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Flutter derivatives identification of closed box girders based on gradient boosting decision tree

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SUMMARY:
Flutter derivatives (FDs) of bridge deck are basic aerodynamic parameters for flutter stability analysis. A bridge wind resistance performance database has been built based on the existing wind tunnel testing results. In combination with some other collected numerical simulation data, the machine learning models for identifying FDs of closed box girders are developed via gradient boosting decision tree (GBDT) in two data-driven patterns. The machine learning models can explore the underlying input-output transfer relationship of dataset. Through the intelligent identification and sensitivity analysis of FDs, as well as the two-dimensional flutter performance analysis, the flutter performance of closed box girder can be further analysed. The prediction error of flutter critical velocity (FCV) under different models is analysed. In this way, the present research work can make the identification of FDs separated from tedious wind tunnel tests and complex numerical simulations to some extent. It can also provide a convenient and feasible option for expanding data sets of aerodynamic parameters and evaluating wind resistance performance preliminarily.

Keywords: flutter derivatives, flutter critical velocity, machine learning.

1. INTRODUCTION

Machine learning provides a novel solution for the intelligent identification and analysis of wind engineering. It has been successfully applied to the aerodynamic parameters identification and wind resistant performance analysis of bridges in past several years. The predicted FDs of cross-sections based on support vector machine (SVM) were used for estimation of flutter critical velocity (FCV) of cable stayed bridges (Lute et al., 2009). The ANN model was derived and trained using a dataset of FCVs, calculated using FDs from experiments and by varying geometrical and mechanical parameters (Rizzo and Caracoglia, 2020). Abbas et al. (2020) used the normalized lift force and torsional moment coefficients at current time step as the output of ANN to predict the aeroelastic response of bridge decks. Liao et al. (2021) proposed a machine learning strategy for flutter prediction based on four widely-used machine learning algorithms. Li et al. (2022) applied ANNs to establish the relationship between aerostatic coefficients and flutter performance for fast prediction of FCV. However, most of the existing research is a direct application of machine learning methods to a specific scenario in wind engineering, without illustrating the applicability of the algorithms and improving them accordingly. Besides, the existing machine learning applications are mostly to build a black box, lacking the interpretation and extension of the model.

In this study, the FDs are trained and predicted by gradient boosting decision tree (GBDT) based on wind tunnel test data and CFD numerical simulation results, and the distribution of FDs is analysed by the post-interpreter of model. According to different models and training results, combined with the predicted FDs and 2D 3DOF numerical simulation analysis, the error analysis of FCV is carried out, and the source of error is explained by the sensitivity analysis of FDs. In this way, the present research work can provide a convenient and feasible option for expanding data sets of FDs and evaluating flutter performance preliminarily.

2. GRADIENT BOOSTING DECISION TREE (GBDT)

In this paper, a hybrid model combining the gradient boosting decision tree (GBDT) and linear regression method is selected for the training of FDs after comparing various machine learning algorithms in previous study (Chen and Ge, 2019). The main idea of GBDT is to use weak classifiers (decision trees) to iteratively train input data before obtaining the optimal model. It accomplishes the task of classification by defining a logarithmic loss function for logistic regression.The minimum value of the loss function is:

$$C_{mj} = argmin \sum L(y_i, f_{m-1}(x_i) + c) \quad (x \in R_{mj}) \tag{1}$$

where the function L is a logarithmic loss function. x_i is the eigenvalue of the input, y_i is the output, and c is a constant. R_{mj} is the zone of the decision tree j domain and i, m, j are counting variables. Then the decision tree fitting function can be expressed as:

$$h_m(x) = \sum_{j=1}^{J} C_{mj} I(x) \quad (x \in R_{mj}) \tag{2}$$

where the function $I(x)$ is an indicator function that returns 0 when the equation in parentheses is false and 1 otherwise. J is the number of iterations. The updated boosting decision tree is the sum of the previously fitting decision trees and the latest fitting function:

$$f(x) = f_{m-1}(x) + h_m(x) \tag{3}$$

3. TRAINING, PREDICTION AND INTERPRETATION OF MODEL

3.1. Data set for machine learning

For machine learning modelling, it is necessary to establish a specialized data sample set of closed box girder, including the dimension of cross-section, wind attack angle, reduced wind velocity, FDs, etc. In this study, a specialized bridge wind resistance performance database has been built, which not only realizes the management, secondary utilization, and sharing of bridge wind tunnel test data, but also provides the necessary data foundation for subsequent machine learning. The wind tunnel test data of 20 long-span bridges with closed box girders are selected from this database. The specific involved parameters include the dimensions of cross-section (as shown in Fig. 1: width of deck-B, box height of beam-H, wind fairing extension length-b, wind fairing angle-α, inclined web slope-β) and the FDs under different reduced wind velocities.

Due to the small amount of data, good training results may not be obtained through wind tunnel test data with large fluctuation. The FDs of the above 20 sets of cross-sections are re-calculated by CFD numerical simulation based on the forced vibration method. The numerical calculation domain is a two-dimensional flow field. Pointwise is used for geometric rendering and mesh generation, and ANSYS Fluent is used for numerical simulation. In order to further improve the machine learning training effect, 20 sets of numerical simulation data of closed box girder from open-source literature are added as mixed datasets to jointly drive the training process of machine learning. Moreover, another 15 sets of closed box girders are designed to make the distribution of the whole sample set more reasonable, and these 15 sets of cross-sections are also calculated by CFD simulation. All the numerical simulation results are compared with the wind tunnel test results or Theodorsen theoretical solutions to check the validity of the data. These 55 sets of data are used as machine learning sample sets.

3.2. Training and prediction of FDs

3.2.1. Fitting accuracy of training set

In this paper, machine learning models are trained on several data patterns. The training effect of FDs based on wind tunnel test data (pattern 1) and numerical simulation data (pattern 2) is shown in Fig. 2. The evaluation index of the model fitting degree is R^2 statistic. R^2 takes a value between [0,1]. The larger the R^2, the better the model is. It can be seen from the Fig. 2 that the fitting degree of pattern 2 is significantly better than that of pattern 1.

3.2.2. Generalization ability of test set

Fig. 3 gives the prediction results for one of the cross-sections in the test set under two data patterns. It shows that the machine learning model is able to predict the distribution of FDs to a certain extent, but the prediction effect of pattern 2 is significantly better than that of pattern 1. The mean relative error (MRE) of models under pattern 2 is only 0.1520.

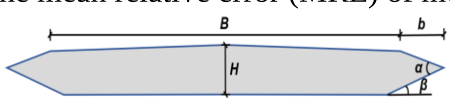

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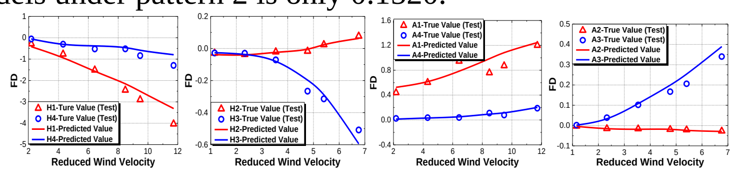
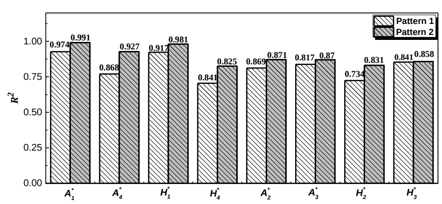
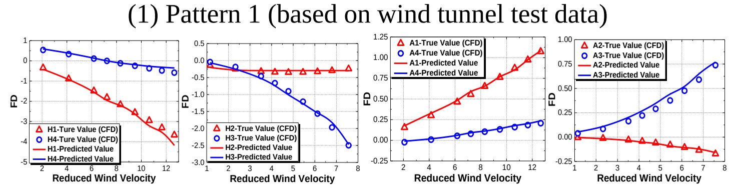
Figure 1. Schematic diagram of section



(1) Pattern 1 (based on wind tunnel test data)





(2) Pattern 2 (based on numerical simulation data)

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Figure 2. Fitting accuracy of training set.

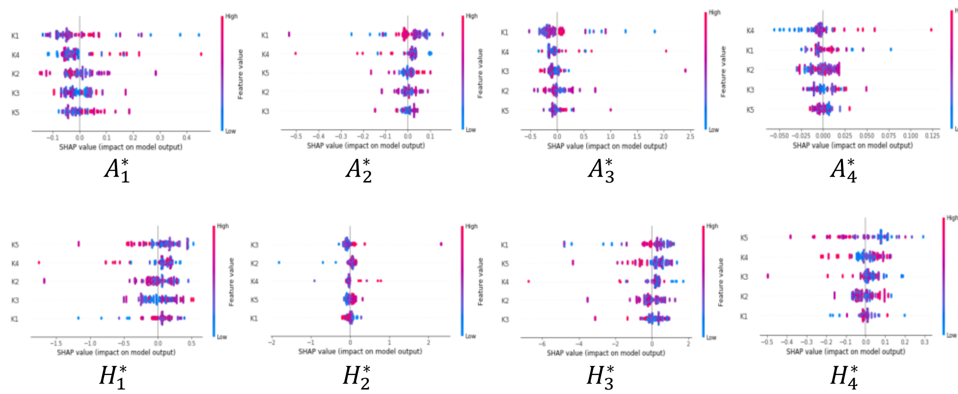
Figure 3. Generalization ability of test set.

3.3. Distribution analysis of flutter derivatives

The process of machine learning is often considered a "black box". In order to express the machine learning model in some explicit way, the Shapley additive explanation (SHAP) is applied here. SHAP is an additive model interpreter which focuses on calculating the SHAP values of each feature as a reflection of how much the feature contributes to the prediction of the model. Fig. 4 shows the SHAP values of several dimensions of the cross-section. (Note: K1, K2, K3, K4 and K5 represent the height of beam, width of deck, wind fairing extension length, wind fairing angle, and inclined web slope, respectively. They are ranked from top to bottom according to the effect magnitude on each FD.) For A_1^*~A_4^*, K1 has the greatest effect on them, and they have the same change direction as K1. It means A_1^*~A_4^* increase with the height of beam, but A_1^*~A_3^* are more likely to be positive and A_4^* is more likely to be negative. For H_1^*~H_4^*, the impact of K5 is large. Except that the situation of H_2^* is unclear, H_1^*, H_3^* and H_4^* all change in the opposite direction to K5 and it is more likely that they are all negative.

4. PARAMETER ANALYSIS OF FLUTTER PERFORMANCE

Several machine learning models were trained in this study and the FDs prediction results with different errors can be obtained by different trained models. These errors are ultimately reflected in the FCV calculation as shown in Fig. 5. When the prediction error of FDs can be reduced to less than 15%, the calculation result of FCV is very close to the true value and the calculation error is less than 2%. This is due to the fact that different FDs have a major and minor effect on the FCV. Fig. 6 shows which FDs have a major impact on FCV by changing the magnitude of the FD sequentially. The main factors affecting the FCV are A_1^*, A_2^*, A_3^* and H_3^*. The FCV decreases with the increase of A_1^*, A_3^* and H_3^* and increases with the increase of A_2^*. This conclusion is only applicable to the closed box girder section within a certain size range.



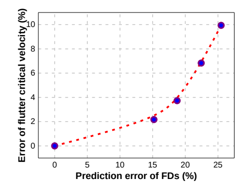


Figure 5. Error analysis.

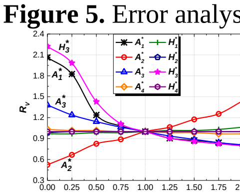


Figure 4. SHAP model explanation.

Figure 6. Sensitivity analysis.

5. CONCLUSIONS

In this paper, the flutter derivatives of closed box girders are identified by gradient boosting decision tree algorithm. The machine learning model is trained based on two data patterns. The data pattern based on numerical simulation is superior to the pattern based on wind tunnel test. The model interpretation after training is also realized to obtain the distribution characteristics of flutter derivatives. The error analysis shows that the machine learning prediction error of flutter derivatives will be weakened in the numerical calculation of flutter critical velocity. The source of error is further explained by flutter derivative sensitivity analysis.

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