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CFD-enabled prediction of aerodynamic coefficients for long-span bridges using machine learning

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Abstract

Long-span bridges are very vulnerable to wind-induced vibrations. Amid wind-induced excitation on long-span bridges, flutter was the most dangerous after the well-known old Tacoma Narrow Bridge (TNB) collapsed in 1940. Currently, the aerodynamic performance of the long-span bridges can be appreciated after conducting the experimental wind tunnel tests or by the mean of computational fluid dynamics (CFD) simulations. However, the traditional wind tunnel tests or CFD are thought to be very cumbersome and costly, especially when there are many design samples to evaluate. This study proposed predicting the aerodynamic coefficients (drag, lift, and moment coefficients) of a streamlined bridge subjected to shape modifications using machine learning approaches based on the CFD simulations dataset. Six machine learning pipelines, including gradient boosting regression(GBR), random forest regression (RFR), Bayesian ridge(BR), AdaBoost Regression (AdaBoost), decision tree regression (DTR), light gradient boosting machine(lightgbm), were built. The results showed that the GBR exhibited the best predictive performance on the drag coefficients, whereas the lightgbm algorithm performed well in predicting the lift and moment coefficients. This study is essential to help bridge designers to make a fast decision at the earlier design stage of modern long-span bridges to meet the increasingly rapid requirement of such mega-structures. This study can also help reduce the number of models to be tested based on preliminary information obtained from the ML models before any in-depth study.

Keywords: long-span bridge, wind-resistant design, flutter, CFD, machine learning, accuracy.

1 Introduction

For super long-span cable-supported bridges, aerodynamic stabilization preventing catastrophic flutter is essential. Researchers have proven that the configuration of the bridge deck shape can remarkably influence the aerodynamic performance and significantly increase the flutter velocity of long-span bridges [1].

Until now, the aerodynamic performance of such flexible and slender structures can be assessed using an experimental wind tunnel test or computational fluid dynamics (CFD). Unfortunately, both wind tunnel tests and CFD simulations are very costly and time-consuming, making the evaluation of such structures challenging, especially when many cross-section designs need to be tested. Researchers have proposed artificial intelligence (AI) to accommodate this weakness, including machine learning and deep learning models [2–5].

Applying AI methods to solve the wind-resistant issue is gaining momentum day by day. Scholars have recently conducted a series of research work to understand better the aerodynamic behavior of long-span bridges [6,7]. For instance, Rizzo and co-author, Liao and co-authors, and Abbas and co-authors have proposed machine learning algorithms (artificial neural network, support vector machine, random forest, gradient boosting) to predict the flutter velocity as well as the nonlinear aeroelastic forces of the long-span bridge subjected to wind excitation[2–4] with reasonable accuracy. To the author's knowledge, no works have predicted the aerodynamic coefficients of the bridge deck where all design parameters were involved in the prediction process. This study proposed to use machine learning pipelines to forecast the aerodynamic coefficients of the streamlined bridge deck subjected to shape variations.

Firstly a series of 2D-URANS (Unsteady Reynolds average Navier-Stokes) CFD simulations were conducted on 73 sample points at three wind angles of attack (*AoA*). The force coefficients obtained from the CFD simulations and the bridge deck design parameters constitute the data used to train the machine learning algorithms. Meanwhile, a correlations study was performed to identify the most influential design parameters on the targets. Finally, the accuracy of the proposed machine learning algorithms was verified and compared using different performance metrics.

2 Problem formulation

2.1 General flowchart of this study

As alluded to earlier, the present study can be divided into several subgroups. Firstly, we generated the design of experiments (DoE) by varying the shape of the bridge deck cross-section. Thereafter, a series of 2D-URANS (Unsteady Reynolds-averaged Navier-Stokes) CFD simulations was performed on each DoE previously generated to compute the aerodynamic coefficients. The whole process, from geometry to computations, was set up during the CFD simulations in a manner to limit human intervention during simulations. In this case, the same CFD settings were adopted to simulate the entire DoE (meshing and simulation setup).

Error and uncertainties are unavoidable in CFD simulation. In the same vein, a rigorous validation approach was adopted to quantify the degree of confidence of the simulation results through comprehensive wind tunnel tests, as discussed in the literature [8]. However, validation results are not addressed in the present study. Additionally, a descriptive statistical analysis was performed on the dataset of interest to extract basic trend information. Moreover, we conducted a correlation study between features and targets to assess the relationship between each design parameter and the simulation results (force coefficients). Furthermore, six machine learning models were introduced to predict the force coefficients based on the CFD dataset previously generated. Finally, the machine learning models were introduced to predict the force coefficients using the design parameters as inputs variables, and their performance was also compared. Figure 1 depicts the entire workflow adopted in the present study.

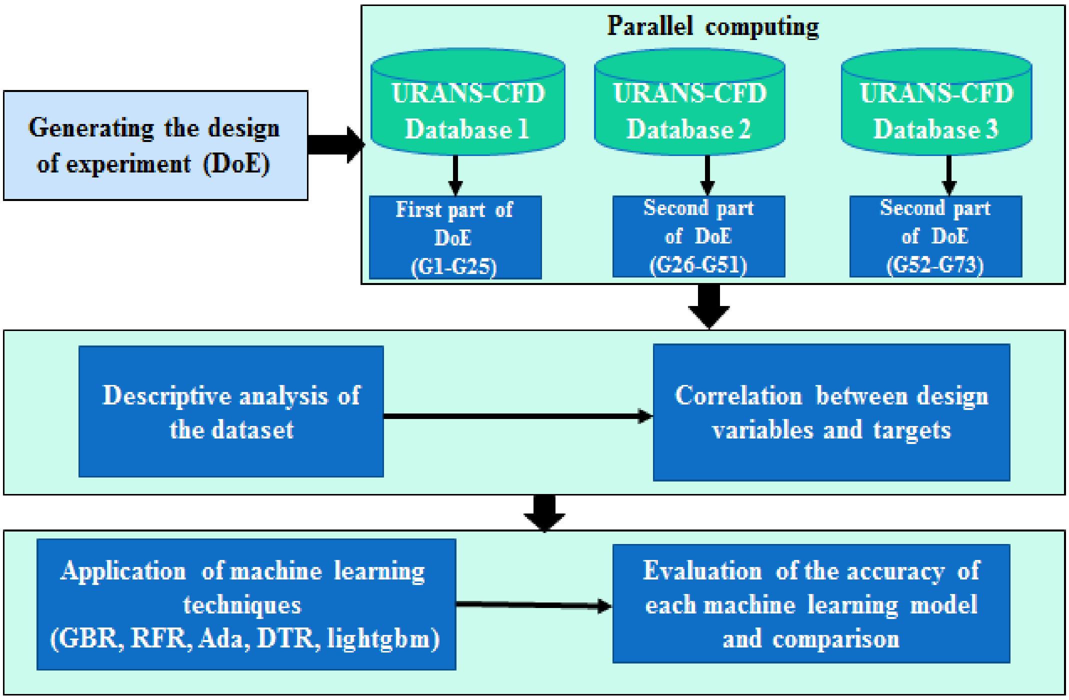


Figure 1 General workflow adopted in the present study

2.2 Description of the dataset

This section is devoted to the descriptive analysis of the whole dataset involved in the present study, including the inputs and the outputs. It consists of the basic understanding of the dataset used to construct all machine learning models involved in the present study. Figure 2 depicts the streamlined bridge deck under consideration and the shape configurations.

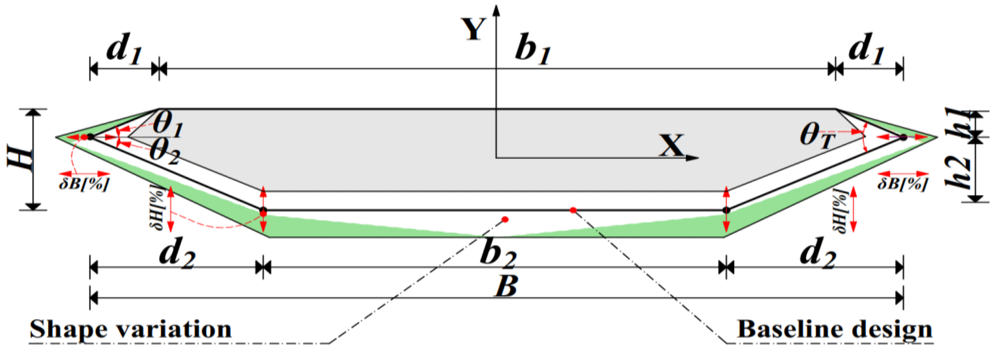


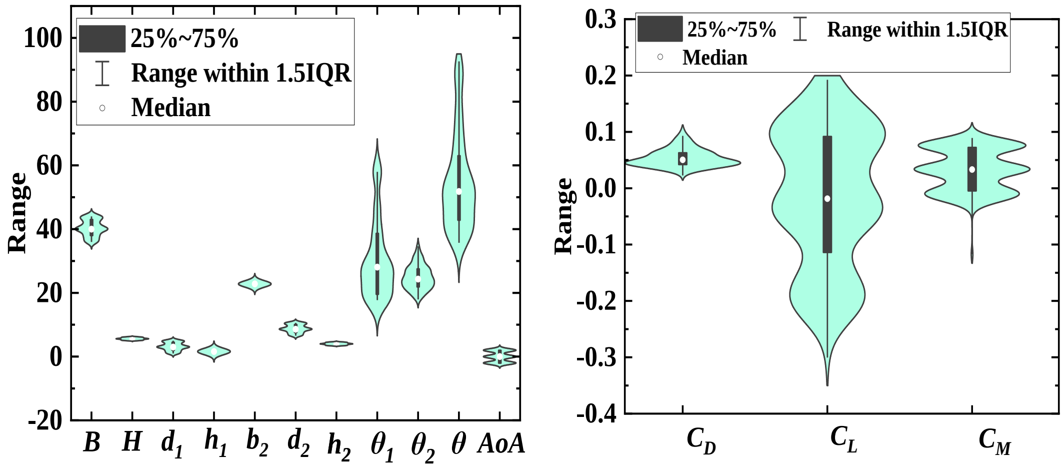
Figure 2 Streamlined bridge deck cross-section and shape modifications in the design space

The violin plots presented in Figure 3(a) are the basic statistical characteristic of the inputs variables or features and the targets involved in this study. The violin plots indicate many pieces of information such as the mean of variables, the median of each variable, the minimum, the maximum of the variables, the range of the variables, the interquartile interval(IQR), first and the third quartile corresponding to 25% and 75%. These characteristics are clearly indicated in the legend of the plots. In the present study, the variable B varied between 36 and 44, and the variable H is situated between 5.04 and 6.27. Whereas the variables h_2, and d_2 are ranging from 3.44 to 4.67, 1 to 5, and 6.6 to 10.6, respectively.

Moreover, the lower fairing angle θ_1, the upper angle θ_2, as well as the total fairing angle θ range from 17.74 to 57.99, 17.98 to 34.64, and 35.72 to 92.63, respectively. The design variable h_1 was not represented since this variable is fixed for all design points. Note that the total number of observations is 219.

As shown in Figure 3(b), the drag coefficients have positive values for all observations, and the range can be estimated between 0.022 and 0.105. In contrast, both lift and moment coefficients can be negative or positive. Lift and moment coefficients for all observations range from -0.030 to 0.192 and from -0.117 to 0.089, respectively. Additionally, the largest quantity of the observations of the drag coefficients occurred at around 0.050, while the largest portion of observations of the lift and the moment coefficients occurred at -0.018 and 0.033, respectively.

Furthermore, the following conclusion can be drawn by comparing the violin plots in Figure 3(b) of the target variables. Firstly, the dataset of the drag coefficient has one mode, whereas the observations of the lift coefficients and moment coefficients have three modes. Secondly, this information could be indices that the observations of the lift and moments coefficients have three subpopulations: one subpopulation corresponding to each of the three angles of the attack involved in the computations of the two targets variables. Additionally, despite the slight difference, identic and unique mode observed in the drag coefficients dataset, there is a set of separation in the mode. That indicates that the drag coefficients may not be very sensitive to a slight change in the angle of the attack (*AoA*). Finally, it is clear that the dataset of the drag coefficient is uniform as opposed to those of the lift and moment coefficients, which are tri-modal.



(a) Input variables (b) Output variables

Figure 3 Violin plots indicating the range of the inputs and outputs variables.

3 Correlation and sensitivity between features and targets

A statistic correlation study was conducted on the dataset based on the Spearman correlation coefficient. The Spearman correlation indicates the nonlinear relationship between two variables (Independent and dependent). The Spearman correlation coefficient can be computed using the following equation (Eq. 1).

$$r_s = 1 - \frac{6\sum_{i=1}^{n} d_i^2}{n(n-1)} \tag{1}$$

Where d_i is the difference in ordering between x and y.

Similar to correlation, a sensitivity analysis belongs to a method that reveals the extent to which output responses from a simulation model depend on each input variable to that simulation model. Sensitivity analysis gives information on where physical experiments should be conducted, what physics or engineering refinements are needed to be predictive, how a simulation should be improved to be helpful, and which inputs are essential to estimate output accurately.

Figure 4 presents the Spearman correlation between design variables and targets. The results show that all variables are correlated to the targets to certain extents. It was observed that the wind angle of attack influenced the correlation between the design variables and the targets. Additionally, the fairing angle of the bridge deck exhibited the highest correlation with the target variables regardless of the wind angle of attack. It is worth mentioning that the closest the correlation coefficient is to +1 (respectively -1), the stronger the relationship between the variables, and the negative sign refers to a dissimilar relationship, while zero (0) means there is no correlation between variables.

Finally, the correlations matrices showed that each variable (dependent or independent) is perfectly correlated to itself. It is essential to mention that the same observations (results) are obtained, whether it is correlation analysis or sensitivity analysis. Meanwhile, the discussions on sensitivity results remain the same as those of correlations.

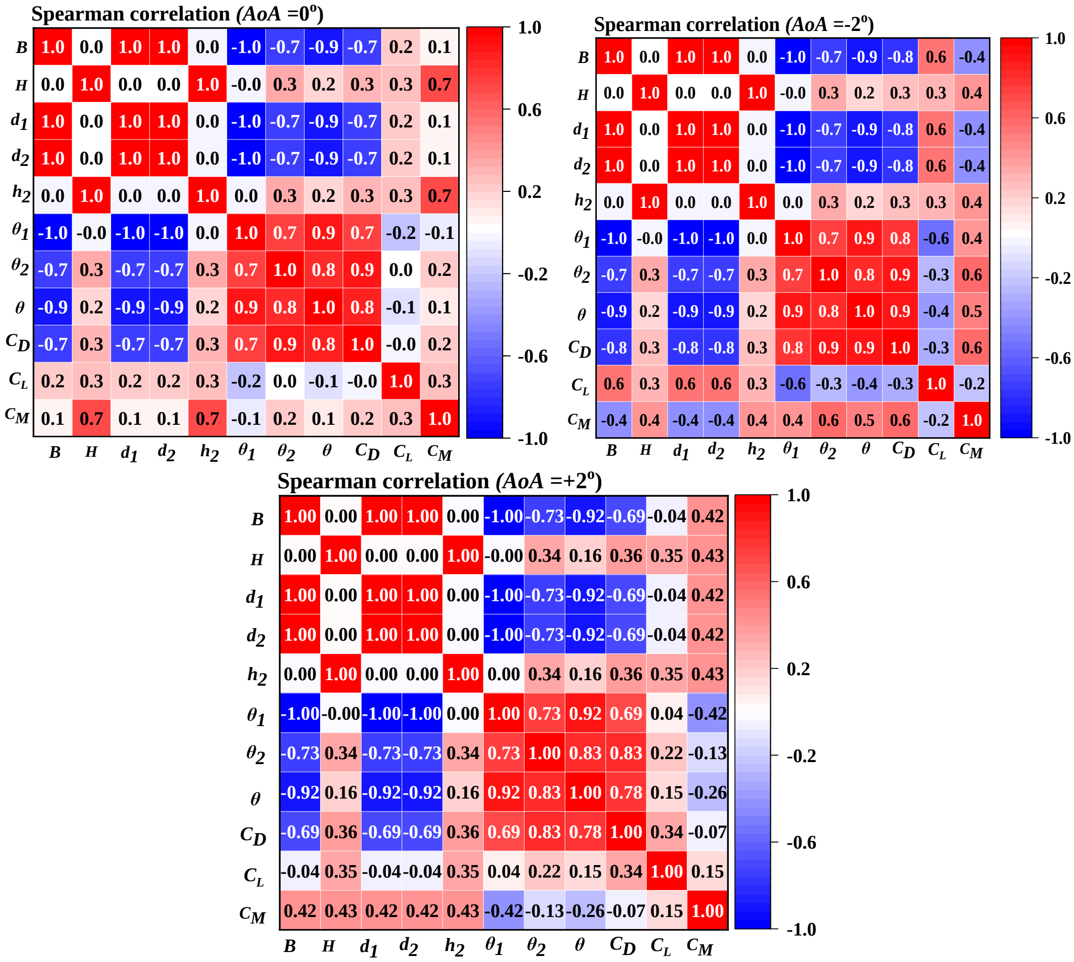


Figure 4 Correlations between design variables and the force coefficients computed from CFD simulations at three different angles of attack.

4 Application of the machine learning algorithms and discussions

The dataset was split into the training set and the test set where each model was deployed on the training dataset, which represented 80% (175 observations) of the total observations, and the remaining 20% (44 observations) represented the test used to assess the degree of accuracy of the model of interest.

After the training process, the results indicated that the light gradient boosting machine (lightgbm) model exhibited the highest accuracy based on the coefficient of determination R-squared metric for both lift and moment coefficients (See Table 1). The predicted accuracy was 96.7% and 96.3% for lift and moment coefficient, respectively. At the same time, the best prediction performance is obtained with the gradient boosting regression (GBR) for the drag coefficient with R-squared equal to 97.8%. Note that only the algorithm that gave the best accuracy is reported in this paper for brevity. Meanwhile, the k cross-validation (k=10) resampling technique was adopted to circumvent the overfitting problem during the machine learning training process. Then, the final performance metrics used to compare the model performance are the average values obtained for the ten iterations of the 10-cross-validation.

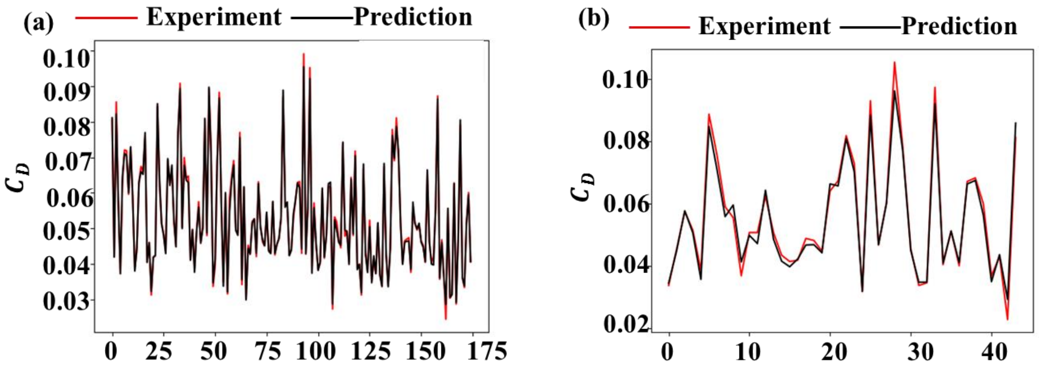


Figure 5 Comparison between the target and prediction of the drag coefficient using gradient boosting regression: (a) Training set, and (b) Test set

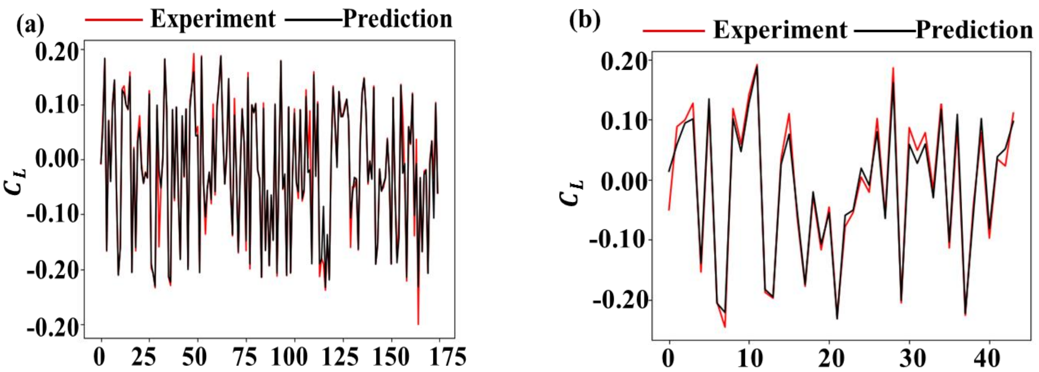


Figure 6 Comparison between the target and prediction of the lift coefficient using lightgbm (a) Training set, and (b) Test set

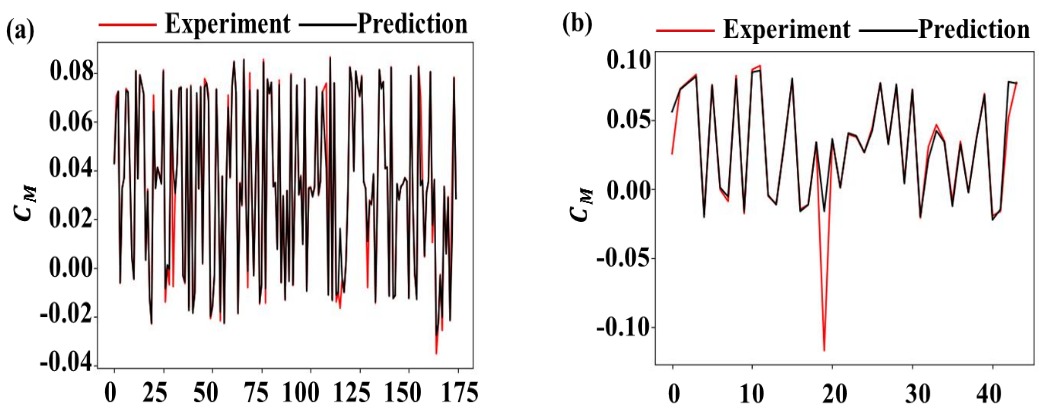


Figure 7 Comparison between the target and prediction of the moment coefficient using lightgbm: (a) Training set, and (b) Test set

Figures 5, 6, and 7 show the comparison between the target and the prediction of the force coefficients for the machine learning models that exhibited the best predictive performance.

On the other hand, the performance metrics used to assess the accuracy of the machine learning models involved in this study are summarized in Table 1. Although different performance metrics assessments were used to check the accuracy of the machine learning models built in the present study, only the coefficient of determination (R^2) was used to compare the models.

Force coefficients	ML models	Mean squared error (MSE)	Mean absolute error (MAE)	R-squared (R^2)
C_D	GBR	0.831e-05	2.104e-03	97.84
	lightgbm	2.800e-05	4.100e-03	91.80
	RFR	2.000e-04	1.105e-02	88.82
	BR	2.100e-03	3.100e-03	94.88
	AdaBoost	2.600e-03	3.300e-03	94.55
	DTR	2.500e-03	1.800e-03	96.16
C_L	GBR	2.400e-03	4.360e-03	83.09
	lightgbm	4.787e-04	9.478e-03	96.70
	RFR	2.200e-04	4.170e-02	84.96
	BR	3.600e-03	5.770e-02	74.98
	AdaBoost	4.100e-03	6.160e-02	72.31
	DTR	3.400e-03	5.140e-02	77.56
C_M	GBR	4.100e-03	7.400e-03	72.60
	lightgbm	4.546e-05	2.063e-03	96.30
	RFR	6.400e-03	1.460e-02	80.28
	BR	0.300e-03	7.300e-02	83.95
	AdaBoost	0.500e-03	1.220e-032	67.83
	DTR	0.400e-03	1.780e-02	70.29

Table 1 Performance metrics of the test set for the entire machine learning models involved in the present study

5 Conclusions and Contributions

This article proposed machine learning pipelines to predict the force coefficients of a streamlined bridge deck with shape variation. The study used six machine learning techniques such as gradient boosting regression (GBR), random forest regression (RFR), Bayesian ridge (BR), AdaBoost Regression (Ada), and decision tree regression (DTR), light gradient boosting machine (lightgbm). The results showed that the GBR exhibited the best predictive performance on the drag coefficients, whereas the lightgbm algorithm performed well in predicting the lift and moment coefficients. The findings substantiate that the machine learning algorithm can accurately predict the aerodynamic coefficients of the bridge deck, hence avoiding the cost of traditional wind tunnel tests or the computational cost of CFD simulations. The proposed machine learning is a cost-effective alternative to make rapid decisions during the design of long-span bridges before any in-depth studies. The proposed models will help satisfy the increasingly growing requirements in an aerodynamic design of modern long-span bridges.

Acknowledgments

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