National Bridge Inventory Data-Based Stochastic Modeling for Deck Condition Rating of Prestressed Concrete Bridges

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Abstract: About 9% of bridges in the United States were classified as deficient bridges at the beginning of 2018 with about $123 billion needed for bridge rehabilitation. The bridge decks represent the highest budget associated with bridge maintenance because they deteriorate faster compared with the other components, because of direct exposure to traffic and harsh climate changes. The subjectivity in determining the condition rating is an imprecise process and may significantly affect the maintenance process, which may vary from one inspector to another. Moreover, most research works in prestressed concrete bridges condition ratings have focused predominantly on modeling and have neglected to study the individual effect of geometric variables with excluding the impact of aging and maintenance on the condition rating. The paper's objectives and proposed contributions are investigating and modeling the impact of explanatory variables on deck condition rating apart from aging and maintenance actions. The findings highlight the design's contribution to reducing the decline of a bridge condition rating. The stochastic regression analysis has been used to propose a realistic deck condition through a probability distribution. Four models have been developed using the National Bridge Inventory (NBI) of California, and results showed a satisfied coefficient of determination. The developed models have been validated with satisfactory results of 87% using the Average Validity Percentage Method. The developed models will help highway agencies make better decisions regarding future maintenance plans by prioritizing the bridge's maintenance. **DOI: 10.1061/(ASCE)SC.1943-5576.0000505.**

Author keywords: Deterioration models; Condition assessment; Deck condition; Prestressed concrete bridges; Monte Carlo simulation.

Introduction

ASCE (2017) reported that about 9% of bridges in the United States are classified as structurally deficient bridges, and the estimated rehabilitation cost for generally deficient bridges is about $123 billion. In California, about 6.2% of bridges are structurally deficient, and approximately 17% of California's bridges are estimated to cost about $12.2 billion for repairs. Prestressed concrete represents about 24% of California bridges (USDOT 2017). There is a need to reduce bridge deterioration and restrict it in its early phases. Therefore, effective bridge management systems (BMSs) that allow for the monitoring of bridge conditions over time can be coupled with reliable deterioration models to help bridge owners customize repair and replacement schedules for their bridge assets. These models are helping to customize bridges repairs or replacement schedules.

The creation and maintenance of a National Bridge Inspection Standard and National Bridge Inventory (NBI) were mandated by the 1968 Federal-Aid Highway Act. [Federal-Aid Highway Act of 1968 (sec. 26, Public Law 90-495, 82 Stat. 815, at 829)]. In 1971, the Federal Highway Administration (FHWA) published the first "Recording and Coding Guide for the Structural Inventory and Appraisal of the Nation's Bridges," which guided the recording and coding of data elements that would comprise the NBI. The NBI database serves as an archival record that includes general inventory, operational, and inspection data for more than 600,000 bridges in all 50 states. The NBI database has been utilized by many researchers as a primary, and reliable, data resource (Ben-Akiva and Gopinath 1995; Veshosky et al. 1994; Mauch and Madanat 2001; Bolukbasi et al. 2004; Morcous 2011; Saeed et al. 2017; Contreras-Nieto 2017; Contreras-Nieto et al. 2018).

There are many complex causes of bridge deterioration. The main reasons for deterioration include inadequate design or construction, aggressive environments, overload, accidental impacts, lack of maintenance, and aging. The bridge deck is subject to the aggressive impacts caused by traffic and environmental effects such as wetting and drying and freeze-thaw cycles, including chloride applications in northern climates as such bridge decks are generally the first element of a bridge structure to exhibit deterioration and thus the first to require maintenance consideration. Consequently, the cost to maintain bridge decks is considerable (Yunovich and Thompson 2003; Bolukbasi et al. 2004; Moomen et al. 2016).

Most of the previous studies that developed models for deck deterioration considered age as one of the main independent variables that affect deck deterioration. However, this study aims to investigate and model the impact of explanatory variables on deck condition rating for prestressed bridges, apart from age and maintenance. Specifically, how geometric variables affect the deterioration rate of prestressed bridges. The findings will help bridge designers to improve the design in a way to reduce the deterioration, which results in decreasing the maintenance cost.

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Background

Deterioration models developed from explanatory variables used in BMSs or other sources have been shown to be effective in predicting future bridge deck conditions. Various approaches have been utilized to model deck deterioration, such as deterministic, stochastic, and artificial intelligence models. The following references illustrate the various approaches and support their use in predicting bridge condition (Kleywegt and Sinha 1994; Veshosky et al. 1994; DeStefano and Grivas 1998; Morcous et al. 2002; Dekelbab et al. 2008; Bu et al. 2012; Lavrenz et al. 2015; Moomen et al. 2016; Qiao et al. 2016; Saeed et al. 2016, 2017; Chang et al. 2017; Inkoom and Sobanjo 2018). The deterministic approach deals with known inputs and outcomes and identifies the significant relation between them using statistical analysis (Veshosky et al. 1994; Shahin 2005; Madanat et al. 1995; Sobanjo and Thompson 2011; Bektas et al. 2012; Inkoom and Sobanjo 2018).

Data-based modeling for bridge deterioration using the NBI and other databases and sources: "life cycle cost analysis LCCA for existing bridge expansion joint alternatives, including the practices of routine joint replacement and removal of joints" (Kelly et al. 2019); "rational means to analyze existing foundations using a hybrid analytical-numerical method so that reuse of foundation can be optimized" (Sayed et al. 2018); "leverage a large amount of data to improve bridge deterioration prediction and enhance maintenance decision making" (Liu and El-Gohary 2016); "develop a reasonable estimate for future bridge conditions using NBI" (Bolukbasi et al. 2004); "condition assessment and prediction of service life of highway bridges using field data" (Mohammadi et al. 1998).

As a way to get more realistic results, stochastic models have been developed to capture the uncertainty and randomness of deterioration models and deterioration behavior based on time (Morcous et al. 2002; Chang et al. 2017; Inkoom and Sobanjo 2018). Williamson (2007) combines deterministic and stochastic approaches through the use of Monte Carlo simulation techniques to account for input parameter variability in the development of bridge deck service life models. This methodology is applied to investigate the relationship between dependent and explanatory variables. Further analysis using the Monte Carlo simulation was conducted to forecast the probability distribution to the explanatory variables, which affects the probability of the dependent variable.

The NBI database is widely used as a data source for modeling deck conditions and examining the significance of explanatory variables against the deck condition. Morcous et al. (2002) studied operational variables and used case-based reasoning to develop a concrete deterioration model. They considered about eight factors from previous studies, which included variables of average daily traffic, truck percent, age, span length, skew angle, total width, beams spacing, wearing surface, and the number of beams. A similar study was conducted by Huang et al. (2010) but with applying the mining technique and adding climatic variables. They have used data mining techniques to find the most significant factors leading to deck deterioration. In addition to age, they studied the inventory, operational, and climate factors based on literature such as number of spans, number of lanes, length of the bridge, area of the deck, max span length, traffic volume, average rainy days per year, and peak monthly rainfall. While other studies have an oriented study, by selecting the climatic factors as main variables, such as the conducted study by Kim and Yoon (2010), this study has focused on deck condition in cold regions for concrete, prestressed, and steel bridges. Kim and Yoon (2010) used a combined technique of multiple regression and geographic information system technology. The examined parameters included age, design load, number of spans in the main unit, deck width, average daily truck traffic, replacement, service on the bridge, and environmental factors. They found that age is the most significant factor, followed by bridge structural characteristics and traffic load. Kim and Yoon (2010) recommended concrete bridges for cold regions as more durable than steel. Subsequently, Winn and Burgueño (2013) used an advanced approach using an artificial neural network (ANN) model to predict the concrete deck condition ratings for bridges in Michigan. The developed model was based on using geometrical and operational bridge data to predict the deck condition in terms of the NBI rating system. Eleven parameters were selected as input variables: age, average daily traffic, percent truck traffic, average daily truck traffic, number of spans, region, steel reinforcement protection, structure type, design load, and surface type. The developed models allowed the BMS to predict bridge deck degradation and optimize the bridge repair strategies within budget constraints. A different technique is used by Hasan et al. (2015), where they applied the Markov process as a stochastic method to predict the future condition of concrete bridge components and identify future maintenance needs. Hasan et al. (2015) utilized visual inspection data for bridges located in Victoria, Australia, along with bridge age, annual average daily traffic, and the percentage of truck traffic. The input data included age, annual average daily traffic, and percentage of truck traffic. They referred to the importance of linking maintenance actions to inspection data to provide a reliable deterioration model. A study by Moomen et al. (2016) uses NBI and bridge management data for Indiana bridges to develop a set of deterioration curves for bridge decks, superstructures, and substructure elements based on physical, operational, and climatic characteristics as the explanatory variables. Bridge location, functional class, and superstructure material type were used to categorize the deterioration models into families, which were then studied against NBI condition ratings as the response variable. For deck deterioration models, it has been found that the most influential factors were bridge age, functional class, service under the bridge, skew, bridge length, deck protection, the number of freeze-thaw cycles, and truck traffic. The developed models explained about 53% of the variation in the deck condition. Furthermore, it has been concluded that the exponential and polynomial curves are the best fit to represent deck condition rating as a function of the deck age corresponding to specific hypothetical values of the independent variables. On the other hand, Chyad et al. (2018) were able to estimate the time it took for bridge deck deterioration to advance to a given NBI condition rating (0–9) in six different climatic regions. The study concluded that environmental factors have a significant impact on the deterioration rate of concrete decks. Manafpour et al. (2018) used the semi-Markov time-based model, based on accelerated failure time (AFT) Weibull fitted-parameters. The combined approach is used to estimate the transition probabilities and sojourn times for the deterioration of concrete bridge decks. This study found that the following variables are significant with the deck condition: type of rebar protection, continuous versus supported spans, deck length, number of spans, bridge location, and whether the bridge is part of the interstate system or not.

The literature suggests that the study of bridge deck condition can be related to explanatory variables derived from NBI inspections, geometrical information, operational data, and climatic data sources. Furthermore, age and maintenance have been shown to have a significant influence on the prediction of bridge deck condition ratings. The studies described illustrating the application of deterministic, stochastic, and artificial intelligence approaches, among others, to the study of explanatory and response variables related to bridge deck condition. However, it is noticeable to find that most of the developed deterioration models are highly dependent upon the bridge age as the most significant contributor to deck deterioration (Dunker and Rabbat 1995; Veshosky et al. 1994;

Kallen and Noortwijk 2006; Kim and Yoon 2009; Tolliver and Lu 2012). The previous concerned efforts, as referred to in literature, have not isolated the impact of age and maintenance.

Methodology

This paper aims to investigate and model the impact of explanatory variables collected through NBI inspections to predict the deck condition rating for prestressed bridges. The bridges' data have been categorized according to age. Then the data sets under consideration are in the same age category. A deterministic approach using regression analysis methods was studied to identify the significant variables affecting deck condition. Then, stochastic analysis techniques were applied using Monte Carlo simulation to develop probability distributions for prediction of deck condition relative to each explanatory variable. The research methodology is shown schematically in Fig. 1 and contains the following steps:

- The literature review covers the state of the art in bridge condition, assessment, deterioration models, as well as the modeling techniques;
- Investigating the significant variables affecting the deck condition of prestressed bridges;
- Data collection and filtering;
- Design and build regression models;
- Statistical analysis for testing significance;
- Model validation;
- Stochastic modeling analysis using Monte Carlo simulation;
- Sensitivity analysis;
- Results analysis; and
- Conclusion and recommendation for future studies.

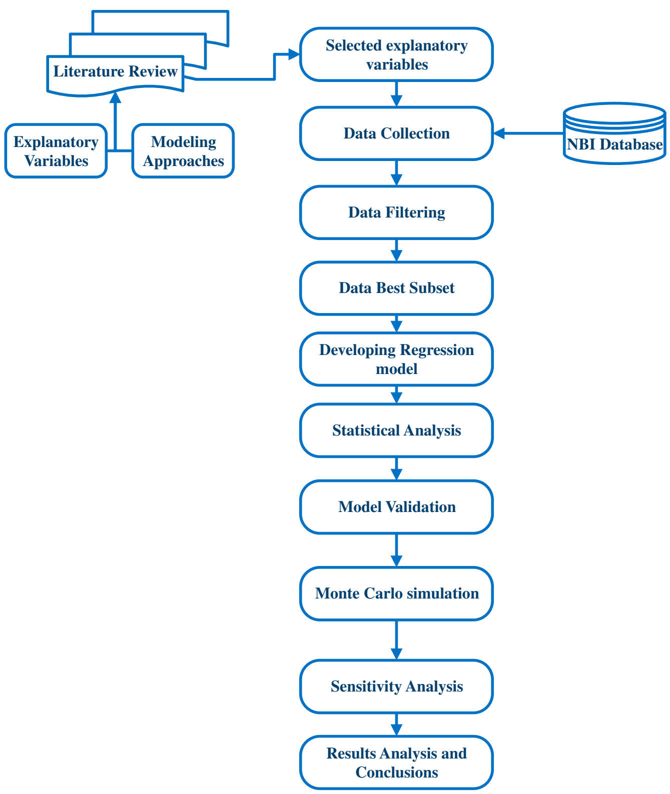


Fig. 1. Research methodology.

Data Collection and Filtering

According to the USDOT (2017), approximately 6,200 bridges from California's total bridge population are classified as prestressed. For this study, the population of prestressed bridges was filtered and refined to develop a subset of bridges having similar characteristics. This was achieved by removing any bridges having a condition rating for deck, superstructure, or substructure of N: Not Applicable, 1: Imminent Failure, or 0: Failed Condition per the coding guide (FHWA 1995) as shown in Table 1. Bridges where the condition rating was omitted were also removed.

Additionally, bridges having a functional classification as urban, those having a length greater than 38 m, and bridges spanning features other than the highway and/or railroad were removed. The resulting subset included four types of service under the bridge: highway, railway, highway-railway, and railroad-waterway, as represented in Fig. 2. An effort was also made to capture bridges having decks at the end of their useful life. The bridge age was limited to those structures having aged between 30 and 39 years and which have not been coded as having been reconstructed. The formation of the data subset in this manner attempts to remove age and major maintenance as explanatory variables, allowing the study to focus on other explanatory variables.

The refined and filtered data were analyzed using Minitab©18, a common software platform for statistical and regression analysis. The dependent variable is the deck condition rating, while the independent variables (predictors) included percentage average daily truck traffic, structure length, deck width, roadway width, skew degrees, max span length, and inspection frequency. The variable descriptions, according to FHWA (1995), are shown in Table 2, and descriptive statistics are summarized in Table 3.

Table 1. Deck condition rating descriptions

Rating	Description
9	*Excellent*: No noticeable or noteworthy deficiencies.
8	*Very Good*: Minor cracking with no spalling, scaling, or delamination.
7	*Good*: Cracking at a spacing of 3 m (10 ft) or more, with light shallow scaling.
6	*Satisfactory*: Minor deterioration including cracks at a spacing of 1.5 m (5 ft) or less, medium scaling, and the deck area spalled or delaminated 2% or less.
5	*Fair*: Minor section loss, between 2% and 10% of the surface area is spalled or delaminated and excessive cracking in the surface.
4	*Poor*: Advanced section loss, large areas of the surface is spalled or delaminated.
3	*Serious*: Deterioration has seriously affected primary structural components and local failures are possible.
2	*Critical*: Advanced deterioration of primary structural elements. Emergency surface repairs required by crews.
1	*Imminent/Failure*: Major deterioration present in critical structural components. The bridge is closed to traffic, but corrective action may put the bridge back in service.
0	*Failed*: Bridge closed and is beyond corrective action.

Source: Data from FHWA (1995).

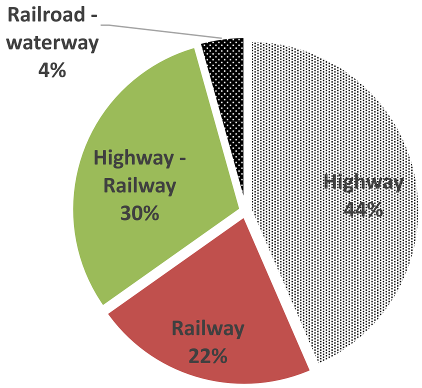


Fig. 2. Distribution of service type under the bridge in selected sample data.

Table 3. Summary statistics of the significant variables with deck condition

Variable	Mean	Standard deviation	Minimum	Maximum
Deck condition	6.792	1.103	5.000	8.000
Degree of skew	33.50	40.62	0.00	99.00
Max span length	26.554	2.440	21.000	30.500
Structure length	63.91	30.30	21.00	128.70
Roadway width	18.97	6.95	9.80	35.90
Deck width	22.11	8.11	10.80	39.60
Inspection frequency	37.00	12.22	24.00	48.00
Percent average daily truck traffic	3.708	2.053	0.000	7.000

Model Development

Regression Model

Eighty percent of the bridges in the filtered bridge subset were used to develop predictive models of deck condition using regression techniques, while the remaining bridges were used for model validation. The regression was initiated using the best subset analysis then proceeded with the model development as clarified in the following subsections.

Investigating the Significant Variables

For identifying the best possible combination of variables, the best subset analysis is used to configure which combination is achieving the highest coefficient of determination (R^2). Iterations that produced $R^2 < 70\%$ were omitted from further study. The results showed that these variables; service type on the bridge (highway or pedestrian), surface type (no additional concrete surface, monolithic concrete, or bituminous), and structure type (slab, stringer/multibeam, tee beam, or box beam or girders) were not significant for predicting the deck condition.

Model Building and Statistical Analysis

The regression equations for the developed models are listed in Table 4, where the model is classified according to the types of service under the bridge. The results of the regression analysis have shown a satisfying coefficient of determination (Average $R^2 = 80\%$). The coefficient of determination indicates that the predictors explain 80% of the variance in response variable deck condition. The P-value (statistical significance) for the developed model is 0.003 (P-value < 0.05). That test indicated that the developed model is significant at α-level of 0.05 and 0.01, and the null hypothesis is rejected, meaning that none of the regression coefficients are zero.

Residual Analysis

In order to examine the regression assumptions, and to verify goodness-of-fit in the regression model, the residuals and their patterns were analyzed. Fig. 3 displays the normal probability of residuals of the developed models. The normal probability plot displays the residuals versus their expected values to verify the assumption that the residuals are normally distributed. As shown, the residuals follow a straight line, and a few points lying away from the line imply a possibility of outliers.

Furthermore, to verify the assumption that the residuals are not independent with each other, the residuals versus order plot are displayed in Fig. 4. The plot showed that the residuals are distributed randomly around the centerline, except for unusual observations such as point 6 and point 23, which lie on the outer positive bands. This analysis is consistent with outliers' observation in Table 5 that presented the observations with large standardized residuals and some with a significant influence on the model characteristics.

Model Validation

Model validation is essential to verify the model accuracy to predict the deck condition; by comparing the predicted against the actual/observed conditions. The prediction of deck condition was determined for the 20% of the sample data subset that was purposefully omitted from the model development process. For these bridges, the predicted deck condition was compared to the reported NBI deck condition.

Table 2. List of variables used in this study with description

Variables in study	Code	Description
Deck condition (integer); *As Response Variable*	C	The existing, in-place bridge as compared to the as-built condition.
Inspection frequency (month)	IQ	The number of months between designated inspections of the structure.
Degree of skew (degrees)	DS	The angle between the centerline of a pier and a line normal to the roadway centerline.
Max span length (m)	ML	Length of maximum span.
Structure length (m)	SL	The length of the roadway that is supported on the bridge structure; from back to the back of the abutments.
Roadway width (m)	RW	It is the most restrictive minimum distance between curbs or rails on the structure roadway.
Deck width (m)	DW	Deck width, out-to-out.
Percent average daily truck traffic (%)	PT	Percent average daily truck traffic.
Service under the bridge (integer)	ST	Types of service under the bridge.

Table 4. Developed regression model for predicting deck condition for prestressed bridges

Number of model	Service under the bridge	Regression model for predicting deck condition
1	*Highway*	6.19 − 0.00133 DS + 0.0230 ML − 0.00638 SL + 0.0540 RW − 0.0884 DW + 0.0181 IQ + 0.2420 PT
2	*Railroad*	5.31 − 0.00133 DS + 0.0230 ML − 0.00638 SL + 0.0540 RW − 0.0884 DW + 0.0181 IQ + 0.2420 PT
3	*Highway-Railroad*	6.45 − 0.00133 DS + 0.0230 ML − 0.00638 SL + 0.0540 RW − 0.0884 DW + 0.0181 IQ + 0.2420 PT
4	*Railroad-waterway*	4.94 − 0.00133 DS + 0.0230 ML − 0.00638 SL + 0.0540 RW − 0.0884 DW + 0.0181 IQ + 0.2420 PT

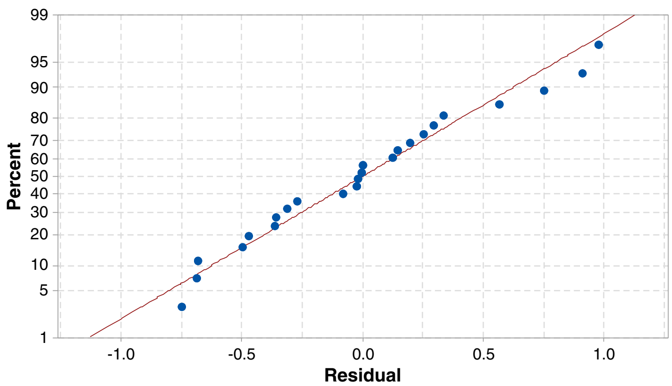


Fig. 3. Normal probability of residual plots for deck condition model.

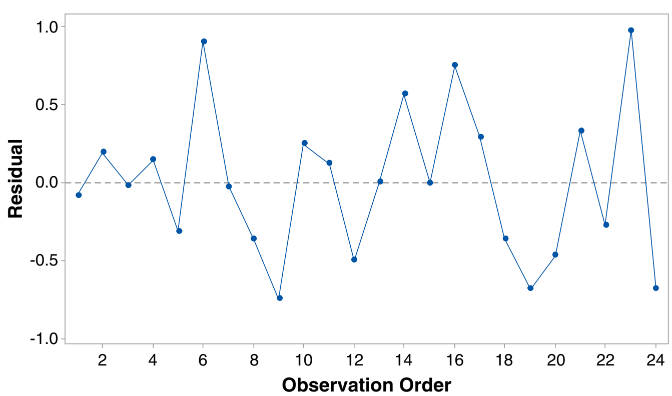


Fig. 4. Residual versus order of data plot for deck condition model.

Table 5. Regression output for unusual observations

Observation	Deck condition	Fit	Residual	Standardized residual	Large residual	Large leverage
6	7	6.093	0.907	2.01	R	
13	5	5.000	0.000	[a]		X
23	7	6.024	0.976	2.25	R	

Note: **R** denotes large standardized residual, **X** denotes a point with large leverage.
[a]Denotes a normal residual.

Three terms for measuring the validity have been utilized by Zayed and Halpin (2005), Al-Barqawi and Zayed (2006), and Fares et al. (2012): (1) The average invalidity and validity percent (AIP, AVP%) in Eqs. (1) and (2), which shows the validation as a percentage; (2) the root-mean-square error (RMSE) in Eq. (3); and (3) the mean absolute error (MAE) in Eq. (4). The resulted value for each of them measures the prediction error; when the value is

Table 6. Validation summary results

Observation	Actual deck condition	Predicted deck condition	AIP	RMS	MAE
1	8	5.63	0.296	5.607	2.368
2	7	5.98	0.144	1.024	1.012
3	7	7.53	0.076	0.286	0.535
4	5	5.48	0.096	0.233	0.483
5	7	6.85	0.020	0.021	0.145
6	6	5.14	0.142	0.731	0.855
			12.95%=AIP	*0.468*	*0.899*
			87.05%=AVP		

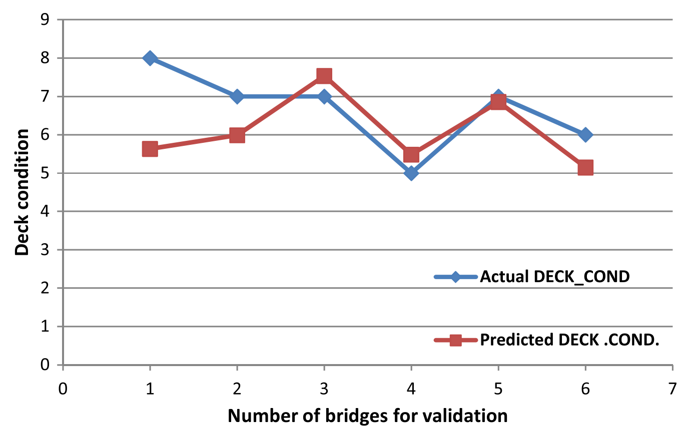


Fig. 5. Actual and predicted deck condition for developed models.

closer to 0.0, the model is intact, while a value closer to 1 shows that the model is not appropriate

$$\mathrm{AIP} = \frac{\sum_{i=1}^{n} |1 - (E_i/C_i|}{n} \tag{1}$$

$$\mathrm{AVP} = 1 - AIP \tag{2}$$

$$\mathrm{RMS} = \frac{\sqrt{\sum_{i=1}^{n} (\mathrm{C}_i - \mathrm{E}_i)^2}}{n} \tag{3}$$

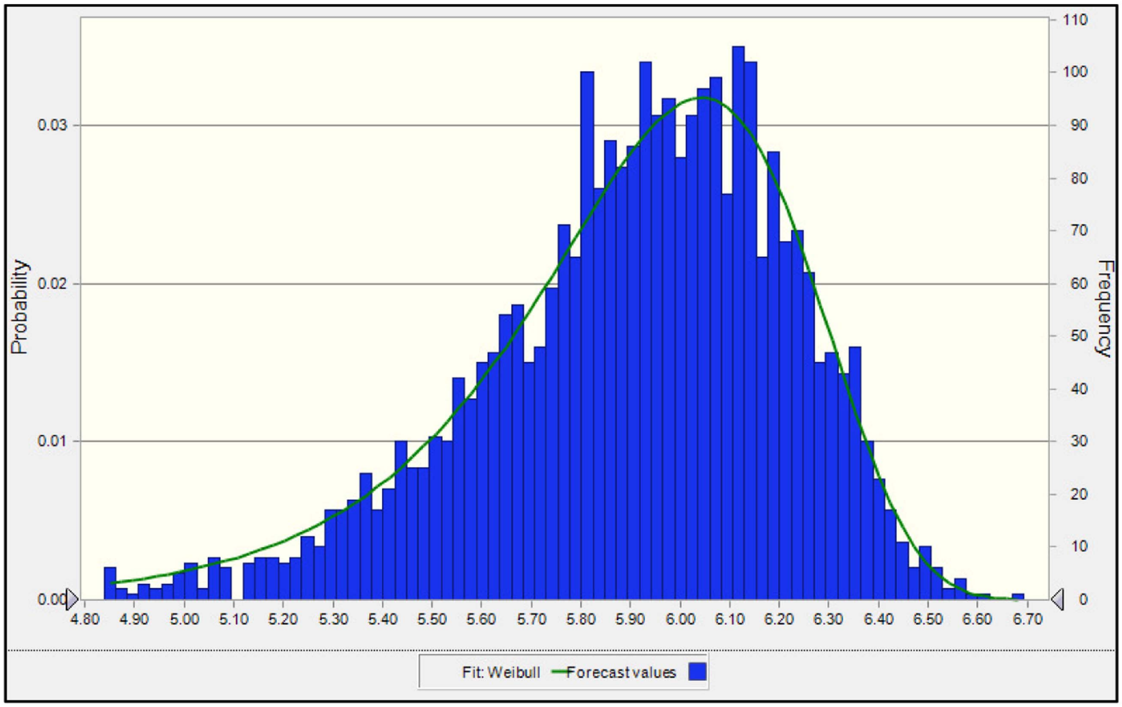
$$\mathrm{MAE} = \frac{\sum_{i=1}^{n} |\mathrm{C}_i - \mathrm{E}_i|}{n} \tag{4}$$

where E_i = predicted value for case i; C_i = actual value; and N = number of bridges for validation.

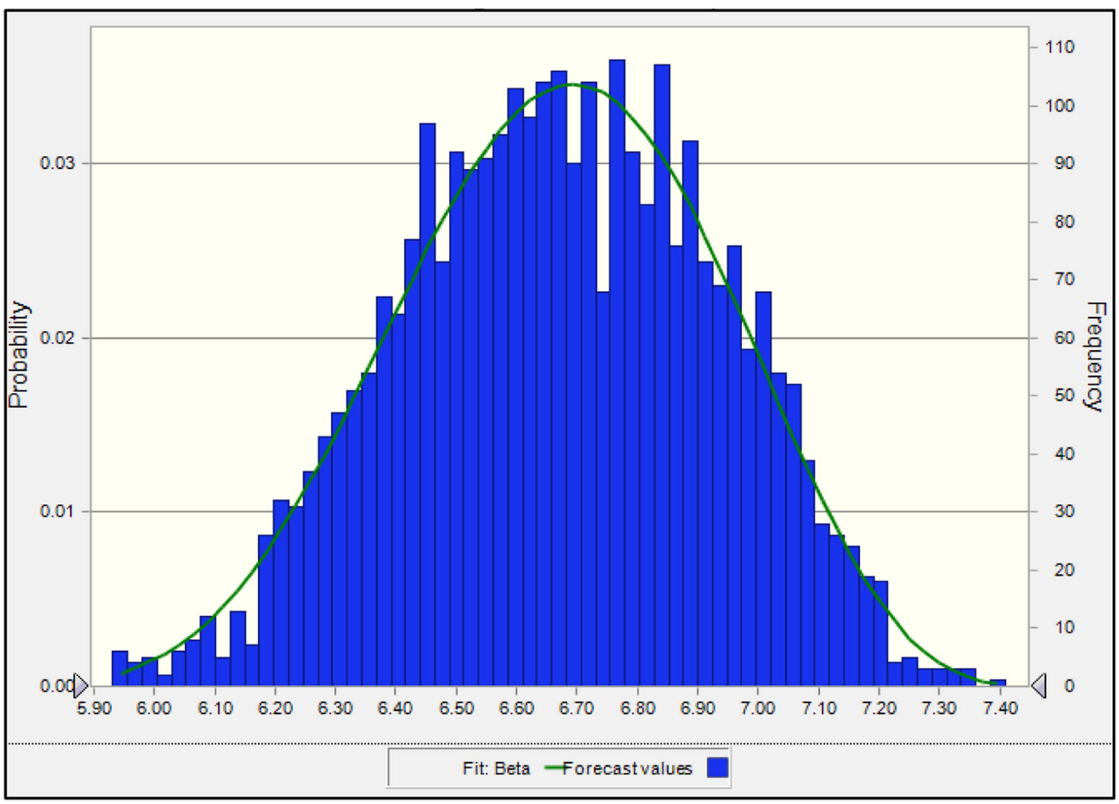
Table 6 summarizes the estimated values for validation terms, which applied for six bridges excluded from the modeling data, where it shows that the $\mathrm{AVP} = 87\%$, $\mathrm{RMS} = 0.46 < 1$, and $\mathrm{MAE} = 0.89 < 1$; as satisfying values to prove that the proposed models can forecast the deck condition. The predicted and actual deck conditions are represented in a scatter diagram in Fig. 5, where most of the actual and predicted points are so close, except the first point.

Stochastic Analysis Using Monte Carlo Simulation

Further analysis has been conducted by using the stochastic approach using Monte Carlo simulation. The forecasting formula has

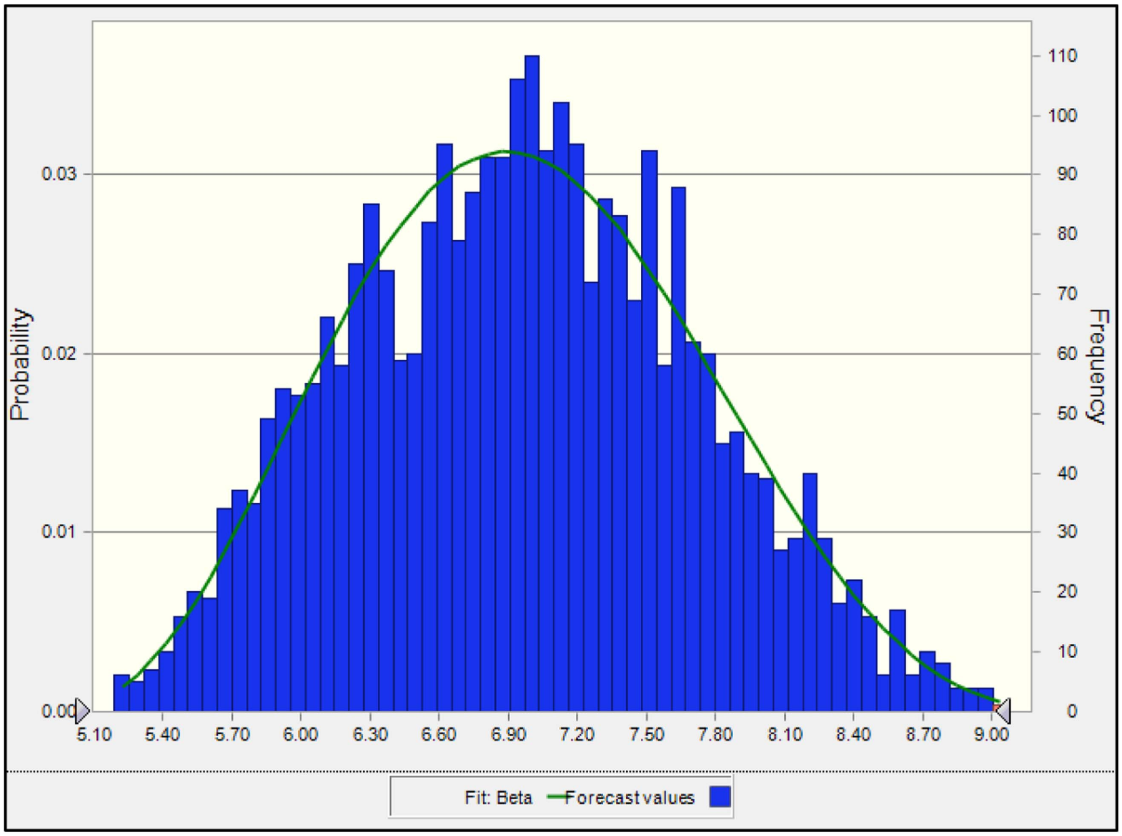


(a)



(b)

Fig. 6. Monte Carlo simulation result for predicted bridge deck condition for three types of service under the bridge: (a) simulation result for predicted bridge deck condition—Model 1; (b) simulation result for predicted bridge deck condition—Model 2; and (c) simulation result for predicted bridge deck condition—Model 3.



(c)

Fig. 6. (*Continued.*)

used the derived regression models to predict the probability of the deck condition. This approach is based on the fitted probability of each range of the explanatory variables. Monte Carlo simulation calculates the model thousands of times, using different randomly selected values of the explanatory variables that consequently show a range of probability for predicted values. This simulation represents the predicted condition as graphical forecasting to simulate the real process. The forecasted charts could be used to estimate the probability or certainty of the outcome.

The simulation has been performed separately for three of the developed regression models: Models 1, 2, and 3. Each of these models represents more than 20% of modeling data, as shown in Fig. 2, where the models were classified according to the types of service under the bridge.

The following steps have been traced using Crystal Ball software as a simulation program:

1. Preparing the input variables as a separate Excel sheet for each model;
2. Fitting data to a distribution: define the fit distribution for each continuous variable, based on range values for each variable using chi-square as the goodness-of-fit statistic for each variable;
3. Define forecast (prediction formula): assigning the mathematical regression formula for evaluating the deck condition as forecast cell; separately for each model;
4. Run simulation: when the simulation is started, Crystal Ball replaces the values in the "Assumption" cells with a random number drawn from the specified distribution for each variable. This process is repeated a predefined number of times/iterations. Each iteration stores the values in the forecast cells. Thereby, the forecast values can be presented in histograms (Andersen and Brandstrup 2008). Increasing the number of iterations will narrow the range to an acceptable level (Kirkpatrick 2001). Herein, 3,000 iterations with confidence level 95% were run to evaluate the probability of predicted deck condition in terms of the probability of independent variables; and
5. Extracting the results of the simulation. These results were presented in Fig. 6 for each model.

Fig. 6 shows the probability of predicted deck condition; it is 100% for condition ranges from 0 to 9. The probability distribution for Model 1 is 97.71% for conditions between fair and good (from 5 to 7), where the highway is the type of service under the bridge. The highest probability of 99.17% was in conditions that range from satisfactory to very good (from 6 to 8) for Model 2. Model 3 has about 91.06% as the highest probability for a range between fair to very good (from 5 to 8).

It is noticed that the highest probability is associated with good conditions for the developed models; this result gives a complete view of the condition rating for data of bridges. The developed models and research methodology can predict the bridge deck condition for the individual bridge as well as the probability of predicted conditions for bridges.

Sensitivity Analysis

Sensitivity analysis shows the relationship between the predictors and the response value. It is used to determine how the independent variable will change the dependent variable, while the other variables are constant. As well as, it identifies the strength of each variable to define their relative importance and correlation direction clearly.

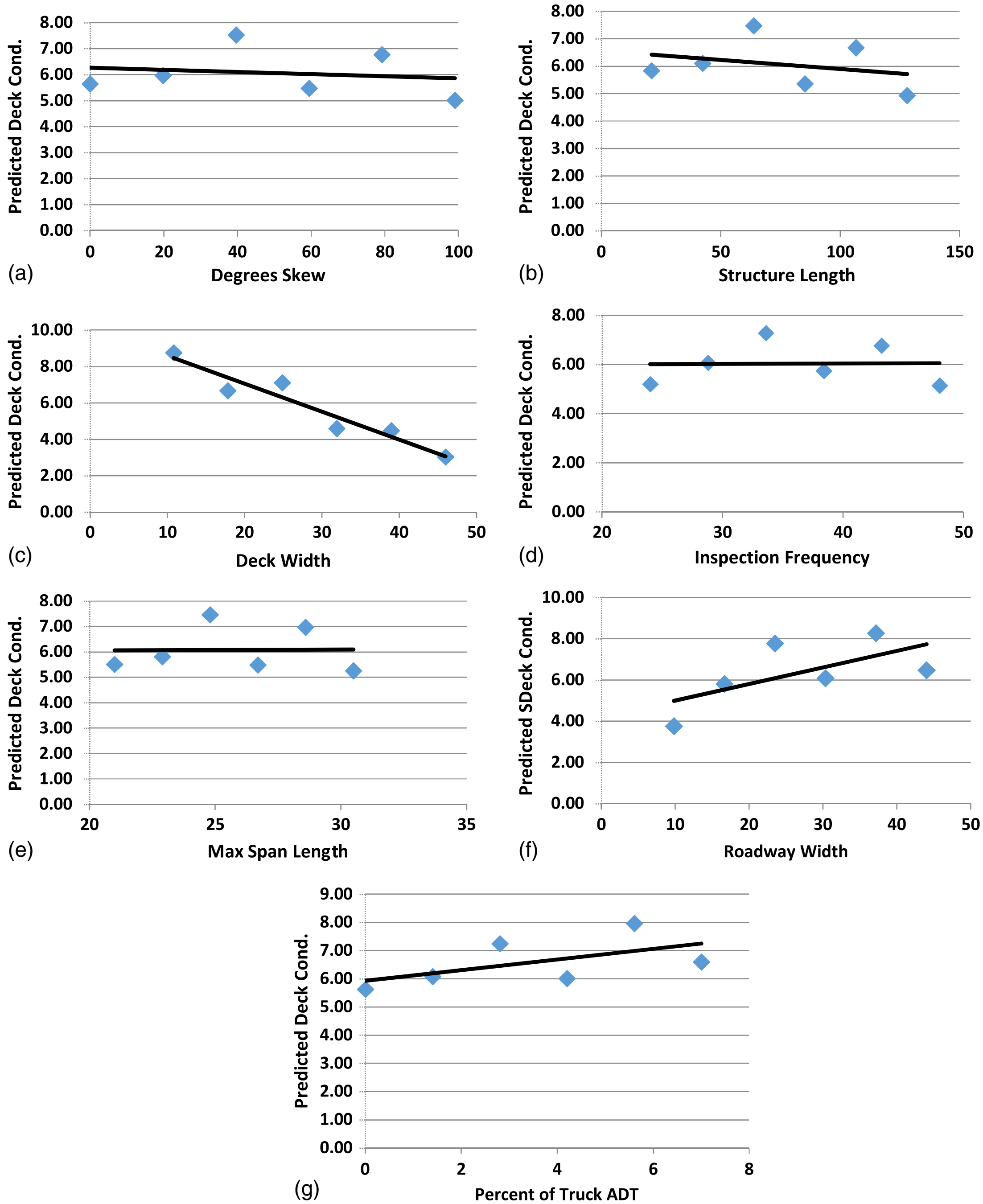


Fig. 7. Sensitivity analysis for variables affecting predicted bridge deck condition: (a) sensitivity analysis for degree skew; (b) sensitivity analysis for structure length; (c) sensitivity analysis for deck width; (d) sensitivity analysis for inspection frequency; (e) sensitivity analysis for max span length; (f) sensitivity analysis for roadway width; and (g) sensitivity analysis for percent average daily truck traffic.

Relative sensitivity for each variable on the deck condition have been calculated and represented in Figs. 7 and 8, which can be analyzed as follows.

It was found that there are variables that were correlated negatively with the deck condition, while other variables were affecting positively. The negative correlation has appeared with three variables—degree skew, structure length, and deck width, as shown in Figs. 7(a–c)—where their increasing has been associated with deck deterioration. That is a logical conclusion, and the statistics agree with the logic behavior. While increasing of the other four variables—max span length, road width, percent of average daily truck traffic, and frequency of inspection, as represented in Figs. 7(d–g)—has been associated with high deck conditions.

The variable of deck width has shown a moderate impact and negative direct correlation with deck condition for all developed models. As displayed in Figs. 7(c) and 8, there is a straight decline for deck width, which can be attributed to the load increasing as a result of deck width increasing, which leads to low bridge conditions by the time; while the other two variables—degree skew and structure length—have no noticeable importance on changing the variables of deck condition. Using different approaches for sensitivity analysis (Excel and Monte Carlo simulation) has come out with

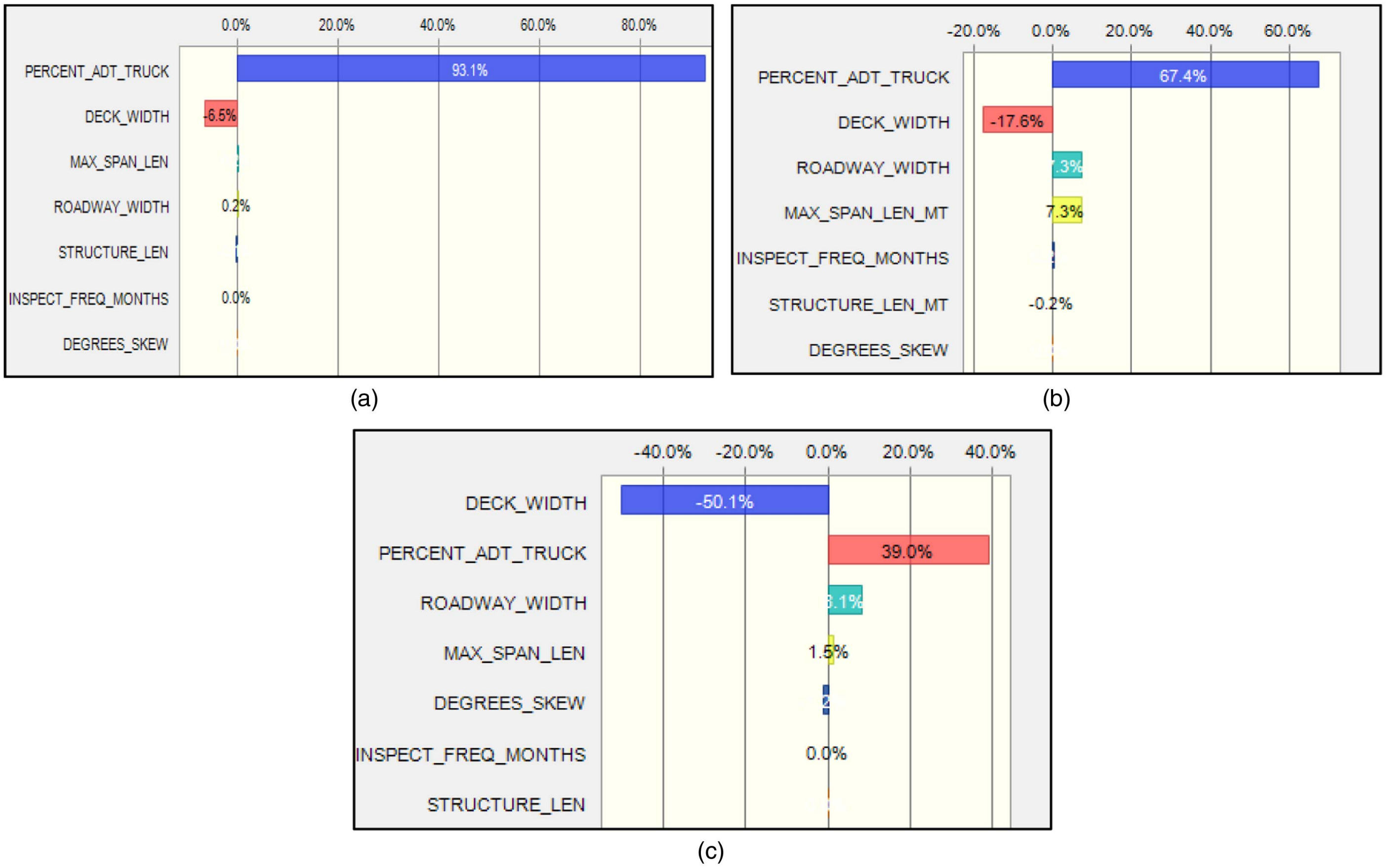


Fig. 8. Sensitivity analysis using Monte Carlo simulation: (a) contribution to variance view for predicted bridge deck condition for Model 1; (b) contribution to variance view for predicted bridge deck condition for Model 2; and (c) contribution to variance view for predicted bridge deck condition for Model 3.

the same trend and relative importance, as shown in Figs. 7(a and b) and 8. The resulted trend is agreed with the findings of Busa (1985), Madanat et al. (1995), Saeed et al. (2017), and Nabizadeh et al. (2018), where they found a negative effect of the degree skew, structure length, and the deck width on the concrete bridge deck.

Figs. 7(f and g) and 8 have represented the sensitivity for roadway width and percent average daily truck traffic, respectively. These variables affected similarly to changing the values of deck condition with positive correlation but with different relative importance, where percent average daily truck traffic represented the highest contribution on deck condition followed by the variable of roadway width for Models 1 and 2, but this contribution ranking was switched for Model 3, as shown in Fig. 8(c). However, that positive correlation has contradicted the result of Saeed et al. (2017), but this trend could be affected by the maintenance action with a high percentage of trucks (current raw data is not available to assure that).

Fig. 7(d) shows the sensitivity analysis for the inspection frequency with a positive correlation with deck condition, but with no noticeable impact (less than 1%). It can be justified, as the good condition did not need a close or small frequency of inspection or maintenance. This means that a high frequency of inspection is positively associated with high deck conditions. The variable of max played a similar contribution and positive trend—span length, as shown in Fig. 7(e). However, a positive correlation has contradicted with the result of Moomen et al. (2016) and Nabizadeh et al. (2018), where they revealed that the max span length is negatively correlated with the bridge condition.

Generally, the sensitivity analysis has presented a satisfying significant impact for each variable on changing the value of predicted deck conditions.

Results

Based on the developed models, the following findings have been revealed for all four models:

- Filtering processes for NBI data before regression is necessary for a reasonable model;
- The initial best subset processes have removed some candidate variables, where they did not show significant influence, such as service on the bridge, structure type, and surface type. Therefore, further research with a different classification of collected data is recommended to examine these variables with the deck condition;
- Using Monte Carlo simulation as a method of stochastic analysis has allowed measuring the direction and strength of the influence of each factor, as well as coming out with a more realistic probability distribution for predicted deck condition;
- Degree skew, structure length, and deck width are affecting negatively on deck condition of prestressed bridges. Thus, considerable maintenance actions should be planned for high related values of these variables;
- High values of max span length, percent of average daily truck traffic, road width, and frequency of inspection are associated with high deck conditions. The positive association for the first

two variables has contradicted with previous studies, which need further research without classified samples;

- The highest relative importance for both percents of average daily truck traffic and deck width refers to the priority for considerable maintenance actions for high related values;
- The developed regression models shown in Table 4 have indicated the same impact of the seven explanatory variables on the deck condition for all four services under the bridge. Therefore, to generalize this result, it is recommended to apply this methodology for collecting data with unlimited types of service under the bridge for prestressed bridges; and
- The data may be affected by maintenance actions, which were not available in the collected data. Therefore, for improving the developed model, it is recommended to link maintenance actions to inspection data to provide a reliable estimate for the deck condition.

Conclusions and Recommendations

This paper has developed deck deterioration models based on regression and stochastic analysis for the NBI database for California. The developed models are predicting the deck condition of prestressed concrete bridges in the function of eight significant variables. The significance of the model has been analyzed and showed a high coefficient of determination ($R^2 = 80\%$), and a significant P-value (P-value $= 0.003$). The model was validated with satisfying results (87%) using the average validity percentage method. It is concluded that degree skew, structure length, and deck width are affecting negatively on deck condition, which is reasonable and agreed with previous studies. Others correlated positively with deck condition such as max span length, percent of average daily truck traffic, road width, and frequency of inspection. The positive impact for the max span length and percent of average daily truck traffic are contradicted with previous studies and need further analysis in linking with maintenance records. The developed models are limited to four service types under the bridge: (highway, railway, highway-railway, and Railroad-waterway). Highway and highway-railway service under the bridge represented the majority of the sample. The predicted deck condition helps highway authorities to prioritize the maintenance and manage the funds' allocation for bridge maintenance or reconstruction. For future research work, the model could be improved if some variables that were not available for current raw data are studied, such as bridge maintenance records and climate variables.

Data Availability Statement

Some or all data, models, or code used during the study were provided by a third party (FHWA bridge inspection data). Direct requests for these materials may be made to the provider, as indicated in the Acknowledgments.

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