Transportation Consortium of South-Central States

Tran-SET

Solving Emerging Transportation Resiliency, Sustainability, and Economic Challenges through the Use of Innovative Materials and Construction Methods: From Research to Implementation

Bridge Load Posting Prediction

Project No. 20STLSU01

Lead University: Louisiana State University

Final Report

December 2021

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16. Abstract

There are approximately 13,000 bridges in Louisiana facilitating movement of people, goods, and services. At present, about 12% of the bridges are load posted, i.e., they are deemed to lack the strength to safely carry all legal loads. With time bridges will age and deteriorate; at the same time, legal loads might increase. Load posted bridges disrupt the movement of goods and commerce. Therefore, objective of this research was to estimate the number of load posted bridges in Louisiana over the next 50 years. For this purpose, herein, a data based approach was used. For a given bridge type, the approach first developed three random forest models, to predict the future deck, sub-structure, and super-structure condition ratings of all the bridges of that type over the next 50 years. The inputs to these random forest models included a large number of bridge parameters obtained from the National Bridge Inventory (NBI). Herein, the bridge types were obtained from the Louisiana Department of Transportation and Development (LADOTD). Next, for a given bridge type, another random forest model was developed which used bridge parameters from NBI along with condition ratings to predict the load posting decision for a specific year in the future. The number of load posted bridge in each type were aggregated to obtain an estimate of the number of load posted bridge over the next 50 years. The random forest models identified several bridge parameters that significantly influence bridge load posting, e.g., condition ratings, age, span length, and roadway width among others. The results showed that while bridge types like light weight concrete pre-cast slab units and timber bridge had a large number of load posted bridges at present, concrete slab type bridge may be of concern in the future.

17. Key Words
Bridge load posting; random forest; future prediction; Louisiana

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SI* (MODERN METRIC) CONVERSION FACTORS

APPROXIMATE CONVERSIONS TO SI UNITS

Symbol	When You Know	Multiply By	To Find	Symbol
		LENGTH		
in	inches	25.4	millimeters	mm
ft	feet	0.305	meters	m
yd	yards	0.914	meters	m
mi	miles	1.61	kilometers	km
		AREA		
in^2	square inches	645.2	square millimeters	mm^2
ft^2	square feet	0.093	square meters	m^2
yd^2	square yard	0.836	square meters	m^2
ac	acres	0.405	hectares	ha
mi^2	square miles	2.59	square kilometers	km^2
		VOLUME		
fl oz	fluid ounces	29.57	milliliters	mL
gal	gallons	3.785	liters	L
ft^3	cubic feet	0.028	cubic meters	m^3
yd^3	cubic yards	0.765	cubic meters	m^3
		NOTE: volumes greater than 1000 L shall be shown in m^3		
		MASS		
oz	ounces	28.35	grams	g
lb	pounds	0.454	kilograms	kg
T	short tons (2000 lb)	0.907	megagrams (or "metric ton")	Mg (or "t")
		TEMPERATURE (exact degrees)		
^oF	Fahrenheit	5 (F-32)/9 or (F-32)/1.8	Celsius	^oC
		ILLUMINATION		
fc	foot-candles	10.76	lux	lx
fl	foot-Lamberts	3.426	candela/m^2	cd/m^2
		FORCE and PRESSURE or STRESS		
lbf	poundforce	4.45	newtons	N
lbf/in^2	poundforce per square inch	6.89	kilopascals	kPa

APPROXIMATE CONVERSIONS FROM SI UNITS

Symbol	When You Know	Multiply By	To Find	Symbol
		LENGTH		
mm	millimeters	0.039	inches	in
m	meters	3.28	feet	ft
m	meters	1.09	yards	yd
km	kilometers	0.621	miles	mi
		AREA		
mm^2	square millimeters	0.0016	square inches	in^2
m^2	square meters	10.764	square feet	ft^2
m^2	square meters	1.195	square yards	yd^2
ha	hectares	2.47	acres	ac
km^2	square kilometers	0.386	square miles	mi^2
		VOLUME		
mL	milliliters	0.034	fluid ounces	fl oz
L	liters	0.264	gallons	gal
m^3	cubic meters	35.314	cubic feet	ft^3
m^3	cubic meters	1.307	cubic yards	yd^3
		MASS		
g	grams	0.035	ounces	oz
kg	kilograms	2.202	pounds	lb
Mg (or "t")	megagrams (or "metric ton")	1.103	short tons (2000 lb)	T
		TEMPERATURE (exact degrees)		
^oC	Celsius	1.8C+32	Fahrenheit	^oF
		ILLUMINATION		
lx	lux	0.0929	foot-candles	fc
cd/m^2	candela/m^2	0.2919	foot-Lamberts	fl
		FORCE and PRESSURE or STRESS		
N	newtons	0.225	poundforce	lbf
kPa	kilopascals	0.145	poundforce per square inch	lbf/in^2

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ACRONYMS, ABBREVIATIONS, AND SYMBOLS

AASHTO	American Association of State Highway and Transportation Officials
ANN	Artificial Neural Network
ADT	Average daily traffic
NBI	National Bridge Inventory
LADOTD	Louisiana Department of Transportation and Development
COSLAB	Concrete slab bridge
COPCSS	Concrete precast slab unit bridges
LWPCSS	Light weight precast slab unit bridges
CODEKG	Concrete deck girder bridges
CONIBM	Steel I-beam bridges
RF	Rating Factor

EXECUTIVE SUMMARY

Approximately 13,000 bridges in Louisiana are facilitating movement of people, goods, and services. At present, about 12% of these bridges are load posted, i.e., they are deemed to lack the strength to safely carry all legal loads. With time bridges will age and deteriorate; at the same time, legal loads might increase. Load posted bridges disrupt the movement of goods and commerce. Therefore, objective of this research was to estimate the number of load posted bridges in Louisiana over the next 50 years. The outcomes of this research can help stakeholders identify types of bridges that may need more repair and rehabilitation in the future to prevent them from being load posted. Thereby, the results can help stakeholders to identify potential maintenance and rehabilitation actions and allocate resources based on anticipated future condition of bridges.

Determining load posted bridges over the next 50 years using the guidelines provided by the American Association of State Highway and Transportation Officials (AASHTO) may not be feasible due to lack of knowledge on future element conditions, which is essential for load posting. Considering the large number of bridges, a data based approach was used to estimate the number of load posted bridges in Louisiana over the next 50 years. The proposed approach consisted of two steps: 1) determining the condition ratings of the sub-structure, super-structure, and the deck for each bridge over the next 50 years and 2) determining the load posting decision based on the future condition rating based on condition ratings and bridge characteristics.

In the first step, for a given bridge type, three random forest models were developed to predict the three condition ratings described above for each bridge belonging to that type. The inputs for these random forest model included a large number of bridge parameters obtained from the National Bridge Inventory (NBI) and the condition ratings for the previous year. For the first year's future prediction, condition ratings from the NBI database were used. For subsequent years, predictions from the random forest models for the previous year were used to obtain the condition rating for the next year. Herein, the bridge types were obtained from the Louisiana Department of Transportation and Development (LADOTD). Specifically, concrete slab, concrete pre-cast slab, concrete light weight slab, concrete deck girder, and steel I beam bridges were considered.

In step two, another random forest model was developed, which used bridge parameters from NBI along with condition ratings to predict each bridge's load posting decision for a specific year in the future. Such models were developed for each bridge type considered herein. Using these models, the load posting prediction was performed for all the bridges of the selected type. The number of load posted bridge in each type were aggregated to obtain an estimate of the number of load posted bridge over the next 50 years. Specifically, on-system bridges were considered herein.

The random forest model from step two were used to obtain insights on key parameters that affect load of bridges. For each bridge type, most influential parameters were identified. While the relative order of parameters differed among bridge types, but these parameters included condition ratings, age, and other geometric parameters like span length, and roadway width. Analysis of existing load posting data shed that bridge types like light weight concrete pre-cast slab units and timber bridge had a large number of load posted bridges. However, the results show that over the next 50 years, a large fraction of the concrete slab type bridges may be load posted.

1. INTRODUCTION

The safety of the public using the transportation system highly depends on the safety and the load carrying capacity of bridges. Furthermore, the load carrying capacity of bridges is also important for movement of goods and facilitating commerce. Therefore, the condition of bridges has been one of the primacy concerns for stakeholders at the state and the federal level such as the state departments of transportation and the federal highway administration. In this regard, to ensure safety of bridges, the Federal Aid Highway Act of 1970 established minimum data collection requirements and qualifications for bridge inspectors. These requirements were extended to all public bridges in the Surface Transportation Assistance Act of 1978. Additional requirements for inspection of bridge components that are under water and fracture critical were introduced in the Surface Transportation and Uniform Relocation Assistance Act of 1987. The data collected form inspections of all the public bridges in the United States has been recorded in the National Bridge Inventory (NBI) database since 1983. Currently, the NBI database is one of the most comprehensive datasets with information bridge condition for the past three decades.

The condition ratings for sub-systems and the element level inspection data are used by stakeholders, such as departments of transportation, to identify deficiencies in bridges to make decisions pertaining to load posting and rehabilitation of bridges. Identification of deficient bridges, load rating them, and load posting (if required) is essential to maintain the safety of bridges and the public using the roadway infrastructure. In this regard, the American Association of State Highway and Transportation Officials (AASHTO) has released the Manual for Bridge Evaluation (MBE) as guidelines for load rating and posting bridges using Load and Resistance Factor Rating (LRFR) and Allowable Stress Rating (ASR) approaches (*1*). The Louisiana Department of Transportation and Development (LADOTD) uses the LRFR methodology for rating most of the bridges, except timber bridges (*2*). The equations for the Rating Factor (RF) for individual structural elements pertaining to LRFR and the ASR are shown in Equations 1 and 2, respectively.

$$RF = \frac{C - \gamma_{DC}DC - \gamma_{DW}DW}{\gamma_{LL}(LL + IM)} \tag{1}$$

$$RF = \frac{C - A_1 D}{A_2 L(1 + I)} \tag{2}$$

In equation 1, $C = \phi_s \phi_c \phi R_n$ for strength limit states used for posting decisions, where R_n is the member nominal resistance, ϕ_s is the system factor, ϕ_c is the condition factor, and ϕ is the resistance factor. $DC, DW,$ and LL are dead loads on a member due to structural elements and components, dead loads due to wearing surface, and live loads respectively and γ_{DC}, γ_{DW}, and γ_{LL} are the respective load factors. IM is the dynamic load allowance factor. In Equation 2, C, D, and L are member capacity, dead loads, and live loads; I is an impact factor for live loads. A_1 and A_2 are factors for dead and live loads respectively.

Using any of the two equations above, a bridge is considered to be safe if $RF \geq 1$ at the inventory level and load posting is not required. However, if $RF \leq 1$ at the inventory level, rating factor is evaluated for all state legal loads and the bridge is posted for loads if $RF \leq 1$ for any of the legal loads. The AASTHO MBE suggests the posted load (W_{posted}) be evaluated as $W_{posted} = W(RF - 0.3)/0.7$ where is the weight of the rating vehicle and RF is its rating factor. The above-mentioned process is performed for elements of the super structure, such as interior and exterior girder, deck, and sub-structure (foundations and pier). The rating factor of the most critical member, i.e. with lowest RF, is used for posting decisions and the posting loads.

The details on bridge parameters required to obtain rating factor for different sub-components include bridge layout, material properties, section properties for structural elements, gusset plate connection details for steel bridges, and information of current condition of structural elements based on latest bridge inspection. With all this information, load rating becomes an exercise in structural analysis.

Considering deterioration of bridges and potential increase in truck loads, it is essential to understand the future condition and load rating/load posting of bridges. If resources are not adequately allocated to address the deteriorating conditions, the number of load posted bridges may increase in the future – affecting commerce, the economy, and the movement of people. Therefore, an estimate of the number of load posted bridges in the future is essential for resource allocation towards rehabilitation of bridges.

2. OBJECTIVES

In light of the need for an estimate of the number of load posted bridges in the future, the overarching research objective was to quantify the number of load posted bridges in Louisiana for the next 50 years. To achieve this objective, the following goals were identified:

1. Determine the key substructure and super structure, traffic, and climactic features (henceforth called as key bridge parameters) that influence load posting.
2. Estimate the future values of the key bridge parameters using probabilistic approaches that can incorporate the effects of maintenance and rehabilitation.
3. Quantify the likelihood of load posting for bridges given their key parameters and estimate the number of posted bridges in the entire inventory.
4. Predict the number of load posted bridges for the next 50 years by combining the results from objectives one through three.

3. LITERATURE REVIEW

Early research on predicting the future condition of bridges focused on understanding the deterioration rates for bridge components using empirical and actual data from bridges. In this regard, Cady and Weyers (*3*) obtained data from 169 bridges with concrete deck exposed to de-icing salts and determined their deterioration rates. Veshosky et al. (*4*) observed that bridge superstructure deterioration takes a convex form over time with slowing rates as the age increases. They found that age was the primary indicator of the super-structure deterioration rate, followed by average daily traffic. Additionally, they also observed that superstructure material does not alter the deterioration rates significantly. These early studies enabled development of a large number of Markov chain (*5*) based models (*6–9*) that enable estimation of the future condition rating of bridges' structural elements. Markov chains belong to a class of stochastic models based on the principle of random walks (*10*) where the state of a system in the time interval on depends on the current state. The time evolution of system's state is defined using a transition probability matrix that describes the probability of transitioning from one state to another.

Cesare et al. (*11*) collected data from 850 bridges in New York and developed Markov chain models to determine the time evolution of deck, piers, and superstructure condition ratings for a set of bridges. They also proposed an approach to incorporate the effects of repair actions on the transition probability matrices. Jiang et al. (*7*) considered bridges in Indiana and selected 170 concrete and 106 steel sample bridges to develop Markov chain models for bridge management. The demonstrated the use of Markov chain models for estimating the percentage of bridges with various deck condition ratings. Even outside the United States, Markov chain models have been proposed for bridge asset management. E.g., Hong et al. (*8*) used Markov deterioration models to inform optimization of repair and rehabilitation measures for bridges in South Korea. More recently, Fernando et al. (*6*) modeled deterioration of bridge element for a steel bridge using Markov chains and combined the condition rating of the bridge components with the structure performance states to determine direct and indirect costs associated with the bridge over time. Markov chain models were also applied to railway bridges (*9*) where Le and Andrews developed Markov models for railway bridges in the United Kingdom. The estimated the degradation process from the maintenance records and developed the transition probability matrix. The also incorporated the effects of various rehabilitation strategies to understand the life-cycle costs for railway bridges.

While the above discussion on Markov chain-based models is not exhaustive, it highlights their ubiquitous use in various countries, bridge types, and types of analysis such as life cycle costs and maintenance optimization. Consequently, these Markov Chain based models have been implemented in widely used for transportation asset management such as Pontis/AASHTOWare (*12*, *13*) and Bridgit (*14*). However, Markov chain-based models have drawbacks such as: (a) need for high quality deterioration data to develop transition probability matrices, which may not be readily available and (b) need for assumptions on deterioration rates and residence times.

Some of the above-mentioned drawbacks have been addressed by methods that use Petri nets, which are also known as PT nets. Petri nets use a graph theory-based representation for stochastic processes in a discrete space. They include places and transitions, which are connected by arcs and the transition between places is defined by rules. With regards to deterioration modeling, places and transitions can be considered as component condition states. Le and Andrews (*15*) used Petri nets to model the condition states of bridges with non-constant deterioration rates while incorporating the effects of maintenance, correlated component performance, and bridge inspection. Yianni et al. (*16*) applied Petri nets to model the deterioration of railway bridges in the United Kingdom based on historical data. They used the model to identify traffic loading, train speed, and galvanic response among the key factors that have the most effect on deterioration. Ferreira (*17*). While Petri nets were used for modeling bridge deterioration and identifying maintenance measures, the feasibility of using them for understanding load posting decisions has not been explored yet.

Studies have also used the data from the National Bridge Inventory (NBI) (*18*) to assess the current condition of bridge components to facilitate better management of bridges. For example, may studies have developed models to predict the condition ratings of bride components such as deck, superstructure, and sub-structure. Chase et al. (*19*) developed new models for bridge deterioration using the NBI data base and coupling it with data mining techniques, geo graphical information systems, and statistical methods. The resulting models predicted condition ratings as a function of age, average daily traffic, precipitation, temperature range, frequency of salting, freeze thaw cycles and construction material. Al-Wazeer et al. (*20*) developed a neural network based approach to convert element level condition data to predict the condition ratings of bridge components. They compared their predictions against NBI translator which also estimates the condition ratings based on element condition data. They reported that the neural network-based approach has higher accuracy. Bektas et al. (*21*) developed decision trees to predict the condition ratings of bridge components using data from NBI and augmenting it with Pontis bridge inspection data. The models developed by Bektas et al. were observed to have higher prediction accuracy compared to then existing methods with R^2 values varying between 0.45 to 0.84.

Furthermore, since the NBI database consists of condition ratings of bridge subsystems over time, researchers have also developed models to predict the future condition of the sub-systems using data based simple regression models. Bolukbasi (*22*) developed cubic polynomial regression models which only considered the age of bridges to predict the bridge components' condition ratings. Lu et al. (*23*) developed a regression model as a function of age, average daily traffic, and truck traffic. They concluded that for predictive purposes, they suggest filtering data to remove bridges for which reconstruction works were not recorded. Son et al. (*24*) also used polynomial models to back predicted sub-system condition ratings so that missing data on past condition ratings can be filled (*24*). They observed that as more historical data became available, the prediction accuracy increased. Such studies improve the data quality for Markov chain based approached to predict the future condition of bridges' structural elements.

More recently, machine learning models have been applied to a wide range of problems in structural engineering including performance and deterioration modeling of bridges. In this regard different types of models have been used such as support vector machines (*25*), random forests (*26*), logistic regression (*27*), neural networks and its variations (*28*). These models have been used for various purposes such as hazard characterization (*29*), damage assessment (*30*, *31*), deterioration modeling

Pan et al. (*32*) proposed a multiple fuzzy linear regression model to predict the condition of bridge decks using subjective data obtained from inspection reports. Their model specifically addressed the uncertainty emanating from human judgement. Large number of studies have used Artificial Neural Networks (ANNs) to model bridge deterioration. For example, Tokdemir et al. (*34*) used neural networks and genetic algorithms to predict the sufficiency ratings of bridge in California.

They optimized network architecture using genetic algorithm and found that the optimized neural network had significantly improved performance compared to the non-optimized neural networks. They used age, traffic, structural and geometric attributes as inputs to their machine learning models. Based on their models, they observed that district and approach characteristics were among the most influential parameters. Kawamura et al. (*35*) also used neural networks to determine the condition state of cracking for concrete decks to determine their load carrying capacity. First, they developed a rule-based approach to determine the cracking condition state for each bridge. This data along with information on traffic details, geometry, drainage, and visual inspection data was used to predict the cracking condition rating. The found neural networks to be suitable for performance evaluation of existing structures, given sufficient data is available.

To address the limitations in Markov chain based approaches to model deterioration, Huang (*33*) obtained data on bridges in Wisconsin and developed neural network models with different network architecture. Huang subjectively classified the condition of bridge decks and predicted it using ANNs, which were given several bridge parameters as inputs. Huang's results identified several key parameters such as age, previous condition, deck area, deck length, skew, and district. They also highlight that record of maintenance is essential to ensure satisfactory performance of bridges. Creary and Fang (*36*) predicted the deck, superstructure and sub-structure condition ratings using ANNs, which used bridge characteristics such as bridge geometry, construction, and service. Additionally, they included predictors based on inspection data, which was identified to be a key predictor. They observed that neural networks with multiple outputs were less accurate than the ones with a single output. Furthermore, they observed that lower condition ratings were more difficult to predict.

Li and Burgueno (*37*) developed several machine learning models to predict the condition ratings of bridge abutments in Michigan. The considered age, bridge length, width, skew angle, annual temperature difference, natural logarithm of average daily traffic, approach surface type structure type, and location as predictors. They found that an ensemble of neural networks was most the most accurate when compared against methods like multi-layer perceptron, support vector machines, supervised self-organized map, and fuzzy neural network. Based on the developed models, they predicted the abutment's condition rating for a 75-year service life of a bridge. Asaad and El-adaway (*38*) used neural networks and k-nearest neighbors to determine the deck condition rating for bridges in Missouri. They optimized the hyperparameters of each of the two methods and compared their accuracy. They identified a neural network model to be the most accurate with an accuracy of 91.4%. Additionally, the identified the key variables that affected the condition ratings of bridge decks which include: sub-structure and superstructure condition ratings, operating and inventory rating, span and structure length, average daily traffic, age, and deck width.

For bridges in Ontario, Canada, Martinez et al. (*39*) developed and compared several machine learning models (neural networks, linear regression, decision trees, ANNs, and deep neural networks) to predict the future bridge condition index. The included predictors like bridge category, material type, last rehabilitation, number of spans, length, width, region, year built, bridge condition index for the current and past two years, and days since last inspection. They observe that training the models on a refined dataset that categorizes and labels data appropriately improved the performance for all models significantly. Based on their comparison, they recommend decision trees due to their prediction accuracy and consistency. Fiorillo and Nassif (*40*) used bridge element ratings to determine the deck, superstructure, and sub-structure condition rating using different machine learning techniques including logistic regression, k-nearest neighbors, and principle component analysis. Additionally, they also proposed machine learning based inverse mapping that maps the NBI condition ratings to bridge element condition ratings. The developed the machine learning models using data from 9000 bridges in the Northeastern United States. They observed that k-nearest neighbors approach provided the best prediction for mapping the bridge element condition to NBI component conditions. The inverse mapping was found to be most accurate when either principal component analysis or logistic regression was used.

The studies mentioned above mainly predict the current condition ratings of bridge components using different inputs including element condition ratings and data from the NBI database. Only few studies have focused on either hindcasting the condition ratings or predicting the future values of condition ratings. Lee et al. (*41*) developed a back propagation based ANN to predict the historical values of bridge condition ratings using inspection records. For this purpose, Lee et al. used non-bridge parameters such as local climate, number of vehicles, population growth around the bridge as predictors, in addition to bridge related parameters. The resulting models had and average error of 6.7-7.5% over a twenty-year period. They highlight the need for identifying different types of non-bridge parameters and number of such parameters for various types of bridges to ensure high prediction accuracy. Liu and Zhang (*42*) have developed convolutional neural networks based on data obtained from the national bridge inventory to predict the future deck, sub-structure, and super structure condition ratings. Their model was trained on data on bridges from Maryland and Delaware and had an accuracy of 85%. The also found that bridge condition ratings are history dependent but suggested further investigation to better understand this dependence.

Some of the above-mentioned methods can provide a good understanding of the future condition of bridges' structural elements and the associated condition ratings, however, they are not sufficient to determine potential load posting decisions since element level data is required for load rating decisions. In this regard, few existing studies have developed methods to predict load posting on bridges. Alipour et al. (*43*) use a data-based approach with bridge details available in the NBI database alone and estimate the number of posted bridges for concrete slab bridges in Illinois. They used a random forest model to predict the load posting decision for current conditions. To the best of PI's knowledge, the studies mentioned above extensively cover studies that predict future condition ratings and load posting of bridges. However, methods are still lacking for predicting the load posting decisions for all the different types of bridges within a statewide inventory of bridges. Furthermore, the literature lacks studies that can predict future load posting for bridges in a statewide inventory.

4. METHODOLOGY

4.1 Data collection and Processing

Data on bridges in Louisiana were collected from NBI database from year 1992 to 2019, which consisted of a total of 303723 bridges records/data points. Specifically, *ON* system bridges were considered herein since these bridges that are monitored by Louisiana Department of Transportation and Development (LADOTD). So, preliminary filtering was done to exclude *OFF* system bridges, and the resulting database consisted of 196004 “ON” service bridge data. The following bridge types were selected since they constituted most of the existing bridges in Louisiana as of 2019.

Table 1. Selected bridges used for our study

Name	**Description**
COSLAB	Concrete Slab
COPCSS	Concrete Precast Slab Units
LWPCSS	Light weight concrete pre-cast slab bridges
CODEKG	Concrete Deck Girder
COPSGR	Concrete Prestressed Girders (AASHTO Type)
CONIBM	Steel – I – Beam (Rolled)

Data obtained from the NBI databased, e.g., condition ratings, ownership, ADT etc. were processed and labeled to make it more amenable to data based approaches that were used herein, which are described in the following sections. The following provides details of parameter that were processed herein.

Condition ratings: In NBI database, condition ratings can be found in Item 58 (deck), Item 59 (superstructure) and Item 60 (substructure) and Item 68. In NBI database, deck, superstructure, and substructure condition ratings and deck geometry evaluation ratings have been categorized on scale from 0 – 9. For analysis, these condition rating values were recategorized as poor (<5), fair (=5) and good (>5) following the recommendation of from the AASHTO Manual for Bridge Inspection (*1*). It is important to note that in NBI bridge data, some bridges were assigned the value “N” or were left blank. Those were labeled as -1. The following 2 shows the labeling of the condition rating values.

Table 2. Recategorized condition rating values

Recategorized Label	Description
0	Poor (NBI condition rating values < 5)
1	Fair (NBI condition rating values = 5)
2	Good (NBI condition rating values > 5)

Functional Class: This item 26 of NBI database categorizes bridges as rural or urban based on the location of the roadway and it is further classified based on whether the bride is on an arterial road, collector road, or a local road. The following table shows the filtering functional class values used in the analysis.

Table 3. Recategorized functional class code values

Recategorized Label	NBI codes
0	1, 2, 6 (Rural arterial road)
1	7, 8 (Rural collector)
2	9 (Local rural road)
3	11, 12, 14, 16 (Urban arterial road)
4	17 (Urban collector)
5	19 (Local urban road)

In case of any missing data, they were labeled -1.

Maintenance Responsibility: Item 21 coded as per NBI with recategorized value is shown in the following Table.

Table 4. Recategorized maintenance code values

Maintenance Agency	Recategorized Label	NBI values
Federal	1	27, 60, 62, 63, 64, 66, 68, 69, 70, 71, 72, 73, 74, 75
State	2	1, 11, 21, 31
Local	3	2, 3, 4, 12, 25, 32
Other	4	61, 67, 80, 76
Private	5	26

The same labeling scheme was used for ownership of the bridge (Item 22) as well.

Kind of Highway: Kind of Highway was not originally in the NBI and was defined using Item 26 (Functional Class). Using Table 3, coded label of the parameter *kind of highway* was prepared as shown in Table 5.

Table 5. Kind of Highway Code values

Type	Recategorized label	NBI Functional Class code value
Roads	0	6, 7, 8, 9, 14, 16, 17, 19
State	2	2, 12
Interstate	3	1, 11

Design Load: The following table shows the recategorized labels for the feature design load (Item 31).

Table 6. Recategorized Design Load code values

Type	Recategorized label	NBI code values
Light	1	1, 2, 4, 7
Heavy	2	3, 5, 6, 8, 9, A, B
Other	0	C and missing data

Scour critical rating: The following table shows the recategorized labels for the feature scour critical rating (Item 113).

Table 7. Recategorized Scour critical code values

Recategorized label	NBI code values
0	0, 1, 2, 3
1	4, 5
2	6
3	7
4	8
5	9
6	T
7	U
8	N
9	missing data

Average daily traffic (ADT): Average daily traffic (Item 29) was labeled as shown in following table 8 following Hearn (*44*).

Table 8. Recategorized ADT values

Recategorized ADT Code value	ADT value in NBI datasheet
1	< 400
2	400 - 999
3	1000 - 4999
4	5000 - 9999
5	10000 - 49999
6	> 50000

Average daily truck traffic (ADTT): This parameter (Item 109) was labeled as shown in following Table 9 following Hearn (*44*).

Table 9. Recategorized ADTT values

Recategorized ADTT Code value	ADTT value in NBI datasheet
1	0 or Not Reported
2	1 - 19
3	20 - 99
4	100 - 499
5	500 - 4999
6	> 5000

Base highway network: Item 12 was labeled as shown in Table 10.

Table 10. Recategorized Base Highway Network values

Recategorized code value	NBI code value	Description
0	0	Inventory Route is not on the Base Network
1	1	Inventory Route is on the Base Network
2	empty	

Age: The 2019 NBI data set was used as the starting base year for analysis, so the age of bridges was calculated using following formulas:

Age = 2019 – year built (Item 27)

Some bridges were reconstructed, and in that case, age was calculated by following formula:

Age = 2019 – year reconstructed (Item 106)

It is important to note that two more attributes, log(ADT) and sine(skew) were created from the attributes ADT and skew angle because the alternative representation gave better performance than the original attributes (*43*). Finally, another attribute 'climatic zone' was added based on NOAA's climate divisions of the United States (*45*). Figure 1 illustrates the approach for preparing the dataset that was used herein.

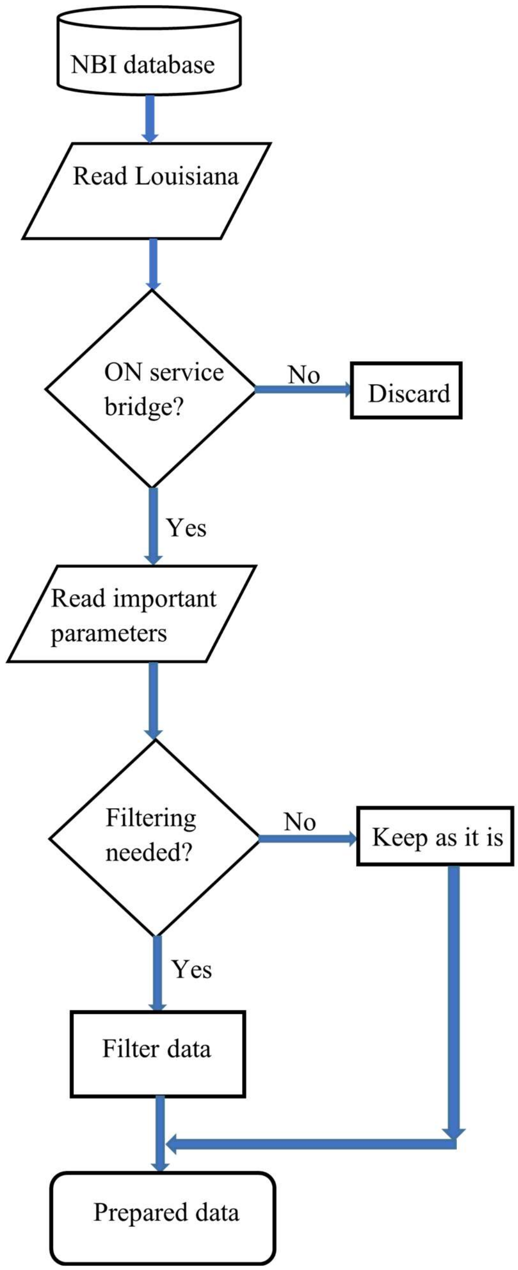

Figure 1. Approach for preparing the dataset

4.2 Feature Identification

In order to achieve the first research goal and identify the key bridge parameters that affect load posting, two approaches were used: univariate feature identification using data tables and random forest based feature selection. The results from this step informed which parameters' future values needed to be modeled for future load posting predictions.

In univariate methods based on data tables, 31 tables were made for every category of bridge mentioned in Table 1. The main aim of these tables was to understand the trends between every parameter and number of loads posted bridges and help in making logical conclusions about load Posting.

Next, Random forest models were trained for each bridge type described in Table 1 to identify key parameters that influence load posting of bridges in Louisiana. Since these models were only used for identifying the influential parameters, all the data was used to train the models. The performance of the models was checked using 5-fold cross validation. A random forest model trains an ensemble of individual decision trees to predict the load posting decision.

To train a decision tree in the random forest, first root node is created which contains all the training data points. The prediction of the root node is obtained as the average of the data points in the node for regression problems or the mode of the data points is used for classification problems (such as load posting). Herein, Gini index was used a cost function to measure the prediction error. Next, in the training process, the root node is split in to two children node using one of the input variables and a corresponding threshold value (bridge parameters like condition ratings, geometry, age, and traffic information). The left child node will contain all the data points where the split variable's value is less than the threshold and in the data points for right child node, the split variable's value will be larger than the threshold value. The split variable and the threshold are selected such that maximum reduction in the cost is achieved. Next, each of the child nodes are considered as the root node and are split further. This process happens iteratively until the nodes can no long be split further due to restrictions on minimum node size (i.e., the minimum number of data points in the node), or tree depth (i.e., number of splits), or statistical significance of the splits. This process trains one decision tree and this process is used for all decision trees in the random forest. The final prediction of a random forest is the mode (for classification) or average (for regression) of the predictions from all the individual decision trees. This process was adopted herein and was implemented in Python. Additional details on random forests may be found elsewhere (*26*).

In the above process, feature importance in a decision tree can be determined from random forest models by calculating the decrease in cost when a node is split using a feature and weighing it by the probability of reaching that node, which can be calculated as the number of samples that reach the node, divided by the total number of samples. *The higher the reduction, the higher the importance of the parameter.* These importance values can be obtained from each decision tree in the random forest and aggregated to obtain feature importance values. The flowchart shown below shows the mathematical process behind random forest feature identification process. Herein, this process was implemented in Python using SciKit learn toolbox.

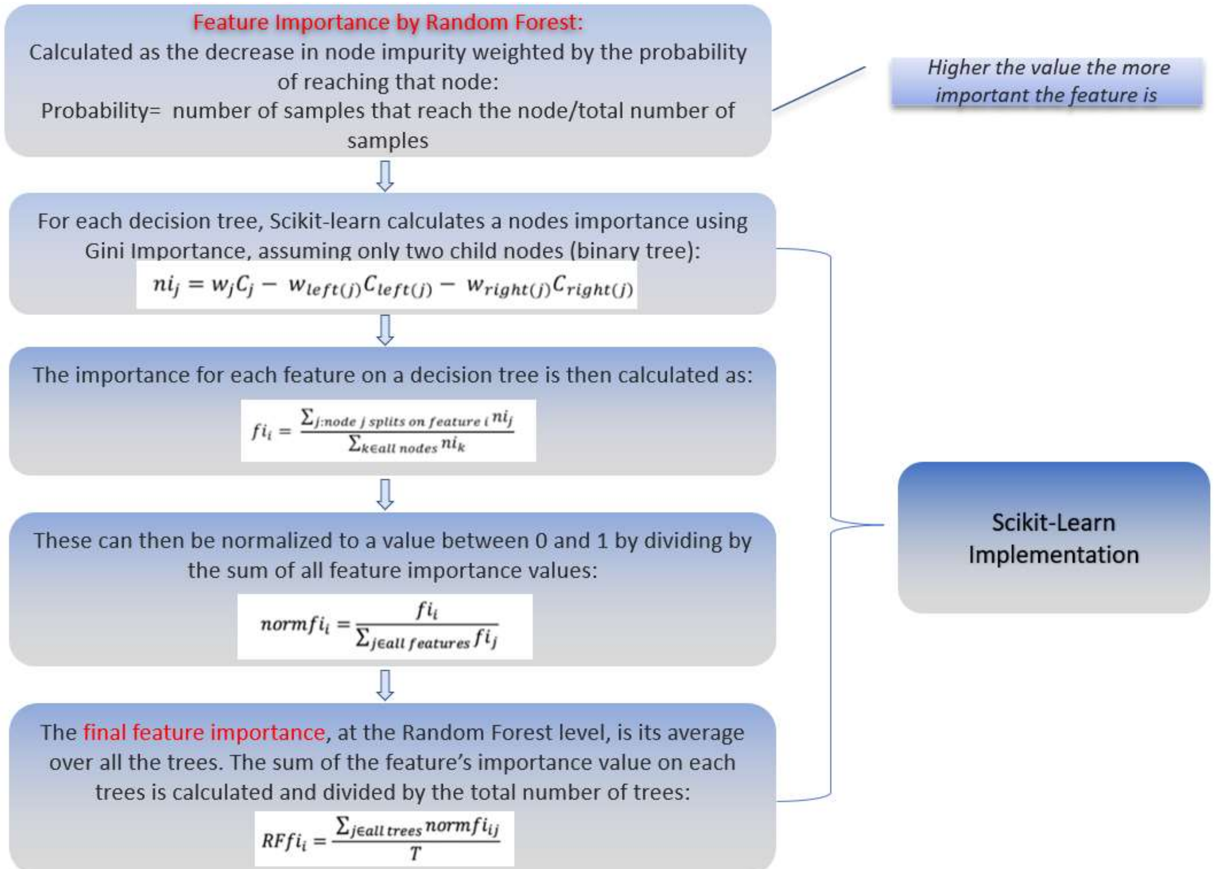

Figure 2. Random Forest feature selection process.

4.3 Future Parameter Value Prediction

Using the approach described in the previous section, key parameters that affect load posting were identified. Among the key parameters, time varying parameters such as component condition ratings, inventory ratings, age, and ADT were considered. Among these time varying parameters, the future values of inventory and operating rating were mot predicted since predicting the future value of these parameters was the same as predicting load posting. ADT value was kept constant throughout the analysis due to lack of ADT values for the next 50 years. Therefore, herein, future values of the condition ratings were selected for prediction for each bridge.

Due to the large number of bridges, a data based approach was selected to determine the future values of these parameters. Specifically, for each bridge type, random forests were used to develop models that can predict the next year's condition ratings, given bridge parameters and current year's condition ratings. The parameters shown in the table below were used as inputs to the random forest models since they were identified as key influential parameters using the approach described in the previous section.

Table 11. Input parameters for random forest models predicting condition ratings

Age	Kind of Highway	Base highway Network	Structure Flared
Deck condition	Design Load	History	Service
Superstructure condition	ADT	Roadway Width	Deck width
Substructure condition	Log(ADT)	Median Code	Traffic direction
Deck Geometry evaluation	Degrees Skew	Main Unit Spans	Deck structure type
Functional classification	Sine skew Angle	Structure Length	Scour critical rating
Maintenance responsibility	ADTT	Max. span length	Climate zone

The data obtained from the National Bridge Inventory was highly imbalanced – i.e., distribution of condition ratings was not even. For example, for CODEKG, only a small fraction of bridges had poor deck condition rating, while for LWPCSS a large fraction had poor deck condition. Ideally, even distribution of condition ratings would be best for modeling using random forests. However, since the data was highly unbalanced, random forest were developed using RUSBoost algorithm in MATLAB. Research conducted by Blackard and Dean (*46*) pointed out the benefits of random forest with RUSBoost algorithm in terms of accuracy for unbalanced data. In random forest, a large number of decision tress are constructed, each with a few randomly selected attributes. By taking the majority vote among all tress, an instance is classified (*26*). Since decision trees in random forest were grown to fullest, all attributes were used in the model to increase accuracy and stability.

The input data to the random forest models was pre-processed and labeled as described in Section 4.1 The random forest models were trained using data from 1992 to 2018. 90% of the data points were used for training while the remaining 10% were used for testing the models. Additionally, 5-fold cross validation was also performed to assess the accuracy and the prediction capability of the trained models. Herein, the random forest models were specifically trained to predict the next year's condition ratings. To test these models, the values of the bridge parameters in Table 11 corresponding to 2018 were given as inputs to estimate the condition ratings for 2019, which were known from the NBI database. The accuracy of the model was decided based on the confusion matrix, which is often used to describe the accuracy of the classification model. Table 12 shows a typical confusion matrix. A good predictive model should have minimal off-diagonal values. Figure 3 shows an overview of the process used herein to predict the future values of condition ratings.

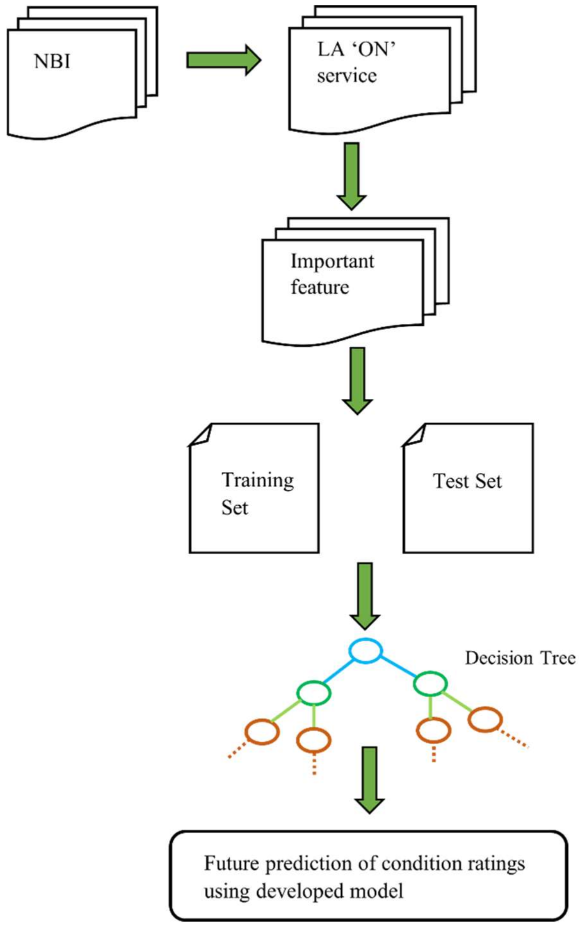

Figure 3. Overview of process for predicting future condition ratings

Table 12. Typical confusion matrix

		Actual	
Predicted values		Positive (1)	Negative (0)
	Positive (1)	True Positive	False Positive
	Negative (0)	False Negative	Tue Negative

During the evaluation of a classifier on the test set, the developed model gives a confusion matrix as output summarizing the number of correct and incorrect instances. Herein, parameters of random forest model such as number of cycles, learning rate, weight factor and classification cost matrix have been decided based on trial and errors to ensure a balanced confusion matrix. In other words, the parameters were tuned to ensure that the number of bridges in each condition were preserved as best as possible.

Trained random forest models were recursively used to estimate the condition ratings for the next 50 years. For the first year's prediction, i.e., 2020, the actual condition ratings from 2019 were used to obtain the condition ratings. For the following years, for example 2021, the values predicted by the random forest model for 2020 were used as an input to obtain the condition ratings for 2021. This process was repeated for 50 years to obtain the condition ratings. Thus, the second objective was achieved.

4.4 Future Load Posting Prediction

A twostep process was used to predict the future load posting for bridges. First a data based approach was used to predict the load posting decision for each bridge where bridge parameters were given as inputs to the models. In the second step, this model was used with future values of bridge parameters obtained using the approach described in section 4.3. Thus, the number of load posted bridges in Louisiana were estimated for the next 50 years.

For the first step, surrogate models such as neural networks, support vector machines, random forests, and logistic regression were considered to model load posting decisions. Criteria for model selection should include considerations for the extent of non-linearity between bridge parameters and posting decision and the overall prediction accuracy of the model. For example, nonlinear relation can be better modeled using neural network models. Additionally, interpretability of the models was also considered. Several models including support vector machines, logistic regression, neural networks, and random forest models were developed. These models were trained using labeled bridge data described in Section 4.1 and were evaluated based on their classification accuracy, misclassification rate obtained from a confusion matrix (*47*), and interpretability. The key bridge parameters identified in Section 4.2 were used as inputs for these models. However, inventory and operating rating were not used as inputs since their future values can not be determined. Using this approach, random forest models were selected for all bridge types. Similar to the random forest models developed for predicting the future values of condition ratings, the parameters of the random forest model were tuned to have a balance confusion matrix such that the number of load posted bridges are preserved as much as possible. In other words, the parameters were tuned to ensure that the off-diagonal terms in the confusion matrix were close to each other. To train the random forest models, 90% of the data was used for training and the rest was used for testing. Additionally, 5-fold cross validation were also performed to assess the predictive capabilities of the trained models.

In the second step these models were used to estimate the future load posting for each bridge over the next 50 years. Thus, for each year the number of load posted bridges were calculated. Furthermore, to gain a better understanding of the distribution of load posted bridges across different bridge types, the number of load posted bridges for each bridge type were also calculated for each year. Thus, third and fourth goals were achieved.

5. ANALYSIS AND FINDINGS

5.1 Key Bridge Parameters

The univariate analysis resulted in tables that show the relation between the frequency of load posting with different bridge parameters one at a time. For example, the following tables show the relation between load posting and ownership of bridges. To create these tables, data on bridges from 1992 to 2019 was used; thus, the total number of data point = # of bridges × 28 years (1992 to 2019). Therefore, the numbers in these tables can be greater than the total number of bridges in Louisiana. From these tables, it can be seen that while the federal government owns a small fraction of bridges for most bridge types, these bridges are more likely to be load posted.

Table 13. Load Posting and Bridge owner for COPCSS

Item 22 Owner	Structures	Posted for Load	% Of Group	% Of Load posted
Federal Government	53	15	28.30	1.86
State Government	22187	793	3.57	98.14
Local Government	0	0	-	0.00
Other	0	0	-	0.00

Table 14. Load Posting and Bridge owner for COSLAB

Item 22 Owner	Structures	Posted for Load	% Of Group	% Of Load posted
Federal Government	17	0	0.00	0.00
State Government	54578	1838	3.37	99.08
Local Government	59	17	28.81	0.92
Other	0	0	nan	0.00

Table 15. Load Posting and Bridge owner for LWPCSS

Item 22 Owner	Structures	Posted for Load	% Of Group	% Of Load posted
Federal Government	15	14	93.33	1.73
State Government	6486	795	12.26	98.27
Local Government	0	0	-	0.00
Other	0	0	-	0.00

Table 16. Load Posting and Bridge owner for COPSGR

Item 22 Owner	Structures	Posted for Load	% Of Group	% Of Load posted
Federal Government	20	0	0.00	0.00
State Government	21868	155	0.71	100.00
Local Government	0	0	-	0.00
Other	0	0	-	0.00

Table 17. Load Posting and Bridge owner for CODEKG

Item 22 Owner	Structures	Posted for Load	% Of Group	% Of Load posted
Federal Government	0	0	-	0.00
State Government	6395	368	5.75	100.00
Local Government	0	0	-	0.00
Other	0	0	-	0.00

Table 18. Load Posting and Bridge owner for CONIBM

Item 22 Owner	Structures	Posted for Load	% Of Group	% Of Load posted
Federal Government	0	0	-	0.00
State Government	6216	621	9.99	100.00
Local Government	0	0	-	0.00
Other	0	0	-	0.00

Based on random forest based feature selection, Table 19, Table 20, Table 21, Table 22, and Table 23 show the top 30 important parameters for each of the bridge classes, in descending order of importance.

Table 19. Top 30 important parameters for COSLAB bridges

Parameter	Importance
NBI 066: Inventory Rating	12.53
NBI 064: Operating Rating	11.31
AGE	8.91
NBI 049: Structure Length	6.17
NBI 051: Bridge Roadway Width, Curb-To-Curb	5.98
NBI 052: Deck Width, Out-To-Out	5.86
NBI 047: Inventory Route, Total Horizontal Clearance	5.37
NBI 045: Number of Spans in Main Unit	4.32
NBI 067: Structural Evaluation_4	3.14
NBI 060: Substructure	2.04
NBI 048: Length of Maximum Span	1.83
NBI 068: Deck Geometry	1.62
SIN_SKEW_ANGLE	1.31
LOG_ADT	1.29
NBI 034: Skew	0.94
NBI 059: Superstructure	0.93
NBI 029: Average Daily Traffic (ADT)_1	0.91
NBI 113: Scour Critical Bridges_y_8	0.85
NBI 058: Deck	0.84
NUM_LANES	0.81
NBI 033: Bridge Median_0	0.80
NBI 031: Design Load_1	0.78
NBI 022: Owner_12	0.76
NBI 067: Structural Evaluation_6	0.76
NBI 005B: Inventory Route: Route Signing Prefix_4	0.73
NBI 026: Functional Classification of Inventory Route_2	0.67
NBI 037: Historical Significance_4.0	0.67
KIND_OF_HIGHWAY_1	0.64
NBI 021: Maintenance Responsibility_2	0.62
NBI 012: Base Highway Network_1	0.60

Table 20. Top 30 important parameters for COPCSS bridges

Parameter	Importance
NBI 066: Inventory Rating	16.32
NBI 064: Operating Rating	16.32
AGE	6.62
NBI 067: Structural Evaluation_4	4.82
NBI 051: Bridge Roadway Width, Curb-To-Curb	4.56
NBI 052: Deck Width, Out-To-Out	4.34
NBI 047: Inventory Route, Total Horizontal Clearance	4.18
NBI 060: Substructure	4.09
NBI 049: Structure Length	3.39
NBI 045: Number of Spans in Main Unit	2.62
NBI 067: Structural Evaluation_2	1.46
NBI 068: Deck Geometry	1.39
NBI 059: Superstructure	1.38
NBI 058: Deck	1.28
NBI 067: Structural Evaluation_3	1.26
NBI 067: Structural Evaluation_6	1.17
LOG_ADT	0.97
NBI 067: Structural Evaluation_5	0.91
NBI 113: Scour Critical Bridges_y_11	0.91
NBI 113: Scour Critical Bridges_y_8	0.90
NBI 048: Length of Maximum Span	0.84
NBI 113: Scour Critical Bridges_y_3	0.81
SIN_SKEW_ANGLE	0.71
NBI 034: Skew	0.68
NBI 067: Structural Evaluation_7	0.67
NBI 029: Average Daily Traffic (ADT)_1	0.65
NBI 037: Historical Significance_5.0	0.63
NBI 026: Functional Classification of Inventory Route_2	0.62
NBI 033: Bridge Median_0	0.60
NBI 029: Average Daily Traffic (ADT)_2	0.59

Table 21. Top 30 important parameters for LWPCSS bridges

Parameter	Importance
NBI 066: Inventory Rating_y	10.38
NBI 067: Structural Evaluation_4	10.02
NBI 064: Operating Rating_y	6.93
AGE	6.14
NBI 048: Length of Maximum Span	4.25
NBI 049: Structure Length	3.90
NBI 045: Number of Spans in Main Unit	3.69
NBI 059: Superstructure	3.00
NBI 035: Structure Flared_1	2.21
LOG_ADT	2.12
NBI 042B: Type of Service: UNDER Bridge_5	2.04
NBI 067: Structural Evaluation_2	1.98
NBI 051: Bridge Roadway Width, Curb-To-Curb	1.92
NBI 035: Structure Flared_0	1.88
NBI 069: Underclearances, Vertical and Horizontal_5	1.81
NBI 046: Number of Approach Spans	1.53
NBI 047: Inventory Route, Total Horizontal Clearance	1.51
NBI 055B: Minimum Lateral Underclearance on Right: Minimum Lateral Underclearance	1.42
NBI 054B: Minimum Vertical Underclearance	1.35
NBI 029: Average Daily Traffic (ADT)_2	1.27
NBI 026: Functional Classification of Inventory Route_4	1.25
NBI 052: Deck Width, Out-To-Out	1.17
NBI 069: Underclearances, Vertical and Horizontal_7	1.15
NBI 068: Deck Geometry	1.04
KIND_OF_HIGHWAY_0	0.98
NBI 005B: Inventory Route: Route Signing Prefix_4	0.92
NBI 037: Historical Significance_4.0	0.91
NBI 042A: Type of Service: ON Bridge_1	0.90
NBI 005B: Inventory Route: Route Signing Prefix_2	0.81
NBI 012: Base Highway Network_0	0.81

Table 22. Top 30 important parameters for LWPCSS bridges

Parameter	Importance
NBI 064: Operating Rating_y	16.71
NBI 066: Inventory Rating_y	16.58
NBI 059: Superstructure	3.52
NBI 049: Structure Length	3.27
NBI 045: Number of Spans in Main Unit	2.87
NBI 052: Deck Width, Out-To-Out	2.83
LOG_ADT	2.81
AGE	2.75
NBI 005B: Inventory Route: Route Signing Prefix_4	2.47
NBI 058: Deck	2.03
NBI 026: Functional Classification of Inventory Route_2	2.01
NBI 067: Structural Evaluation_3	1.86
NBI 051: Bridge Roadway Width, Curb-To-Curb	1.74
NBI 109: Average Daily Truck Traffic_1.0	1.70
NBI 022: Owner_1	1.67
NBI 047: Inventory Route, Total Horizontal Clearance	1.60
NBI 067: Structural Evaluation_6	1.50
NBI 048: Length of Maximum Span	1.41
NBI 109: Average Daily Truck Traffic_2.0	1.39
NBI 022: Owner_2	1.36
NBI 021: Maintenance Responsibility_1	1.35
NBI 029: Average Daily Traffic (ADT)_1	1.35
NBI 067: Structural Evaluation_2	1.29
NBI 021: Maintenance Responsibility_2	1.21
NBI 060: Substructure	1.20
NBI 067: Structural Evaluation_4	1.17
NBI 031: Design Load_1	0.89
NBI 113: Scour Critical Bridges_y_7	0.60
NBI 042B: Type of Service: UNDER Bridge_2	0.58
NBI 104: Highway System of the Inventory Route_1	0.58

Table 23. Top 30 important parameters for CODEKG bridges

Parameter	Importance
NBI 066: Inventory Rating_y	14.19
NBI 064: Operating Rating_y	13.71
AGE	4.19
NBI 049: Structure Length	3.67
NBI 048: Length of Maximum Span	3.51
NBI 060: Substructure	3.10
NBI 052: Deck Width, Out-To-Out	3.04
NBI 067: Structural Evaluation_2	2.28
NBI 047: Inventory Route, Total Horizontal Clearance	2.17
NBI 051: Bridge Roadway Width, Curb-To-Curb	2.11
LOG_ADT	1.99
NBI 045: Number of Spans in Main Unit	1.91
NBI 059: Superstructure	1.79
NBI 029: Average Daily Traffic (ADT)_1	1.70
NBI 067: Structural Evaluation_4	1.46
NBI 022: Owner_1	1.41
NBI 005B: Inventory Route: Route Signing Prefix_4	1.33
NBI 109: Average Daily Truck Traffic_1.0	1.28
NBI 058: Deck	1.24
NBI 034: Skew	1.22
NBI 031: Design Load_2	1.17
NBI 054B: Minimum Vertical Underclearance	1.05
NBI 104: Highway System of the Inventory Route_0	1.02
NBI 046: Number of Approach Spans	0.87
NBI 021: Maintenance Responsibility_1	0.86
NBI 055B: Minimum Lateral Underclearance on Right: Minimum Lateral Underclearance	0.85
NBI 021: Maintenance Responsibility_4	0.82
NBI 104: Highway System of the Inventory Route_1	0.74
NBI 031: Design Load_1	0.74
SIN_SKEW_ANGLE	0.73

The table above shows that inventory and operating rating were always identified among the most important parameters for all bridge classes. The relative importance of these parameters was expected since these operating rating are used to make load posting decisions. However, predicting the future value of these parameters was the same as predicting load posting. Therefore, herein, the future value of inventory and operating rating of bridges was not predicted. In addition to these parameters, condition ratings for the deck, sub-structure and super structure were also observed to highly influential in affecting load posting decisions, which was also expected since bridges in poor condition are more likely to be load posted. Although, not in top 10, but design loads, climate zone and scour critical rating were observed to be important parameters. Further investigation is needed to understand the effect of bridge geometry such as span lengths, roadway widths, and number of spans on load posting decisions.

5.2 Random Forest Models for Predicting Future Condition Ratings

Important parameters affecting load posting included geometric features of bridges which are less likely to change in the future. Average daily traffic was also important and will change with time. However, its value was kept constant throughout the analysis due to lack of ADT values for the next 50 years. Therefore, only the future values of the condition ratings were predicted for each bridge using the approach described in Section 4.3. Random forest models were developed to predict the future condition ratings for the deck, super-structure, and the sub-structure using input the most influential parameters as inputs, discussed in Section 5.1. Such models were developed separately for all the bridge classes considered herein. Table 24 shows the confusion matrix for superstructure condition rating for COPSGR 'ON' system bridges. It can be seen from Table 24 that the random forest model predicted 822 data correctly out of 839 data (97.9% accuracy). The model also gave good precision, recall and F score value indication accuracy. Similar models were developed for all other bridge types and were used to estimate the future value of the condition ratings of the bridges. Table 25 shows the training and test accuracy of the random forest models developed to predict the future condition ratings.

Table 24. Confusion matrix for superstructure condition rating – COPSGR

		Actual values		
		Poor	Fair	Good
Predicted values	Poor	5	0	1
	Fair	0	5	6
	Good	0	10	812

Table 25. Accuracy of random forest models predicting future condition ratings

Bridge yype	Condition rating	Training accuracy (%)	Test accuracy (%)
CODEKG	Deck	93.99	94.83
	Superstructure	95.08	95.26
	Substructure	92.08	92.24
COPCSS	Deck	96.27	93.41
	Superstructure	96.59	92.55
	Substructure	95.17	88.77
COPSGR	Deck	98.73	99.52
	Superstructure	98.26	97.97
	Substructure	98.37	98.09
COSLAB	Deck	97.13	97.17
	Superstructure	97.82	97.68
	Substructure	96.47	97.58
CONIBM	Deck	94.92	94.87
	Superstructure	94.34	91.38

	Substructure	92.43	90.94

The results of future condition ratings of Louisiana 'ON' system bridges from years 2020 to 2069 (50 yrs) are presented below. Figure 4 (a-e) presents the future deck condition ratings for different bridge types from year 2020 to 2069. Herein DCR represents deck condition rating and the numbers 0, 1, and 2 refer to poor, fair, and good condition. The results in Figure 4 reveals that with the passage of time, the number of bridges in poor condition rating will increase while the number of bridges with good condition rating will decrease. Herein, ADT was not changed and the ADT of 2019 was used. Herein, the random forest models do not explicitly consider maintenance. But maintenance performed on bridges from 1992 to 2019 is inherently reflected in the data which is used to train the random forest models. Therefore, maintenance is implicitly considered in the random forest models. Figure 5 (a-e) shows the trends for condition rating for the superstructure (SupCR). Again, the numbers 0, 1, and 2 refer to poor, fair, and good condition. Akin to observations from Figure 4, the number of bridges in poor condition rating will increases with decrease in the number of bridges in good condition rating provided that there is no change in maintenance activities or ADT. Figure 6 shows the trends in how the sub-structure condition rating might change in the future. SubCR represents sub-structure condition rating and the numbers 0, 1, and 2 refer to poor, fair, and good condition. These trends are similar to the ones observed in Figures 3 and 4.

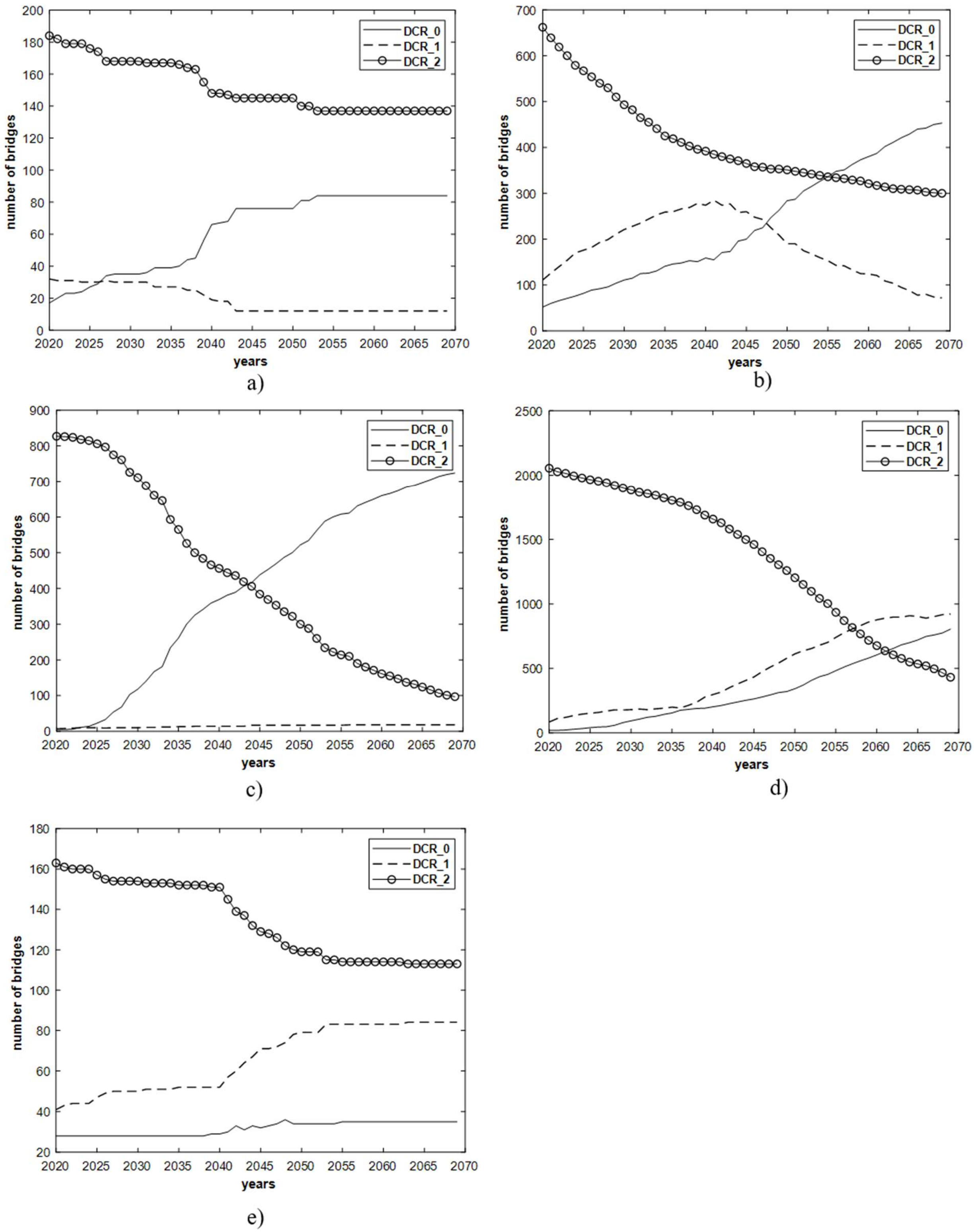

Figure 4. Future deck condition ratings for a) CODEKG; b) COPCSS; c) COPSGR; d) COSLAB; e) CONIBM

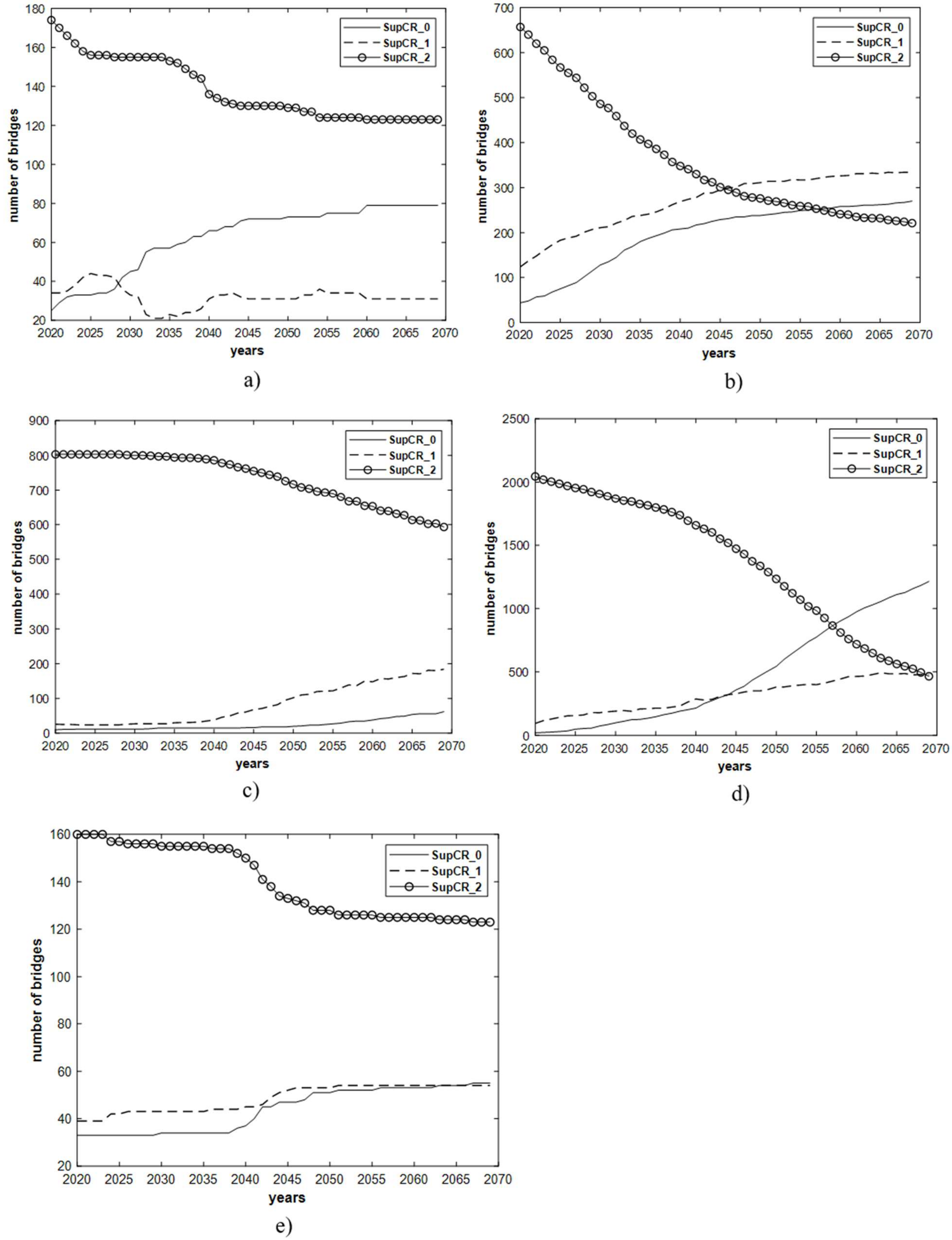

Figure 5. Future superstructure condition ratings for a) CODEKG; b) COPCSS; c) COPSGR; d) COSLAB; e) CONIBM

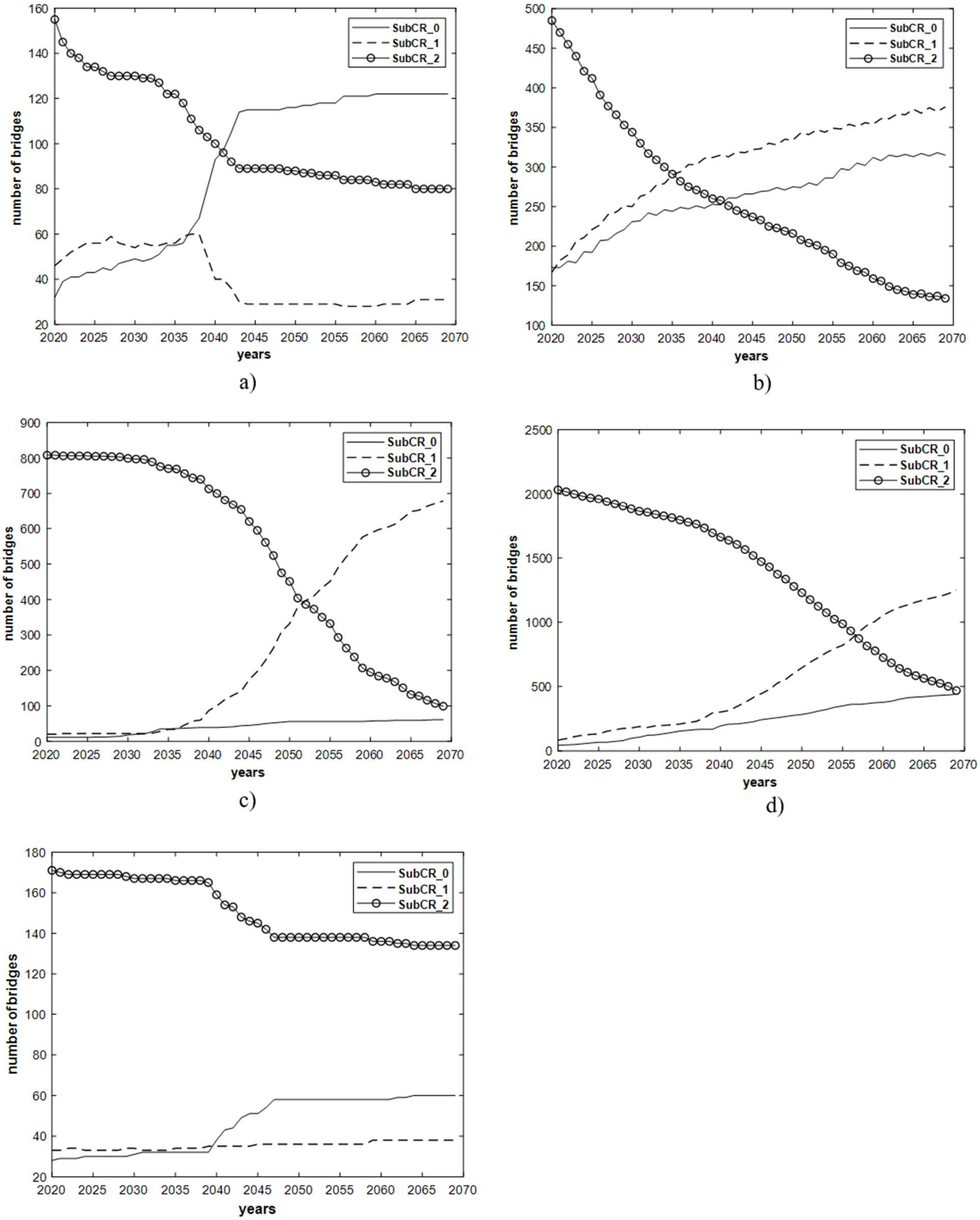

Figure 6. Future substructure condition ratings for a) CODEKG; b) COPCSS; c) COPSGR; d) COSLAB; e) CONIBM

5.3 Load Posting Prediction

The results from the previous sub-section were used as inputs for the random forest models that predict load posting of bridges. The prediction accuracy of these models is shown in Table 26. Herein, for training data from 1992 to 2019 was used where 10% of data was excluded from the training data set and was used for testing the models. The accuracy of these models in 5-fold cross validation were similar to the values reported in Table 26.

Table 26. Prediction accuracy of the random forest models for different bridge types

COPCSS	COSLAB	LWPCSS	CODKEG	CONIBM
89.33%	98.98%	76.54%	98.71%	92.67%

Using the approach described in Section 4.4, the number of load posted bridges over the next 50 years for different bridge types are obtained and are shown below in Figure 7. From the figure, it can be seen that concrete deck girder (CODEKG) and steel I-beam (CONIBM) bridges are expected to have few load posted bridges over the next 50 years. At present concrete slab bridges have a very small fraction of load posted bridges but the results suggest that a large fraction of them will become load posted over the next 50 years. Similar observations can be made for concrete precast slab unit bridges (COPCSS). These results can help stakeholders such as the LADOTD allocate sufficient resources to ensure that the number of load posted bridges do not increase as estimated in Figure 6.

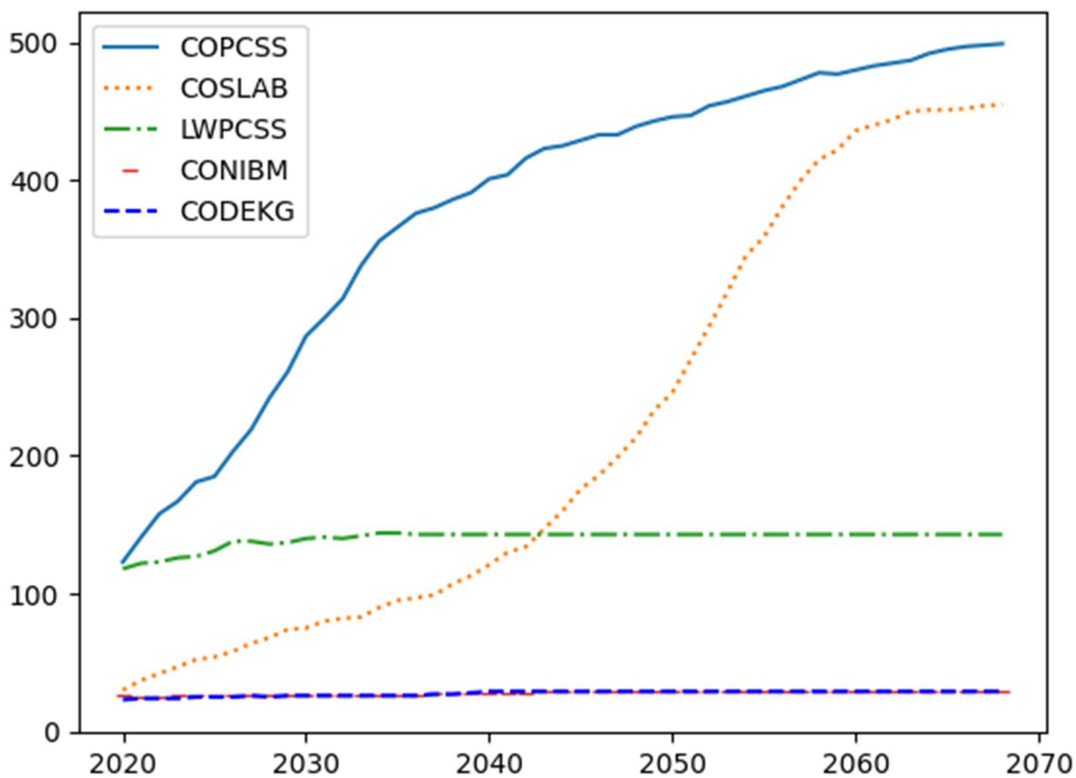

Figure 7. Number of load posted bridges for various bridge types

6. CONCLUSIONS

The objective of this research was to estimate the number of load posted bridges in Louisiana over the next 50 years. For this purpose, a data-based approach was proposed which used information on bridges from the National Bridge Inventory. Herein, specifically, on system concrete slab, concrete pre-cast slab, concrete light weight slab, concrete deck girder, and steel I beam bridges were considered. First, key parameters that affect load posting were determined using data tables and random forest models. Based on this analysis, condition ratings for the deck, substructure, and superstructure were determined as the parameters whose future values are essential for load posting predictions. Therefore, three random forest models were developed to predict the three condition ratings described above for each bridge belonging to that type. Next, to predict load posting decisions, another random forest model was developed which used the predicted values of condition rating along with key parameters as inputs. The following conclusions and observations can be drawn from the results presented herein:

- The results of key parameter identification show that inventory and operating rating, condition ratings, age, scour critical rating, design load, and bridge geometry are among the key parameters.
- Random forest models, using RUSboost algorithm, developed for prediction of future condition rating values show that such models can accurately predict the future condition ratings for deck, sub-structure, and super structure.
- Similarly, random forest models developed for predicting load posting decisions also predict with good accuracy and show that such data based models can be effectively used to predict load posting decisions.
- Results show that concrete deck girder (CODEKG) and steel I-beam (CONIBM) bridges are expected to have few load posted bridges over the next 50 years. At present concrete slab bridges have a very small fraction of load posted bridges but a large fraction of them could become load posted over the next 50 years. Similar observations can be made for concrete precast slab unit bridges (COPCSS).

The outcomes of this research can help stakeholders identify types of bridges that may need more repair and rehabilitation in the future to prevent them from being load posted. Thereby, the results can help stakeholders to identify potential maintenance and rehabilitation actions and allocate resources based on anticipated future condition of bridges.

Future research should quantify the uncertainty around the predictions since validation of the results, especially the prediction for the next 50 years, is not feasible at the moment.

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