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Prediction of Static Critical Wind Speed of Centrally-Slotted Box Deck Bridge Using Artificial Neural Network

Mohammed Elhassan [1,2], Le-Dong Zhu [1,2], Wael Alhaddad [3], Zhongxu Tan [1,2]

[1] *Department of Bridge Engineering, College of Civil Engineering, Tongji University, Shanghai, China, moh.nimir777@gmail.com*

[2] *State Key Laboratory of Disaster Reduction in Civil Engineering, Tongji University, Shanghai, China*

[3] *Department of Structural Engineering, Tongji University, Shanghai, China*

SUMMARY

The traditional methods of wind tunnel test and numerical simulation to study wind-induced static instability response of long-span bridges can be costly and time-consuming, especially in the preliminary design stage. Machine learning algorithms can be used for fast and reliable assessment of wind-induced static stability to avoid the time and cost associated with traditional methods. In this paper, Artificial Neural Network (ANN) model was developed and optimized based on the dataset set obtained from wind tunnel study during aerodynamic shape optimization to predict the static critical wind speed (U_{cr}) of centrally-slotted box deck section. A parametric study was also conducted to confirm the credibility of the developed ANN model in representing the relationship between the inputs and the output parameters. The results show that the proposed model can accurately predict the static critical wind speed U_{cr}, and can be used at the preliminary design stage to reduce the time, cost, and the total number of wind tunnel tests. The parametric study showed that the wind angle, *a/b,* and *h/H* have the greatest influence on the U_{cr} value compared with the other parameters.

Keywords: Centrally-Slotted Box Deck, Static Critical Wind Speed, Artificial Neural Network.

1. INTRODUCTION

Over the last decades, with the application of new materials and the progress of construction technology, the span length of modern bridges has considerably increased. Modern long-span cable-supported bridges with a main span of 1500 -3500 meters become more susceptible to strong wind. Wind-induced static instability and aeroelastic instability are considered critical factors that control the construction and design of long-span bridges.

Recent studies and wind tunnel experiment results showed that wind-induced static instability of long-span bridges might occur, which can cause bridge to overturn abruptly without any back-and-forth oscillation (Hu and Jiang, 2019); thus, it's much more dangerous to bridges than flutter and should be completely avoided or should happen later than flutter. Therefore, both wind-induced static and dynamic instability must be considered while optimizing the aerodynamic shape of such long-span bridges.

In recent years, the rapid development of Machine Learning (ML) algorithms and its technique provides a promising tool that can be used to help solve these problems (Wu and Snaiki, 2022). A combination of ML models based on data sets obtained via limited wind tunnel tests or CFD simulations can efficiently reduce the workload of aerodynamic shape optimization.

In this connection, the main purpose of the present work is to develop machine learning model to predict the static critical wind speed of centrally-slotted box deck section of a cable-stayed bridge (Figure1) using Artificial Neural Network (ANN) model and investigate the effect of each shape parameters on static critical wind speed.

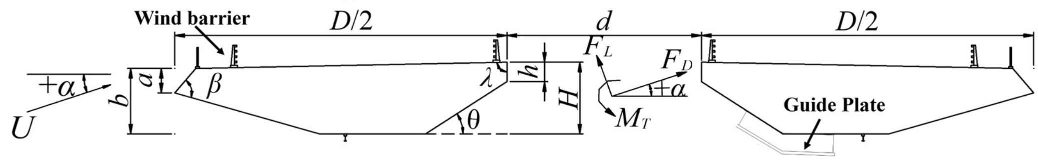


Figure 1. The schematic diagram for centrally-slotted box deck and typical shape parameters.

2. DESCRIPTION OF A GENERAL PREDICTION FRAME AND ANN MODEL

Figure 2 shows the overall framework of the proposed approach for U_{cr} prediction and the parametric study. The data was collected from the wind tunnel study and numerical simulation (Zhu and Zhu,2022), where it contains 100 datasets with 10 features adopted as input parameters, while the static critical wind speed U_{cr} was considered as the output parameter. Figure 3(a) illustrates the distributions of the dataset and the pairwise relationship of input parameters and outputs where the dataset distributions showed that presented input parameters are highly correlated with the U_{cr} (due to the space limitation, only five input parameters and the output parameter histograms were shown). In addition, descriptive statistical analysis was also conducted to evaluate the data, as shown in table1.

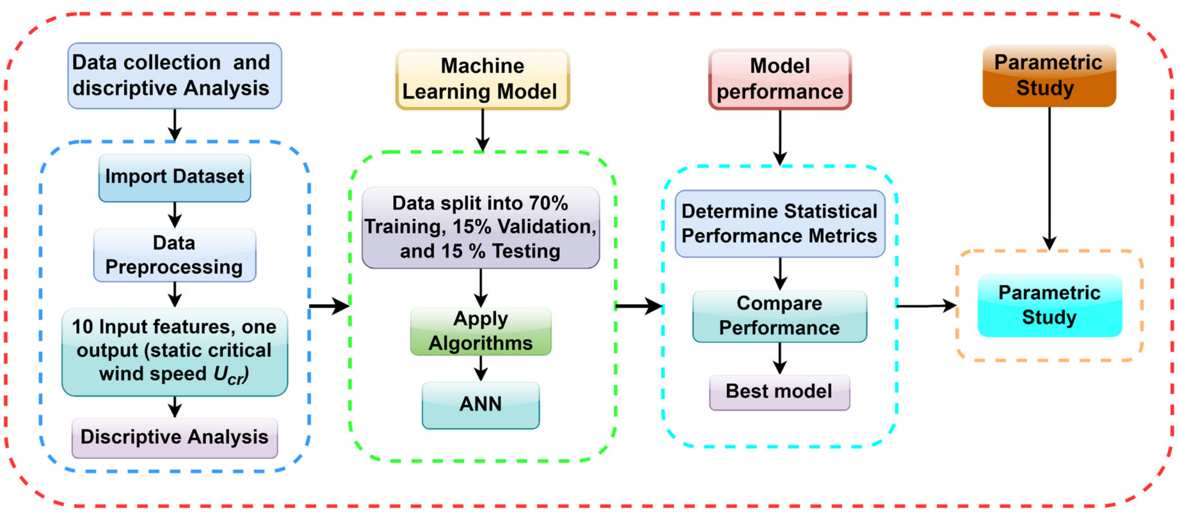
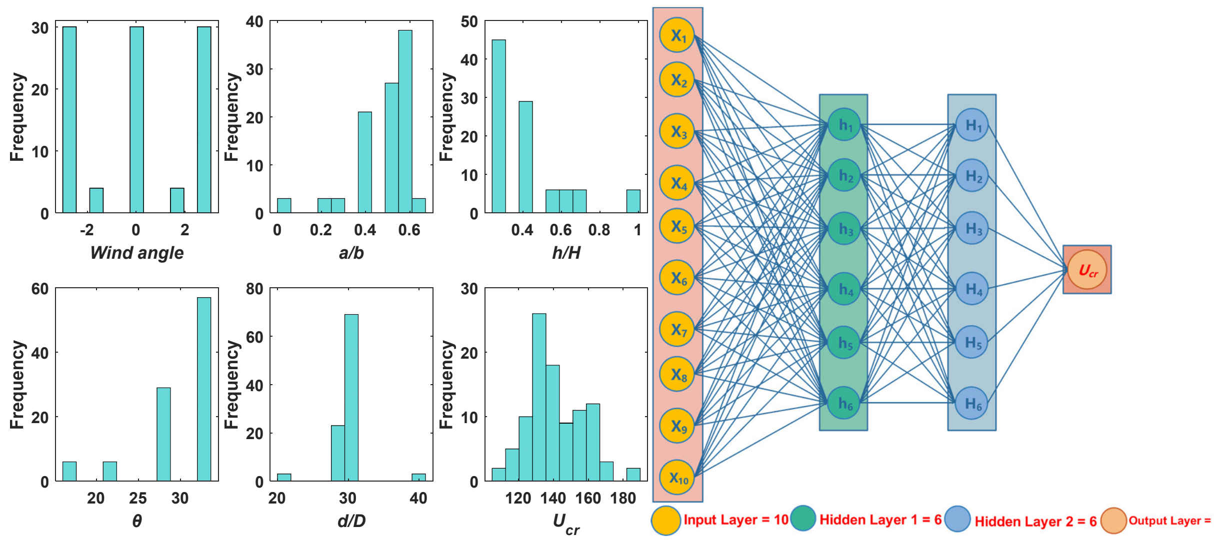


Figure 2. The Overall framework of the proposed approach.

The ANN topology is illustrated in Figure 3 (b), where the multilayer feed-forward ANN is employed. The network consists of input, output, and two hidden layers. The identity function was utilized as an activation function in the neurons of the input and output layers, while the hyperbolic tangent sigmoid function was used in the neurons of the hidden layer. The Levenberg-Marquardt Backpropagation Learning technique was used as an optimization tool to update weight and bias values and train the network, while Root Mean Square Error (*RMSE*) was used as the cost function (weights) to update the explicit parameters. The data set was divided into 10 folds (k=10) using the k-fold cross-validation method, with Training (*Tr*), validation (*Val*), and testing (*Ts*) ratios of 70%, 15%, and 15%, respectively. In order to optimize the number of neurons in the hidden layer (hyperparameters), several ANN models for aerodynamic force coefficients are generated with different numbers of neurons in the hidden layer (from 1 to 30). Four different error indices, *RMSE*, Man Absolute Error (*MAE*), Mean Absolute Percentage Error (*MAPE*), and Coefficient of Determination (R^2), were used to assess each model, then the optimized model was selected.



(a) (b)

Figure 3. (a) Distributions of the dataset and the pairwise relationship of input parameters and the output. (b) The architecture of the adopted network.

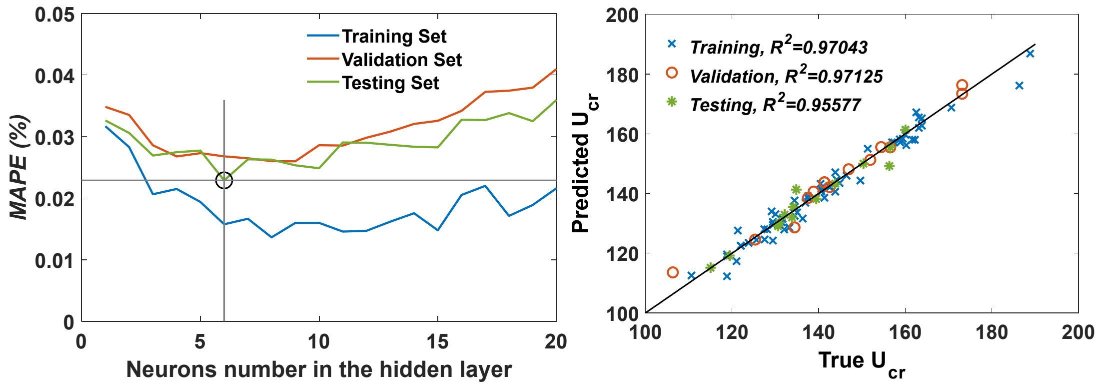
Table 1. Parameters of the centrally-slotted box deck

Parameters	Mean	Min	Max	Standard Deviation
$\alpha°$	0.0°	-3°	3°	2.398
a/b	0.483	0	0.67	0.138
h/H	0.418	0.27	1	0.198
$\theta°$	29.806°	16°	33°	4.746
d/D	29.731	20	40	2.536
Wind barrier/H	0.134	0	0.569	0.242
Guide plate length/H	0.250	0	1.067	0.454
Length of main span(m)	1400.	1300	1600	54.659
Vertical bending frequency (HZ)	0.152	0.13	0.164	0.006
Torsion frequency (HZ)	0.385	0.299	0.398	0.029

3. RESULTS AND DISCUSSION

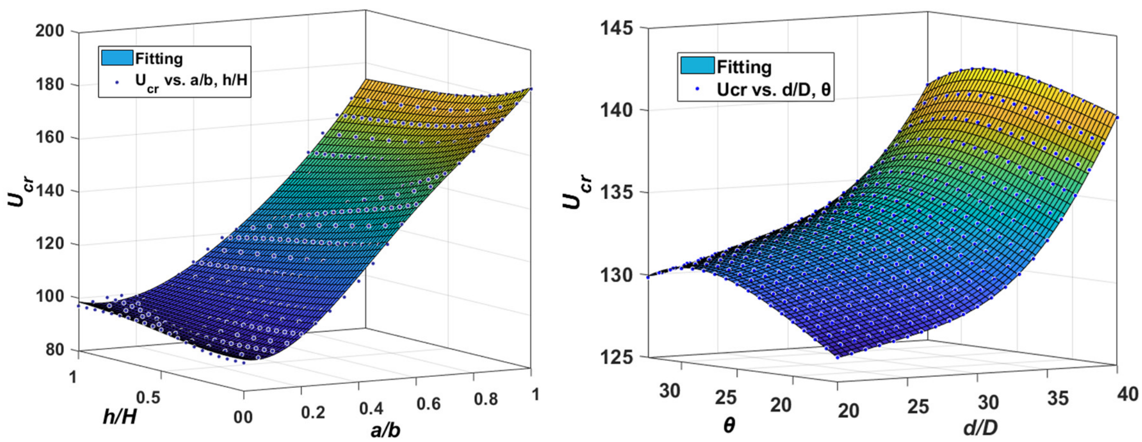
Figure 4 (a) shows *MAPE* metric for the built ANN model with the number of neurons equal to 6 because it gives a higher performance for predicting the static critical wind speed. Figure 4 (b) shows the regression for the built ANN model, where the results accuracy reaches approximately 0.97, 0.97, and 0.96 for the Training, validation, and testing sets, respectively, which proof the accuracy of the model. Parametric study was also conducted, where a reference section was selected from the dataset, each time only the parameter under investigation will change while the other parameters kept unchanged (including the wind barrier and guide plate) (Figure 5). The results show that wind angle, *a/b*, and *h/H* have the greatest influence on the U_{cr}.

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\frac{|\hat{y}_i - y_i|}{y_1} \tag{1}$$



(a) (b)

Figure 4. (a)The quality of the developed models in terms of *MAPE* (b) Regression plot of the optimum ANN model for selected Training, validation, and testing sets for U_{cr}.



(a) (b)

Figure 5. The effect of shape parameters on static critical wind speed (a) (a/b &h/H), $\alpha=3^0$, $\theta=28^0$, d/D=28.8, length=1400m. (b) (d/D& θ^0), α=3°, a/b=0.56, h/H=0.40, length=1400m.

4.CONCLUSIONS

In this paper, ANN model was built based on dataset set obtained from wind tunnel study to predict the critical static wind speed U_{cr} of long-span bridge. The results shown that the built model can accurately predict the critical wind speed, and thus, can be used at the design stage for a fast and reliable assessment of the wind-induced static instability. The influence of shape parameters on static critical wind speed was also investigated and the result showed that wind angle, a/b, and h/H have the highest influence on the U_{cr}.

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