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Predicting Load-Deflection of Composite Concrete Bridges Using Machine Learning Models

Manh Van Le[1*], Indra Prakash[2], Dam Duc Nguyen[1]
[1]University of Transport and Technology, 54 Trieu Khuc, Thanh Xuan, Hanoi, Vietnam
[2]DDG (R) Geological Survey of India, Gandhinagar 382010, India; indra52prakash@gmail.com

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***Corresponding author:**
Email address:
lemanhds@utt.edu.vn

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Abstract: The main objective of this study is to predict accurately the load-deflection of composite concrete bridges using two popular machine learning (ML) models namely Random Tree (RT) and Artificial Neural Network (ANN). Data from 83 track loading tests conducted on various bridges in Vietnam were collected and analyzed. Various input parameters namely bridge's cross-sectional shape, length of concrete beam, number of years in use, height of the main girder, distance between the main girders were selected for the modelling. Validation indicators like R, RMSE, and MAE, and Taylor diagram were used for validation and comparison of the models. Results of this study showed that both RT and ANN are good for prediction of the load-deflection of composite concrete bridges, but RT outperforms ANN. Thus, the developed ML models can facilitate efficient bridge health monitoring and management by predicting the load-deflection of simple-span concrete bridges.

Keywords: Load–deflection, prediction load–deflection, simple-span concrete bridges, machine learning, prediction.

1. Introduction

Load-deflection in bridges refers to how much a bridge bends under various loads. This deflection is influenced by factors such as the bridge's weight, the weight of vehicles or pedestrians, wind load, and the properties of the bridge's material. The deflection is one of the important indicators to evaluate the safety level of the bridge structure. In the 1930s the Bureau of Public Roads attempted to provide a correlation between bridge vibration problems and bridge structural characteristics. They studied the vibrations of bridge structures. This study concluded that structures having unacceptable vibrations determined by subjective human response had deflections that exceeded L/800 , and this conclusion resulted in the L/800 deflection design limit [1]), In the 1970s, Wright and Walker performed a study reviewing the rationality of the deflection limitation provisions and Roeder, et al. revisited the subject decades later in 2020 [2] suggesting that the current AASHTO live load deflection limits L/800 for vehicular traffic bridges and L/1000 for pedestrian are not always sufficient in controlling excessive bridge vibration and should ultimately be removed. AASHTO specifications require that deflections be controlled by limiting span-to depth ratio L/D preferably great than 1/25 for composite steel bridges and by limiting the maximum unfactored deflection to:

• L/800 for most design situations, and

• L/1000 for urban areas where the structure may be used in part by pedestrian traffic where L is the span length of the girder.

Bridges designed by the AASHTO LRFD Specification have an optional deflection limit, evaluating AASHTO live-load deflection limits showed that the justification for existing deflection limits was not clearly defined and the best available information indicated that they were initiated to control undesirable bridge vibrations and assure user comfort.

Vibration control is often achieved through a relationship between the first flexural natural frequency of the bridge and live-load deflection. Reducing the deflection will increase the stiffness of the bridge and reduce the vibration of the bridge, but this is clearly not the way to go.

Today, to achieve economic and technical efficiency. People tend to reduce the cross-sectional size of the structure, using materials (concrete and reinforcement) with high strength. That can lead to excessive deformation (deflection, lateral displacement) of the structure. Excessive deformation may affect the normal use of the structure: unsightly or cause fear to road users, or cause traffic insecurity. Therefore, it is necessary to calculate and predict the actual exploitation deflection of the work and control it not to exceed a specified limit value.

In recent years, advanced Artificial Intelligence (AI) models are used for solving prediction problems such as prediction of properties of construction materials and structures based on training with past data. Hoang et al. [3] indicated that Gaussian process regression (GPR) can be used to estimate the compressive strength of high-performance concrete with good learning performance. Yuvaraj et al. [4] predicted fracture characteristics of high strength and ultra-high strength concrete beams by using Support vector regression (SVR). The predicted results were in good agreement with the experimental values.

Hoan et al. 2020 [5] an AI technique called gene expression programming (GEP) to generate a deflection model for predicting the deflection of reinforced concrete (RC) beams using fibre reinforced polymer (FRP) bars as the main reinforcements through the effective moment of inertia.

Thus, bridge deflection due to live load is one of the important parameters to ensure good control of bridge vibration and construction safety. Theoretical deflection due to test load can be determined by methods of structural mechanics depending on bridge length, bridge stiffness (EI) or can be controlled based on span-to depth ratio. However, the design data often have certain differences with the actual exploitation, especially the bridge works have been exploited for 20 years or more. Deterioration of reinforced concrete bridge decks is an increasing problem in all types of bridge superstructures, and it is caused by various internal and external factors. Bridge deck deterioration reduces service life by reducing load capacity of the structure and the quality of the riding surface. One of the factors is bridge deterioration is attributable to excessive bridge flexibility and deflection.

Therefore, predictive studies on the actual operational deflection of the works, especially the old ones, are important for assessing the current status of the bridge to ensure the load-carrying capacity and service life and safe operation of bridge works. In addition, predicting the deflection development due to live load of the bridge over time of operation is of great significance to help the bridge design step have a better orientation on the life and load capacity of the structure.

In this paper, the authors use artificial intelligence methods to evaluate the influence of geometrical characteristics, year of operation and the time of load testing to the maximum load test deflection of concrete bridges in order to create a premise for building models to predict the deflection change due to bridge live load over time of operation.

2. Materials and Methods

2.1. Predicting load–deflection of concrete bridges

The principe of mesurant the deflections truck-loading test is to determine the displacement of the measuring point in the vertical direction, which is determined by the following formula

$$V=\frac{n_2-n_1}{k} \quad (1)$$

In which:

n_1 – readings on the Dial indicator in the absence of load;

n_2 – readings on the Dial indicator during truck-loading test;

k – amplification factor of indicator.

Calculating deflections in any structural member can be quite challenging. There are many variables and factors that contribute to the deflection analysis. These factors include, but are not limited to, the sustained loading, elastic vs. inelastic behaviour, the elastic modulus of concrete, and the moment of inertia. The maximum deflection of a concrete beam occurs at the midspan of the beam for central concentrated load P. Assuming elastic behaviour, the deflection can be calculated using Equation 2-2

$$\Delta_{gi}=\frac{PL^3}{48EI} \quad (2)$$

For simple support beams, the mid-span deflection is determined as Equation 2-3: The deflection caused by 1 axle of the vehicle at the section x distance from the support beams.

$$\Delta_{LL}=g(1+IM)\frac{P(L_{tt}-a)x[L_{tt}^2-(L_{tt}-a)^2-X^2]}{6L_{tt}EI} \quad (3)$$

In which:

a- Is the distance from the load to the left boundary;

L_{tt}- Calculated length of concrete beam;

x- Is the distance from section calculated to the left boundary;

E- modulus of elasticity;

I- moment of inertia;

g- load distribution coefficient;

1+ IM- dynamic amplification factor.

To calculate the deflection of the vehicle, we apply the above formula to calculate the deflection due to each axis, then add the deflection due to the axes together. The most unfavourable loading on the influence line at the mid-span cross-section.

The maximum deflection of a concrete beam occurs at the midspan of the beam for a uniformly distributed load q of live load across the length of the beam:

$$\Delta_{LL}=\frac{5}{384}\frac{gqL^4_{tt}}{EI} \quad (4)$$

So, when calculating the deflection in equation 2-3, if the vehicle load has many axes, apply the above formula to calculate the deflection caused by each axis and then take the total deflection due to those axes.

Thus, the deflection due to live load or due to permanent load both depends on the stiffness of the structure (EI), length of concrete beam L, load distribution coefficient of the bridge.

The study was carried out by the results of load testing of more than 80 bridges across all regions of Vietnam with the operation period from 4 years to 43 years from the time of commissioning to the time of load testing of the bridges. Most of the data on measurement tests performed by the authors, the rest is taken from the database of the Road Administration of Vietnam http://vbms.vn/. The works selected for the study are all in the form of T-Girder Bridge Deck – girder structures simple support beams with lengths varying from 12m to 33m.

The truck-loading test was carried out at the site of the bridge by truck with a load of 300kN. The truck-loading test is carried out by placing the vehicle in the right centre and eccentricity method, in order to select the largest measured bridge deflection.

Experimental equipment: Deflection experiments using dial indicator, measure in 0.01 mm increments with this large dial indicator Comes with limit pins and an outer frame clamp, mounted at the bottom of the beam at the mid-span position.

This result can be most clearly determined by the chart in Figure 1 below when conducting a load test of 75 bridge processes:

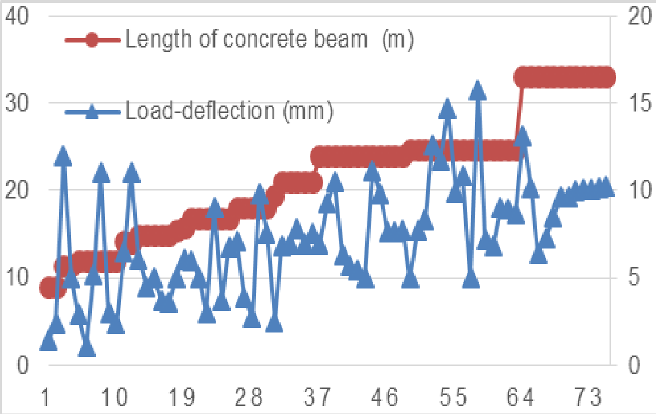


Figure 1. The diagram influence length of concrete beam on the load-deflection

In addition, one of the factors that has the greatest influence on the load-deflection is the years of exploitation. Figure 2 shows the relationship between the load-deflection and the years of exploitation.

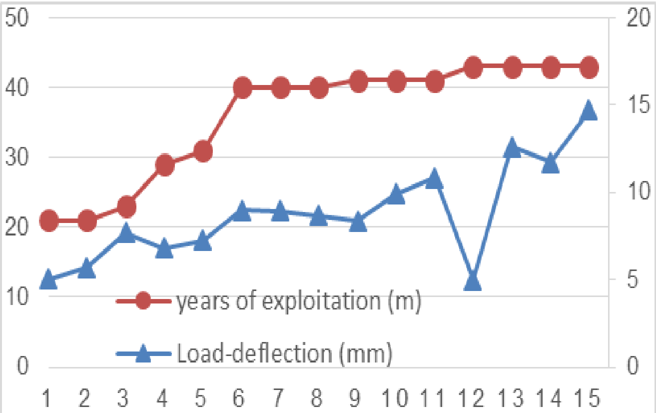


Figure 2. The relationship between the load-deflection and the years of exploitation

The chart in Figure 2 was built from the results of testing 15 simple-span reinforced concrete beam bridges with a length of 24.7m located on National Highway. With quite similar operating conditions, when these bridges are all in the Central and Southern regions, the main beams are prefabricated at the factory with the same technology, but different exploitation times will lead to a certain change in measured deflection which is proportional to the exploitation time, the longer the bridge is in operation, the larger the measured deflection value.

Therefore, in order to be able to study using artificial intelligence to predict the structural deflection of reinforced concrete bridges with simple support beams, it is possible to select parameters to bridge stiffness (height of main girder, cross-sectional shape, etc.), a parameter related to the load distribution coefficient (distance between the main girders) and the length of concrete beam L. From there, a complete picture of the influence of the parameters on the results of spherical deflection can be built.

2.2. Data used

Table 1. Statistical analysis of data used in this study

No		∑	Mean	Std	Min	25%	50%	75%	Max
X1	cross-sectional shape	83	1.651	0.48	1	1	2	2	2
X2	length of concrete beam (m)	83	24.62	6.40	9	21	24.54	33	35
X3	Year of exploitation	83	20.47	10.71	4	14	15	22	43
X4	height of main girder (m)	83	1.308	0.26	0.9	1.07	1.21	1.64	1.73
X5	distance between the main girders (m)	83	1.96	0.57	0.95	1.52	2.25	2.4	2.75
Y	maximum truck-loading test deflection (mm)	83	7.036	3.00	1.06	4.66	6.945	9.16	15.72

In this work, the collection of data from 83 bridges located in different parts of Vietnam, with varying periods of use ranging from 4 to 43 years was done to build the database for Machine Learning. For the modelling, five parameters namely X1 (bridge's cross-sectional shape), X2 (length of concrete beam), X3 (number of years in use), X4 (height of the main girder), and X5 (distance between the main girders) were selected as input variables while one maximum truck-loading test deflection as output variable (Y). Out of these, the maximum truck-loading test deflection was measured in millimetres using a deflection measurement of a dial indicator with 0.01mm increments during a truck-loading test using a 300kN load mounted at the mid-span position on the bottom of the beam with limit pins and an outer frame clamp. In addition, the data included two bridge's cross-sectional shape (I and T coded as 1 and 2). Figure 3 shows the distribution of input and output values. Data of this study was also presented in Ha et al. [6] and Le et al. [7].

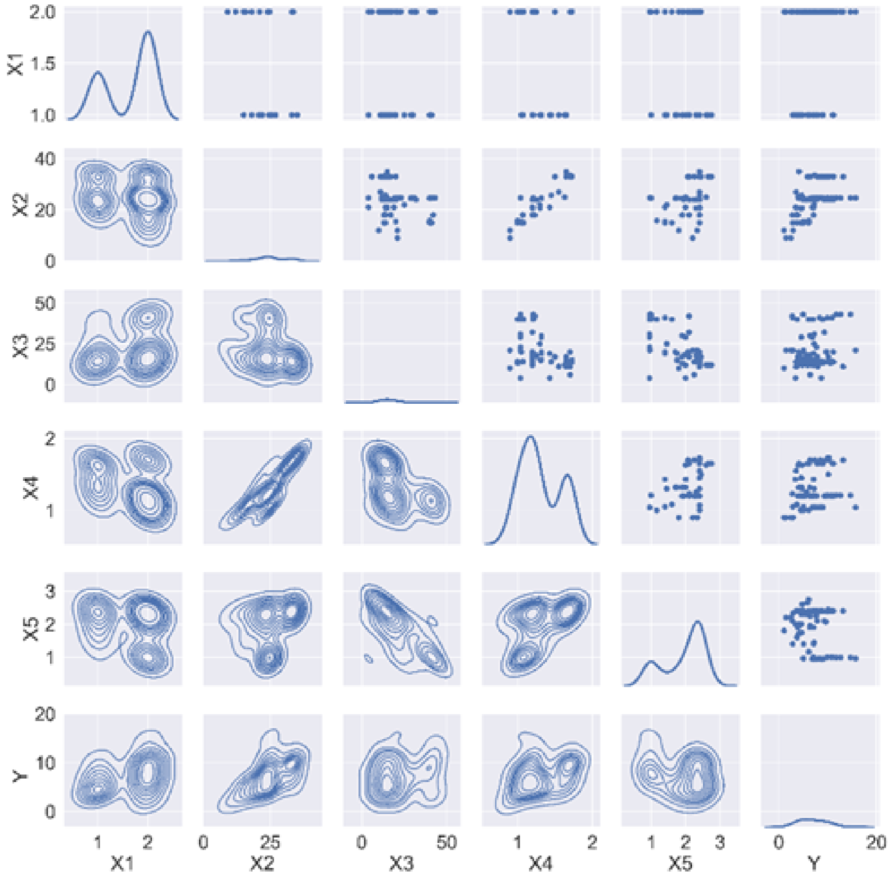


Figure 3. Distribution analysis the data used in this study

2.3. Methods used

2.3.1. Random Tree (RT)

RF algorithm - a popular ML technique was first introduced by Leo Breiman and Adele Cutler in 2001 [8]. It is based on the concept of decision trees, but instead of using a single decision tree, Random Forest builds an ensemble of decision trees, which are combined to make predictions [8]. In RT, multiple decision trees are built on different subsets of the data and features, and the predictions of the trees are combined to make the final prediction [9]. In each iteration of the algorithm, a random subset of the data and a random subset of the features are selected for building the decision trees [10], which helps to reduce the risk of overfitting and improves the generalizability of the model.

RT has been applied in a wide range of applications, including finance, healthcare, and bioinformatics. In this work, RT was used as a base model to develop various novel ensemble models for prediction of vertical deflection of steel-concrete composite bridges

2.3.2. Multi-layer perceptron (ANN)

Artificial neural network is a set of interconnected nodes used for understanding and solving modelling problems that have complex relationships between causal factors and responses. Multi-layer Perceptron Neural Network (MLP) is one of the most effective artificial neural network techniques for modelling and prediction, thus it has been used as the benchmark model by many researches The MLP has a high capability of universal approximation such that it.

2.3.3. Validation indicators

In this study, correlation coefficient (R), Root mean square error (RMSE) and mean absolute error (MAE) which are statistical terms commonly used in data analysis for evaluation of the performance of ML models, were selected for validation of the proposed models. R is a statistical measure that quantifies the strength and direction of the relationship between predicted and actual values. It is a value that ranges between -1 and 1, with -1 indicating a perfect negative correlation, 0 indicating no correlation, and 1 indicating a perfect positive correlation [11,12]. RMSE is calculated by taking the square root of the average of the squared differences between predicted and actual values [13]. MAE is calculated by taking the average of the absolute differences between predicted and actual values. MAE is less sensitive to outliers than RMSE and is a good choice when the data has a non-normal distribution [13]. RMSE and MAE are two common metrics used to evaluate the accuracy of predictive models in statistics and ML. Lower RMSE and MAE indicates better performance of the predictive models [14,15].

In addition to RMSE, MAE, and R, Taylor diagram was also used to compare the performance of different ML models in this study. It is a polar coordinate plot that shows how well a set of model simulations match observed data in terms of their R, RMSE, MAE, and standard deviation [16]. Each model simulation is represented by a point on the diagram, and the closer the point is to the reference point (which represents the observations), the better the model's performance

3. Results

Model training was carried out using training dataset. In order to obtain the good performance, the models were trained with the hyper-parameters indicated in Table 2.

Table 2. Hyper-parameters used for training the models

No	Hyper-parameters	Models	
		RT	ANN
1	Batch size	100	100
2	Debug	False	False
3	Do not check capabilities	False	False
4	Num decimal places	2	2
5	KValue	0	-
6	Allow unclassified instances	False	-
7	Break ties randomly	False	-
8	Min variance prop	0.008	-
9	Num folds	0	-
10	Gui	-	False
11	Auto build	--	True
12	decay	-	False
13	Seed	1	0
14	Hidden layers	-	5
15	Learning rate	-	0.3
16	Momentum	-	0.2
17	Nominal to binary filter	-	True
18	Normalize attributes	-	True
19	Normalize numeric class	-	True
20	Max Depth	0	-
21	Min num	3.0	-
22	Reset	-	False
23	Resume	-	False
24	Training time	-	500
25	Validation set size	-	0
26	Validation threshold	-	20

Validation of these two models was also carried out on both training and validating datasets using various statistical methods (R, RMSE, and MAE), and the results are shown in Figure 4, Figure 5 and Table 3. Figure 4 a,b shows the R values of RT and ANN models using training dataset. It shows that the R value of RT (0.894) is higher than that of ANN (0.762). Figure 4 c,d shows the R values of RT and ANN models using validating dataset. It shows that the R value of RT (0.850) is higher than that of ANN (0.730). Figure 5 shows the plots of predicted and actual values of the vertical deflection of bridges using two models. It can be seen that on both training and validating datasets the predicted values are much close to the actual values. With RMSE, it can be observed from Table 3 that the RMSE value of RT (1.4) is much lower than that of ANN (2.492) in the case of training dataset. Table 3 also shows that the MAE value of RT (0.769) is much lower than that of ANN (2.01) in the case of training dataset. Similarly, the MAE value of RT (1.46) is lower than that of ANN (1.992) in the case of validating dataset. Analysis of Taylor diagram shows that RT is the nearest point to the reference line compared with ANN for both training and testing datasets (Figure 6).

Generally, both RT and ANN models performed well for prediction of the load–deflection of steel-concrete composite bridges in this study but RT outperforms ANN.

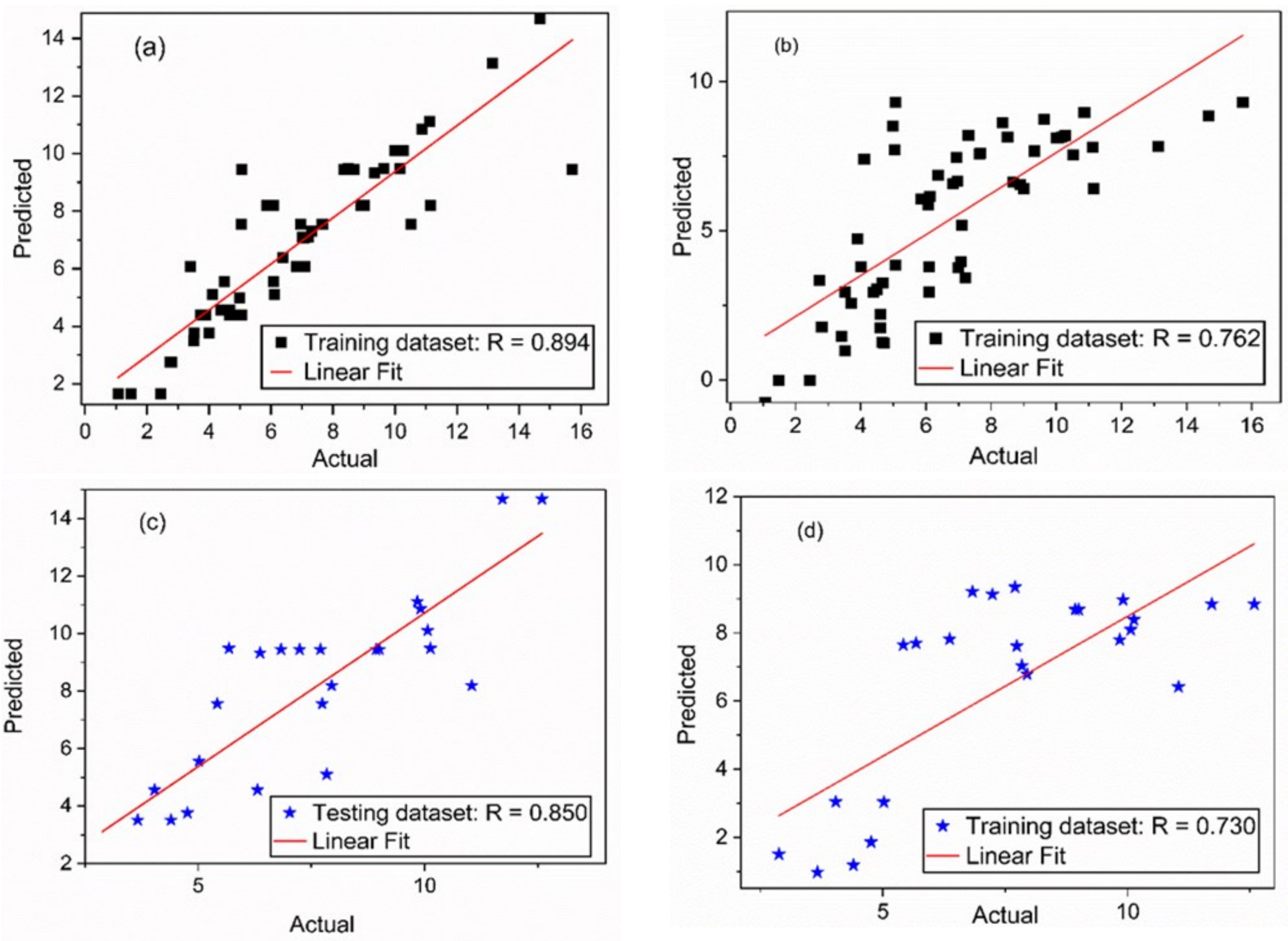
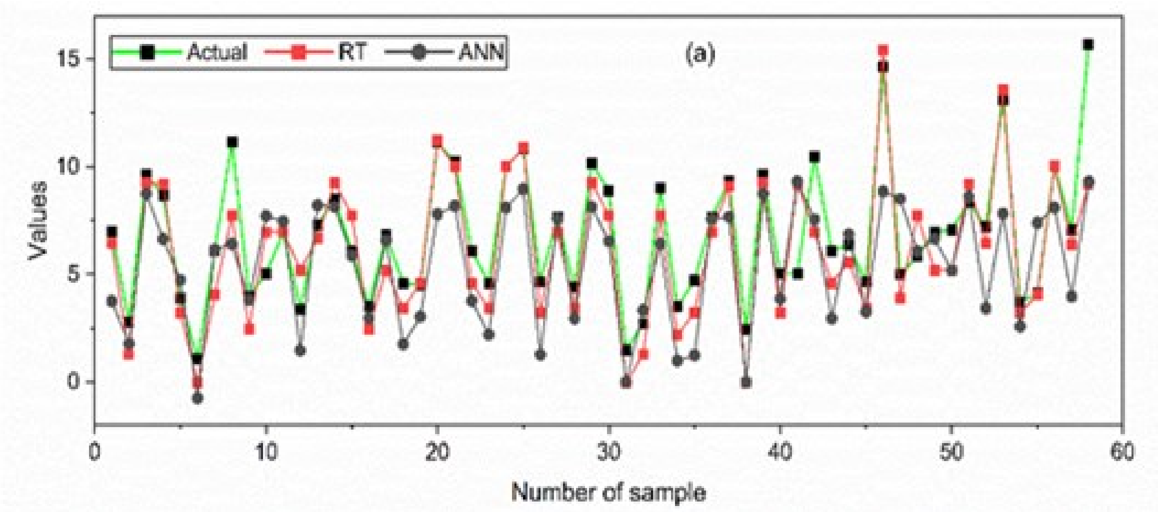


Figure 4. R values of the models: (a) training RT, (b) training ANN, (c) testing RT, and (d) testing ANN



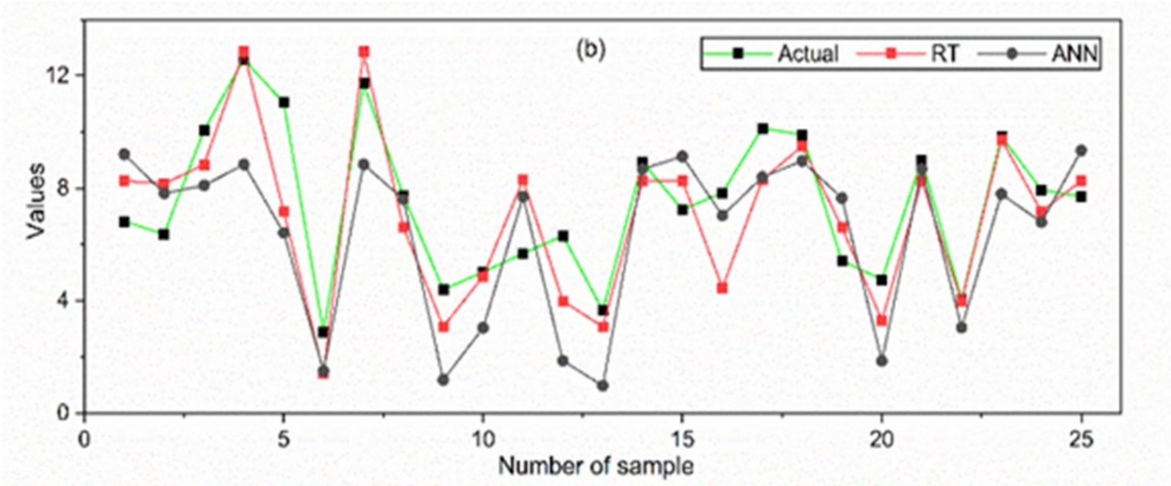


Figure 5. Actual and predicted values of the models (a) training dataset and (b) testing dataset

Table 3. Evaluation of the models

No	Parameter	Training dataset			Testing dataset		
		R	MAE	RMSE	R	MAE	RMSE
1	RT	0.894	0.769	1.40	0.85	1.46	1.808
2	ANN	0.762	0.201	2.492	0.73	1.992	2.321

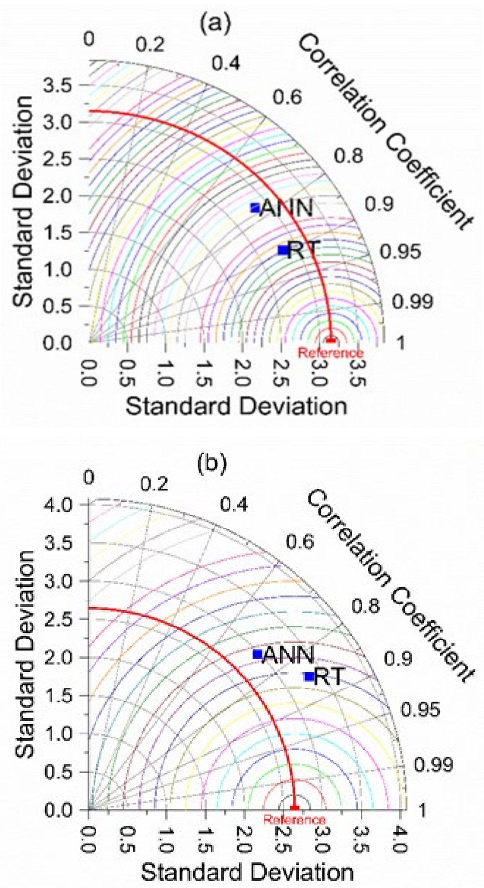


Figure 6. Evaluation of the models using Taylor Diagram

4. Conclusion

In this study, two state of the art ML models namely RT and ANN were applied and compared for prediction of the load–deflection of steel-concrete composite bridges using 83 track loading tests at 83 bridges of Vietnam with five input variables namely X1, X2, X3, X4, X5. Various validation methods namely R, RMSE, and MAE were selected for evaluation and comparison of the performance of the models. Results showed that both RT and ANN performed well for prediction of the load–deflection of steel-concrete composite bridges but RT has a better performance compared with ANN. Thus, it can be concluded that RT is a powerful tool in prediction of the load–deflection of steel-concrete bridges. Finding of this study might help the bridge engineers in quick and accurate prediction of the load–deflection of steel-concrete bridges which will help in saving time and costs for bridge health monitoring and assessment. The limitations of this study primarily stem from the restricted number of tests utilized in the data set. The scope for enhancing the accuracy and reliability of the predictions could be broadened by increasing the number of tests. Furthermore, future research could explore the application of more advanced machine learning models, such as deep learning or hybrid/ensemble ML techniques, to potentially improve the predictive performance.

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Data Availability Statement

The data, models, or code that substantiate the conclusions of this study are available upon a reasonable request directed to the corresponding author. This may include all or part of the mentioned resources.

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