_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ P_{n1} & P_{n2} & \cdots & P_{nn} \end{bmatrix} \quad (2)$$

The elements of a TPM satisfy the following conditions [20]:

i. $0 \leq P_{ij} \leq 1$ for all i, j

ii. $\sum_{j=1}^{n} P_{ij} = 1$ for all i, j

iii. $P_{ij} = 0$ for $i > j$

The third condition is assumed for the purpose of modelling deterioration. Therefore, the system will remain in the same state during the discrete period of time or will move to a more deteriorated state.

There are different methods to estimate the transition probabilities. In this study, the percentage prediction method was used to derive the elements of the matrix [34]:

$$p_{ij} = \frac{n_{ij}}{n_i} \quad (3)$$

where:

n_{ij} is the number of bridges that moved from state *i* to state *j* during a single period of time;

n_i is the total number of bridges in state *i* before the transition

Through the application of Equation (3), the obtained TPM computed using the Dataset 1 described in Section 2 is equal to:

$$P = \begin{bmatrix} 0.59 & 0.41 & 0 & 0 & 0 & 0 \\ 0 & 0.87 & 0.13 & 0 & 0 & 0 \\ 0 & 0 & 0.94 & 0.06 & 0 & 0 \\ 0 & 0 & 0 & 0.93 & 0.07 & 0 \\ 0 & 0 & 0 & 0 & 0.97 & 0.03 \\ 0 & 0 & 0 & 0 & 0 & 1 \end{bmatrix} \tag{4}$$

By means of a discrete Markov process, the state vector Q_t which corresponds to a vector containing the element rating for any time t, can be obtained as the initial condition state vector Q_0 multiplied by TPM to the power of t [18] :

$$Q_t = Q_0 \times P^t \tag{5}$$

For a newly constructed bridge element at the time of the first inspection, the initial state vector will be equal to $Q_0 = [1\ 0\ 0\ 0\ 0\ 0]$ [18]. Finally, the estimation of the condition rating as a function of time $R_{P,t}$ is obtained as [18]:

$$R_{P,t} = Q_t \times R' \tag{6}$$

Where R' is a vector of condition ratings which for the processed database is equivalent to $R' = [8\ 7\ 6\ 5\ 4\ 3]$. Consequently, a deterioration curve can be constructed by computing the expected value of condition rating for each discrete time step over the lifetime of the network of bridges.

4. Semi Markov models

Aging is mathematically defined as an increasing probability of transition to a worse condition state as time progresses [20]. Semi Markov models are an extension of discrete Markov models where the aging effect can be captured through the random time that is inserted between state transitions [20]. This random time is referred as sojourn (or waiting) time and is denoted as T_{ij}, with probability density function (PDF) designated by f_{ij}, and survival function (SF) designated by S_{ij} [33]. In order to estimate the transition probabilities in a Semi

Markov process, it is necessary to calculate the sum of the sojourn times in the states ($T_{i \to k}$), i.e. the time the process will take to move from state i to k, which can be expressed as [33]:

$$T_{i \to k} = \sum_{j=1}^{k-1} T_{j,j+1} \tag{7}$$

With $i = \{1,2,\cdots,n-1\}$; $k = \{2,3,\cdots,n\}$. Accordingly, the single step transition probabilities can be determined as [9]:

$$P_{i,i+1}^{t,t+1} = Pr[X(t+1) = i+1 |\, X(t) = i] = \frac{f_{1 \to i}(t)}{S_{1 \to i}(t) - S_{1 \to i-1}(t)} \tag{8}$$

where $f_{1 \to i}(t)$ and $S_{1 \to i}(t)$ are the PDF and SF of the sum of the sojourn times from state 1 to state i respectively. The TPM of the Semi Markov process is hence populated after generating all the transition probabilities using Equation (8):

$$P^{t,t+1} = \begin{bmatrix} {P_{11}}^{t,t+1} & {P_{12}}^{t,t+1} & 0 & \cdots & 0 \\ 0 & {P_{22}}^{t,t+1} & {P_{23}}^{t,t+1} & \cdots & 0 \\ \cdots & \cdots & \cdots & \cdots & \cdots \\ 0 & \cdots & \cdots & P_{n-1,n-1}^{t,t+1} & P_{n-1,n}^{t,t+1} \\ 0 & 0 & \cdots & 0 & 1 \end{bmatrix} \tag{9}$$

For the present work, the distribution of the sojourn times is assumed to follow a two parameter Weibull distribution. Therefore, the PDF and SF of the sojourn times are given by [33]:

$$S_i(t) = e^{-(\lambda_i t)^{\beta_i}} \tag{10}$$

$$f_i(t) = \lambda_i \beta_i \, (\lambda_i t)^{\beta_i - 1} e^{-(\lambda_i t)^{\beta_i}} \tag{11}$$

The parameters λ_i and β_i are estimated from historical observations recorded in the Dataset 1. To this end, two intervals of time are defined, namely *u* and *v* (*u* ≠ *v*), and the probabilities of the bridge deck to remain in a certain condition rating *i* for more than *u* and *v* years are assessed, i.e. $x_{i,u}$ and $x_{i,v}$ respectively [33]. These probabilities are computed from the relative frequency of events similarly as for the Markov process [21], and the results for the selected intervals are shown in

Table 3. Subsequently, the parameters λ_i and β_i are derived from the following expressions [33]:

$$\begin{cases} S_i(u) = e^{-(\lambda_i u)^{\beta_i}} \\ S_i(v) = e^{-(\lambda_i v)^{\beta_i}} \end{cases} \Rightarrow \begin{cases} \ln[S_i(u)] = -(\lambda_i u)^{\beta_i} \\ \ln[S_i(v)] = -(\lambda_i v)^{\beta_i} \end{cases} \Rightarrow \ln\left(\frac{\ln[S_i(u)]}{\ln[S_i(v)]}\right) = \beta_i \ln\left(\frac{u}{v}\right) \quad (12)$$

$$\beta_i = \frac{\ln(\ln[S_i(u)] - \ln[S_i(v)])}{\ln(u) - \ln(v)}\ ;\ \lambda_i = \frac{1}{u}(-\ln[S_i(u)])^{\frac{1}{\beta_i}} \quad (13)$$

Once both parameters are evaluated for every *i*, the TPM for the Semi Markov process can be computed.

Table 3

5. Hidden Markov models

Monitoring data from historical inspections frequently contains measurement errors and selection biases [23], which affect the accuracy of the deterioration predictions. To address this issue, Hidden Markov models (HMM) have been used to incorporate the bias of the observations into the forecasting models [20], [23]. HMMs assume that there is some true condition state which is "hidden" to the observer [20]. In other words, the sequence of true states $S_1, S_2, \cdots, S_n$ at the inspection times $t_1, t_2, \cdots, t_n$ is hidden behind the sequence of the observed states $V_1, V_2, \cdots, V_n$ [20]. Therefore, considering the bias in the monitoring data allows the unobserved true condition states to be captured [23].

The sequence of the true states follows a simple Markov chain, so the probability a_{ij} representing the probability of moving to state S_j depends only on the state S_i, which can be expressed as $a_{ij} = P\left[q_{t+1} = S_j \middle| q_t = S_i\right]$ [35]. On the contrary, the observed sequence does not hold the Markov property [20]. The conditional probability of the observations given the true states corresponds to [20]:

$$e_{ij} = Pr[V_k = j | S_k = i] \quad (14)$$

These probabilities are collected in an error or misclassification matrix where $0 \leq e_{ij} \leq 1$, and $\sum_{j=0}^{n} e_{ij} = 1$ [20]:

$$E = \begin{bmatrix} e_{11} & e_{12} & \cdots & e_{1n} \\ e_{21} & e_{22} & \cdots & e_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ e_{n1} & e_{n2} & \cdots & e_{nn} \end{bmatrix} \tag{15}$$

The probability of correctly identifying the condition state corresponds to e_{ii}, while for all $i \neq j$ there exists a misclassification reflecting the variability in the inspections [20]. This variation is attributed to the fact that the condition rating is a qualitative measure affected by the subjectivity of the inspectors. This phenomenon was investigated by the FHWA [38] who conducted a study to evaluate the reliability of the visual inspections. Forty-nine bridge inspectors completed routine and in-depth inspections to the same bridges. The results showed that 95% of the element condition ratings vary within ±2 rating points around the mean, and 68% of these ratings vary within ±1 rating point [38]. The error probabilities referred as emission probabilities in the formal notation for Hidden Markov models may be assessed by expert judgement or by maximum likelihood [20].

One of the basic problems involved when using HMMs is to adjust the parameters of the model λ, i.e. the sequence of the states π, the transition probabilities a_{ij} and the emission probabilities e_{ij}, to maximize the probability of the observation sequence given the model [35]. There is no analytical solution to maximize the probability of the observation sequence; hence, an iterative procedure such as the Baum-Welch algorithm can be used to locally maximize the observation sequence given a selected model λ, and re-estimate the model parameters $\bar{\lambda}$ until a stopping criterion is reached [35]. The mathematical description of this procedure is not herein presented, for a detailed explanation the reader is referred to [35], [41].

Matlab [42] function “hmmtrain” was used to estimate the transition and emission probabilities for the Hidden Markov model using the Baum-Welch algorithm. An initial estimation of the transition and emission probabilities matrices together with the sequence of observations are the inputs of the function. The initial guess for the transition probability matrix is computed with the same procedure described in Section 3 but using the Dataset 2; in this manner the model includes the inspectors’ variability as explained in Section 2. The obtained matrix is equal to:

$$a_{ij} = \begin{bmatrix} 0.521 & 0.4455 & 0.0335 & 0 & 0 & 0 \\ 0.0014 & 0.8566 & 0.1335 & 0.0085 & 0 & 0 \\ 0.0044 & 0.0205 & 0.9044 & 0.0615 & 0.0092 & 0 \\ 0 & 0.024 & 0.0477 & 0.8747 & 0.0536 & 0 \\ 0 & 0 & 0.043 & 0.037 & 0.897 & 0.023 \\ 0 & 0 & 0 & 0 & 0 & 1 \end{bmatrix} \qquad (16)$$

Note that the transitions to better states are allowed but the increase is attributed to imperfect inspections rather than an improvement in the quality of the structure resulting from maintenance.

For the emission probability matrix it is assumed that the inspectors’ misclassifications could be ±2 condition ratings based on the FHWA findings [38]. The most likely values for the emission probabilities will be estimated through the Baum-Welch algorithm, so for the initial guess all the non-zero elements of the matrix are assumed to be equal:

$$e_{ij} = \begin{bmatrix} 1/3 & 1/3 & 1/3 & 0 & 0 & 0 \\ 1/4 & 1/4 & 1/4 & 1/4 & 0 & 0 \\ 1/5 & 1/5 & 1/5 & 1/5 & 1/5 & 0 \\ 0 & 1/5 & 1/5 & 1/5 & 1/5 & 1/5 \\ 0 & 0 & 1/4 & 1/4 & 1/4 & 1/4 \\ 0 & 0 & 0 & 1/3 & 1/3 & 1/3 \end{bmatrix} \qquad (17)$$

The sequence of observations corresponds to the succession of condition ratings along the years from each bridge deck. The transition and emission probabilities obtained through the Baum-Welch algorithm were:

$$\overline{a_{ij}} = \begin{bmatrix} 0.826 & 0.146 & 0.028 & 0 & 0 & 0 \\ 0.019 & 0.919 & 0.02 & 0.042 & 0 & 0 \\ 0.064 & 0.034 & 0.673 & 0.101 & 0.128 & 0 \\ 0 & 0.032 & 0.001 & 0.943 & 0.024 & 0 \\ 0 & 0 & 0.064 & 0 & 0.907 & 0.029 \\ 0 & 0 & 0 & 0 & 0 & 1 \end{bmatrix} \tag{18}$$

$$\overline{e_{ij}} = \begin{bmatrix} 0.091 & 0.904 & 0.005 & 0 & 0 & 0 \\ 0 & 0 & 0.999 & 0.001 & 0 & 0 \\ 0 & 0 & 0.138 & 0.808 & 0.054 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 \end{bmatrix} \tag{19}$$

Note that for the lower condition states, the obtained emission probabilities indicate that the true conditions are correctly observed by the inspector, while for the better condition ratings the inspectors tend to assign lower than the true condition. This effect is in accordance with the FHWA research [38] which concluded that inspectors are hesitant to assign high condition ratings for better condition elements.

Based on the transition and emission probabilities previously obtained, the Matlab function “hmmgenerate” is used to generate random sequences of emission symbols (the observed states) and random sequences of states (true or hidden states) during a 100-year period. Then, the average of 10000 sequences of states is computed.

6. Artificial Neural Networks

Artificial Neural Networks (ANN) are information-processing techniques conceptually motivated by the way the densely interconnected and parallel structure of the human brain processes information [24]. Several types of ANN have been applied to solve the bridge deterioration modelling problem. One of the most widely used model that has demonstrated great capabilities to solve the prediction deterioration problem are multilayer perceptron networks (MLP). This model is based on fully connected, layered, feed-forward networks [24], that utilize back propagation technique for training. Additionally, other approaches have been developed such as *i)* case base reasoning which looks for previous cases that are similar to the current problem and reuse them to solve the problem [28] *ii)* ensemble of neural networks which is composed of a series of individual ANNs working in parallel so predictions are made by collecting and combining the outputs of individual networks through a weighting process [26] *iii)* Elman neural networks integrated with a backward prediction model which generates missing condition ratings when the input data is insufficient [43].

A MLP network has been used in the present work to model the deterioration of bridge decks based on Dataset 1. The input parameters for the network correspond to the variables that more significantly influence the condition of the bridge deck. The selection of the input variables is a crucial issue considering that the nature of the problem cannot be captured with only a few variables, but can be over-fitted with redundant variables [26]. The NBI database comprises of 116 different bridge attributes (full list refer to [4]). Hence, a first selection of the potential influential parameters based on literature review and engineering judgement comprised 12 attributes namely age, structure length, deck width, skew angle, type of design and/or construction, functional classification, design load, maintenance responsibility, kind of material and/or design, wearing surface, ADT (Average Daily Traffic) and ADTT (Average Daily Truck Traffic) . Afterwards, statistical analysis was performed to validate the significance of the association and the correlation of the independent variables with the dependent variable. However, the database possesses complex multidimensional data so that the evidence obtained from the traditional statistical tests was not sufficiently strong to draw consistent conclusions. Therefore, the predictors selection was done through a variance-based sensitivity analysis that computes the importance of each predictor in determining the neural network, i.e. how much the network predicted value changes for different values of the independent variables [44]. The strength of this method is that it can deal with nonlinear responses and produces good estimations when the size of the dataset is large. After conducting the sensitivity analysis, the obtained normalized importance of the independent variables is shown in Figure 2.

The variables with the lowest importance were sequentially removed until the performance of the network reached its optimal value. The final parameters selected as input variables were age, structure length, deck width, functional classification, kind of material and/or design, and ADTT. The quantitative variables were standardized, and the categorical variables were transformed into a binary system before employing them in the model.

Finally, Matlab Neural Network Toolbox [42] was used for the development of the MLP model. The network was trained with a Bayesian regularization backpropagation training function, for its ability to reveal potentially complex relationships. 70%, 15% and 15% of the input data was randomly allocated for training, validating and testing the network respectively. The number of hidden layers and the number of neurons in each layer were selected to be 3 and 20 respectively, after several iterations to obtain the best network performance. The maximum number of epochs during the training was set on 10000. The activation function for the hidden layers was the hyperbolic tangent sigmoid transfer function, while the output layer uses a linear transfer function. The obtained weights and biases from the ANN model are available for the public domain as supporting information.

7. Results

This section provides lifetime deterioration curves developed from the four previous presented models. To enable the comparison a single plot with the degradation curves representing the average condition of the bridge decks belonging to the network is shown in Figure 3. It can be noted that due to the variability in the inspections, the initial condition state for the ANN model starts in a different state than state “8”. It can also be observed that the three Markov processes predict a higher deterioration rate for the early years of the bridge decks compared to the ANN. In general, the ANN model maintains a good condition rating for longer than the rest of the models. However, at the end of the studied period, the hidden Markov model predicts the highest condition ratings. This effect can be explained by the fact that when considering the variability in the inspections, the model assigns a true condition rating higher than the observed for the better states and hence the accumulated deterioration at the end of the period is lower.

It can be seen that the deterioration curves developed by the different models produce distinct degradation paths over the lifetime of the bridge decks. It is difficult to determine which of the models provide a better representation of the overall deterioration process of the bridge decks within the network. Hence, as an attempt to quantitatively measure the fitness of each model, the predictions are compared against the average condition rating recorded in the respective database per age (D1 average condition represented as dots in Figure 3). The metrics used to quantify how well the models matched the measured data were the mean square error (MSE), the mean absolute error (MAE) and the accuracy factor [45]. MSE is more sensitive to outliers than MAE which has led some authors to recommend the use of the latter for model fitness evaluation [46]. On the other hand, the accuracy factor indicates how much the predictions differ from observed data, where a value of “1” indicates a perfect model and can be expressed as [45]:

$$Accuracy\ factor = 10^{1/n} \sum_{i=1}^{n} \left| \log_{10} \left(\frac{predicted\ value}{observed\ value} \right) \right| \tag{20}$$

Table 4

It is observed from Table 4 that the lowest errors and best accuracy factor are reached by the ANN model, while the highest errors and worst accuracy factor correspond to the Semi Markov model. Based on the MSE measure the Markov and the Hidden Markov models have approximately the same accuracy; nevertheless, the MAE measure indicates that the Hidden Markov model provides a better representation of the data than the Markov model. Likewise, the accuracy factor also suggests that the predictions obtained from the HMM diverge less from the measured data than the Markov model predictions.

8. Discussion

Overall, all the models evidenced a distinct degradation pattern that concluded, at the end of the studied period, with a varying condition rating among the models. The worst condition was predicted by the Semi Markov model followed closely by the Markov model, reaching a rating of 4 which is generally considered as the threshold level to perform rehabilitation or replacement measures. ANN model was also approaching the rating 4 while the Hidden Markov model was entering condition rating 5. As mentioned in Section 7, the better condition predicted by the HMM resulted from considering the variability in the inspections. However, the selection of this model might conduct to inadequate maintenance activities considering that typical values of concrete decks life expectancy in the US are between 24-48 years [47]. In general, all the models are not in line with this experience.

Even though Semi Markov models have been proposed extensively and its advantages over Markov chain models have been highlighted [20], [22], there were no significant differences among the obtained results. In fact, it was found that the Semi Markov model differed the most with the observed condition ratings.

This might be attributed to the lack of historical data to appropriately estimate the parameters of the distribution of the waiting times. Some studies have employed expert judgement to define these parameters [33]. However, this approach adds subjectivity to the deterioration modelling. Maximum likelihood estimation (MLE) method has also been employed for parameter estimation [20]. Nonetheless, MLE can be heavily biased for small samples which is the case for the estimation of the waiting times for the worst condition states, where the available data is limited due to the reconstructive efforts performed to prevent bridges from reaching structurally deficient conditions (as seen in Table 2). Therefore, the estimation of the parameters for the Semi Markov model poses a higher complexity on its implementation from a mathematical point of view than Markov chain model. Hence, unless sufficient data for reliable parameter estimation of the waiting times is available, Semi Markov models will not improve the prediction capabilities of Markov chains.

On the other hand, the Hidden Markov model enabled the inclusion of inspections variability which has been demonstrated to take place due to the subjective inspection procedure. Even though the HMM revealed a satisfactory accuracy compared to the rest of the models, the actual hidden process can never be observed [20], hence the model was fully determined by the data-based estimation of the emission probabilities which conducted to an unrealistic result when compared to typical values of concrete decks life expectancy as previously mentioned. The emission probabilities could have been determined also by expert judgement [20]. However, this involves a subjective estimation approach. Consequently, the estimation of the additional matrix increases the complexity of the implementation of HMM compare to Markov chain models.

Finally, ANN model demonstrated a superiority in the prediction accuracy. The most influencing parameters affecting the bridge decks condition were identified to construct a MLP network which was able to correctly identify the condition ratings on average in 95% of the cases when exposed to the training data. The lowest percentage of correctly predicted values was obtained for the worst condition rating due to the low number of inspection records on the database to appropriately train the network for transitions to this rating. Nonetheless, the number of datapoints was sufficient to obtain satisfactory predictions. These results are in accordance with the literature review where the ANNs have always demonstrated great predictive capabilities [24], [26]. However, the training of the network involves high computational cost in comparison with Markov chain models, which can be seen as a limitation considering that the database is periodically updated providing further knowledge about bridges that should be employed in predicting their future condition, but that will imply variations on the inputs to train the ANN and consequently the weights and biases should be once again found.

In general, the reliability of the predictions might have been affected by the inherent limitations of the models and aggravated by the accuracy of the database, which was found to contain data imbalance and deterioration trends that might not be realistic despite the filtering performed to remove effects from maintenance actions before developing the models (Section 2). For instance, some of the deck ratings over the complete span of 26 years did not vary significantly or did not vary at all. This behaviour differs from what is expected and might be related with regular and minor maintenance activities that are not recorded in the database. This latter effect is particularly evidenced in several bridge decks with 70 years age having ratings of 6 or 7. On the contrary, newly built bridges (0-5 years old) documented a deck rating of 6, i.e. satisfactory condition but with deterioration including cracks and around 2% of spalling or delamination in the deck area; which meant an unforeseen high deterioration rate at an early stage (decrease of 3 condition ratings in less than 5 years). As a consequence of the inconsistent deterioration trends observed in the NBI database, some studies have applied additional filtering to the data [15], [16]. For instance, in [15] a maximum and minimum age for each condition rating was imposed and data points outside the limits were removed. Similarly, in [16] it was assumed that any bridge deck should be reconstructed after the average age at which reconstruction works take place e.g. 30 years. Therefore, any deck rating assigned after that age should be eliminated. Nevertheless, these approaches are based on expected deterioration trends so might introduce subjectivity to the predictions depending on the selected ranks or might restrict the available data for the development of the models.

9. Conclusions and future directions

Four different deterioration models namely Markov models, Semi Markov models, Hidden Markov models and Artificial Neural Networks were implemented in the present work to predict and compare the degradation of bridge decks based on condition ratings retrieved from the NBI database. The Markov model herein applied consisted in a homogeneous Markov chain which is the most frequent model used in the BMS. The simplicity in its implementation together with its capabilities to capture the randomness of the deterioration process are some of the main reasons for its selection. However, in a homogeneous Markov chain the transition probabilities are not time dependent which is one of the features that has been widely criticized. For this reason, alternative deterioration modelling approaches were implemented to compare and analyse the impact of the Markov chains assumptions on the prediction results. It was shown that all models exhibited a distinct deterioration curve. However, there were no significant differences among the results obtained by Markov and Semi Markov models. Nevertheless, the Semi Markov presented higher errors and worse accuracy factor than the Markov model. Furthermore, it was found that the predictions obtained by the Hidden Markov model provided a better representation of the observed condition ratings than the Markov model. Amongst all, the ANN model achieved the lowest errors and best accuracy factor. In addition to the higher prediction accuracy, the feature of employing the parameters affecting bridge deck deterioration for assessing the condition, makes ANN model a more convenient alternative to be implemented on existing BMS to predict the condition of individual bridge decks.

While the study focused on Rhode Island, in future works, the models and methodologies herein presented can be replicated in other regions using NBI data or other similar databases, in order to analyse if different deterioration trends are obtained. Accordingly, the impact of the inspection and condition assessment practices performed by each state on the development of deterioration models can be investigated. Moreover, additional deterioration modelling approaches such as more advanced AI techniques and Petri-nets could be included as part of the comparison.

Finally, the deviation of the predictions from the typical values of concrete decks life expectancy as well as some challenges encountered during the development of the models are attributed to *i)* an unbalanced and scattered database *ii)* minor non-recorded maintenance actions preserving the condition without increasing the rating *iii)* shortcomings of VI as primary condition assessment tool, i.e. assessing a bridge condition only by VI is significantly subjected to variability of the condition ratings as demonstrated by [38], In order to overcome the latter limitation, NDE technologies have been used to more objectively detect and characterize the deteriorated condition of bridge elements. For instance, in [48] several NDE methods namely electrical resistivity, half-cell potential, ground penetrating radar, impact echo, and chain drag, were combined to enable the identification of different deterioration phenomena for a complete assessment of concrete decks. Moreover, when a particular defect has been detected, e.g. active corrosion, condition assessment can be accompanied by additional measurements such as chloride content or carbonation depth which serves for the quantification of the severity of the deterioration phenomena. At present, NDE technologies are being used but surveying large amounts of bridges for BMS is still cost- and time-consuming, usually involving traffic disruption and uncertainties in their measurements which need to be carefully addressed. Similarly, structural health monitoring (SHM) systems are also a powerful and reliable technique for short- and long-term bridge condition assessment. Nevertheless, SHM systems are often costly and their complexity resulting from data acquisition, structural modelling, big data analysis, and routine maintenance required for long-term operation limit their prompt adoption on BMS.

Despite the current challenges for integrating NDE/SHM assessment tools into the BMS, research efforts should be undertaken in this direction so bridge condition assessment could move from operational indicators (i.e. condition ratings) to research indicators, which address from a quantitative perspective the structural safety and serviceability of a bridge, Consequently, deterioration modelling could be more realistic considering that the input parameters will be based on quantitative resistance measures.

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Figure 1. Distribution of bridges by year of construction and deck structure type

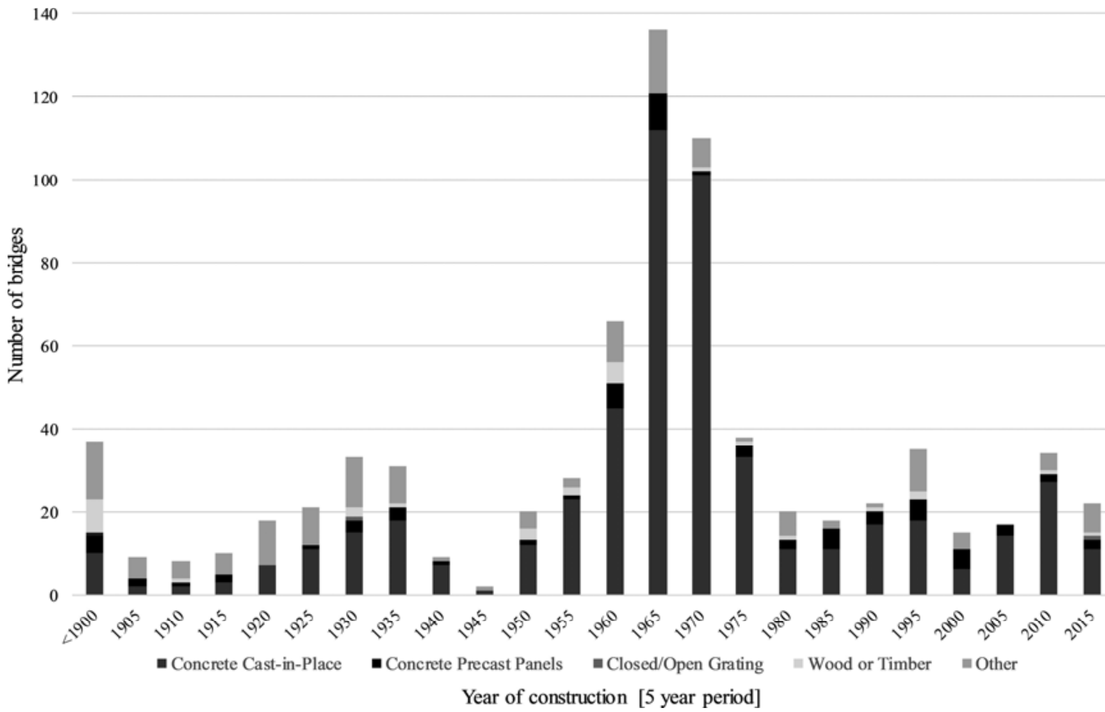

Figure 2. Normalized importance of the independent variables

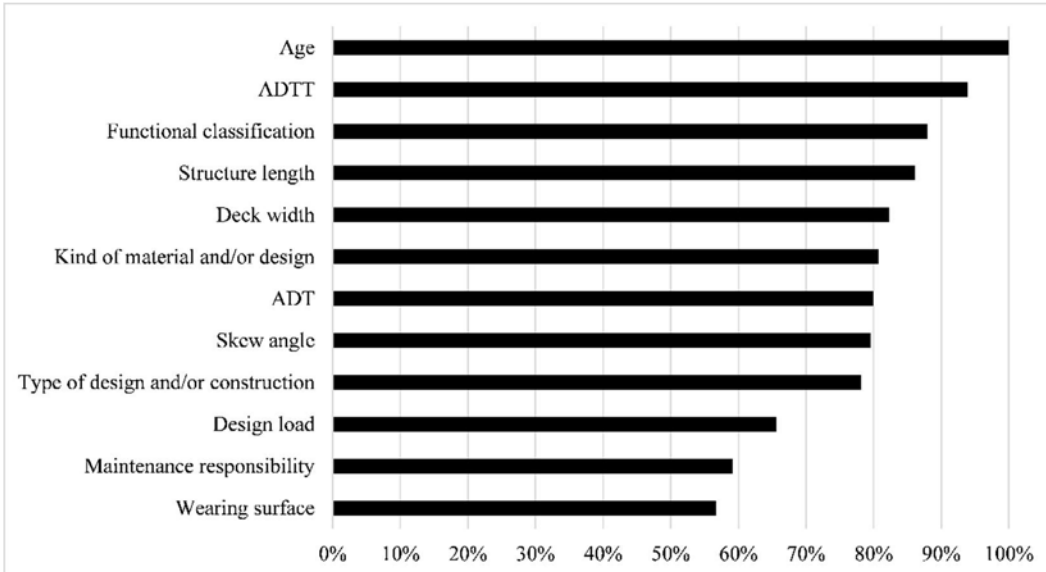

Figure 3. Deterioration curves for bridge decks

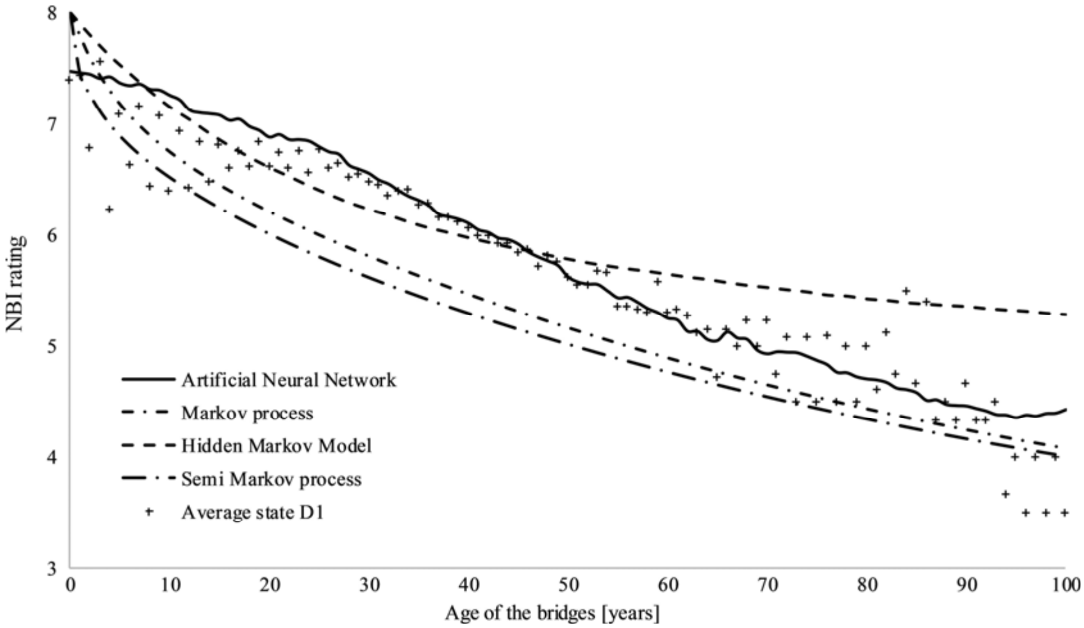

Table 1. Condition rating system for decks used in the National Bridge Inventory (NBI) [36]

Code	Condition	Description
9	Excellent	As new
8	Very good	No problems noted
7	Good	Some minor problems
6	Satisfactory	Structural elements show some minor deterioration
5	Fair	All primary structural elements are sound but may have minor section loss, cracking, spalling or scour
4	Poor	Advanced section loss, deterioration, spalling or scour
3	Serious	Loss of section, deterioration, spalling or scour have seriously affected primary structural components. Local failures are possible. Fatigue cracks in steel or shear cracks in concrete may be present
2	Critical	Advanced deterioration of primary structural elements. Fatigue cracks in steel or shear cracks in concrete may be present or scour may have removed substructure support. Unless closely monitored it may be necessary to close the bridge until corrective action is taken
1	“Imminent” failure	Major deterioration or section loss present in critical structural components or obvious vertical or horizontal movement affecting structure stability. Bridge is closed to traffic but corrective action may put back in light service
0	Failed	Out of service, beyond corrective action

Table 2. Distribution of bridges according to selected parameters for each dataset

Main Structure Type						Functional Class			Condition Ratings		
Kind of material and/or design			**Type of design and/or construction**								
	D1	D2		D1	D2		D1	D2		D1	D2
Concrete	18	34	Slab	12	25	RPI Arterial	4	8	CR 8	104	127
Concrete continuous	10	14	Stringer/Multi-beam or Girder	167	208	RP Arterial	7	7	CR 7	984	1260
Steel	119	149	Girder and Floorbeam System	5	5	RMi Arterial	5	7	CR 6	1385	1769
Steel continuous	24	27	Tee beam	7	9	RMa Collector	9	14	CR 5	418	648
Prestressed concrete	42	56	Box Beam or Girders - Multiple	16	21	RMi Collector	2	5	CR 4	137	204
Wood or Timber	0	1	Frame	6	9	R Local	15	17	CR 3	24	24
Other	5	7	Truss - Thru	1	4	UPI Arterial	43	53			
			Arch - Deck	2	3	UP Arterial	18	25			
			Suspension	1	1	UPF Arterial	36	47			
			Other	1	3	UM Arterial	43	55			
						U Collector	19	28			
						U Local	17	22			

Rural Principal (RP); Rural Principal Interstate (RPI); Rural Minor (RMi); Rural Major (RMa); Urban Principal Interstate (UPI); Urban Principal (UP); Urban Principal Freeways (UPF); Urban Minor (UM)

Dataset 1 (D1) comprises a total of 218 bridges; Dataset 2 (D2) comprises a total of 288 bridges

Table 3. Input parameters for the Semi Markov process

CR	u [years]	$x_{i,u}$ [%]	v [years]	$x_{i,v}$ [%]	β_i	$1/\lambda_i$	λ_i
8	30	0.000	50	0.000	0.950	3.178	0.315
7	30	0.110	50	0.028	0.950	13.029	0.077
6	30	0.396	50	0.222	0.950	32.548	0.031
5	30	0.309	50	0.149	0.950	25.361	0.039
4	30	0.592	50	0.426	0.950	59.125	0.017

Table 4. MSE and MAE accuracy measures

Model	MSE	MAE	Accuracy factor
Artificial Neural Network	0.2068	0.3154	1.3552
Markov process	0.3336	0.5371	2.3312
Hidden Markov model	0.3302	0.4219	1.7521
Semi Markov process	0.4276	0.6086	2.6763