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Explainable machine-learning-based prediction model for wind-induced interference factor of two neighboring high-rise buildings

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SUMMARY:
High-rise buildings are usually built in the urban center and are close to each other. The unfavorable interference effects may remarkably amplify their wind loads and dynamic responses. However, there is still a lack of reliable and accurate prediction models of interference factor (IF). To this end, machine-learning-based methods are adopted in this study to establish an accurate prediction model for the IF of two neighboring high buildings. 33150 interference cases considering different interfered locations, reduced wind speeds and damping ratios are used in this study. Four ensemble machine learning methods, such as random forest, adaptive boosting, gradient boosting regression tree, and extreme gradient boosting (XGB), are utilized to attain the best performance of the prediction model. The collected data are randomly assigned into the training and test sets, and the optimal hyper-parameters are found based on the grid search method combined with 10-fold cross-validation. It is found that the XGB model has the best predictive performance with the highest coefficient of determination and lowest mean square error estimate. Shapley additive explanation method is also adopted to explain the importance and contribution of the factors that influence the IF to avoid the "black-box" problem hidden in the machine-learning methods.

Keywords: Explainable machine learning; Wind-induced interference factor; High-rise building.

1. INTRODUCTION

Super high-rise buildings are often grouped in proximity in the metropolitan center. The mutual interference effects from adjacent buildings will inevitably magnify or suppress the aerodynamic forces and dynamic responses, which may lead to vortex-induced resonance or aerodynamic instabilities. Unfavorable interference effects would cause considerable threats to structural safety and occupant comfort. It is of great significance to understand the mutual interference effects of close-spaced high-rise buildings (Lo et al., 2020).

The wind tunnel test still is the primary approach to investigate the interference effects at present. In the past several decades, numerous scholars have adopted various methodologies to investigate potential parameters influencing the interference effects, including turbulence intensities, relative locations, cross-section shapes, and aspect ratios. Xie and Gu (2007) utilized the high-frequency force balance technique (HFFB) to study the base-bending interference effects of grouped high-rise buildings, and linear regression equations were proposed to estimate the IF. In addition, some scholars also proposed empirical equations for assessing the IF factors.

However, it should be emphasized that most equations are based on linear regression, while the complex and non-linear features of interference effects may not be revealed. Therefore, it is still desirably necessary to establish an accurate and reliable predictive model for IF.

ML techniques have superior ability to describe and interpret complex and non-linear features between inputs and outputs. Several pioneers have successfully applied ML techniques to predict wind pressures, across-wind loads and responses, and other aspects (Hu et al., 2020). To our knowledge, no previous studies have focused on predicting IF using ML-based models. In addition, the “black-box” problem exists in many ML-based predictive models, and the relationships between inputs and outputs remain unclear. To this end, this study focuses on the explainable ML-based predictive model for accurately predicting the IF of two neighboring high-rise buildings. SHAP (Shapley Additive exPlanations) is used to interpret the importance and contributions of influencing parameters in predicting the IF to avoid the “black-box” problem.

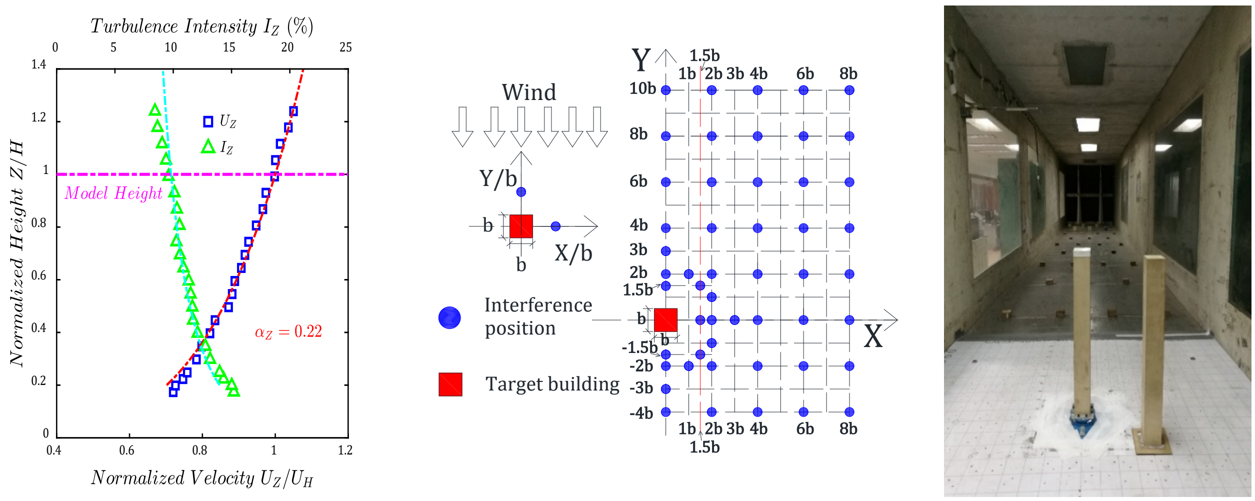
2. OVERVIEW OF MACHINE LEARNING MODELS

In this study, four typical ensemble machine learning methods, namely, random forest (RF), adaptive boosting (Adaboost), gradient boosting regression tree (GBRT), and extreme gradient boosting (XGB), are used to establish accurate prediction models (Lin et al., 2021). Ensemble methods combine the decisions of multiple weak learners to improve the overall predictive performance. According to the way of generation, the ensemble method can be clarified into two categories, parallel ensemble method (Bagging) and sequential ensemble method (Boosting). RF is a classical method of bagging. It consists of a large number of individual decision trees gathering in parallel as an ensemble. The final predictions are obtained by a deterministic averaging process of the ensemble. The basic idea of boosting methods is to generate a weak learner at each step and add it into the former ensemble. The residual is also fitted by the former ensemble and the generated weak learner to reduce the overall variance and bias. Adaboost, GBRT, and XGB belong to the classical boosting methods.

3. DATABASE CONSTRUCTION FOR INTERFERENCE FACTOR

3.1. Brief introduction of the wind tunnel test

Wind tunnel tests were conducted at the TJ-1 boundary layer wind tunnel at the State Key Laboratory of Disaster Reduction in Civil Engineering, Tongji University. Turbulent boundary layer flow corresponding to category C in the Chinese code was simulated, and the measured results showed good agreement. A square-section prism with sizes of 0.07 m in width and depth and 0.63 m in height was adopted as the principal building, and its aspect ratio was 9. The interfering building was identical to the principal building in order to simplify any interfering factor. HFFB was adopted in this study to obtain the aerodynamic forces from the principal building. The sampling frequency and time duration were set as 1000 Hz and 100 s, respectively. The measured wind speed atop the building height was about 8 m/s. The natural frequency of the model-balance system was 70 Hz, which is much higher than the concerned frequency range of aerodynamic forces and can be eliminated by the signal filter. Only the oncoming wind flow normal to the face of the principal building was considered, and a total of 51 interference positions were investigated. The simulated wind profiles, interference position configurations, and photograph of the wind tunnel test are given in Fig. 1.



(a) Simulated wind profiles (b) Interfered positions (c) Photographs

Figure 1. Experimental setup of wind tunnel tests.

3.2. Definition of interference factor

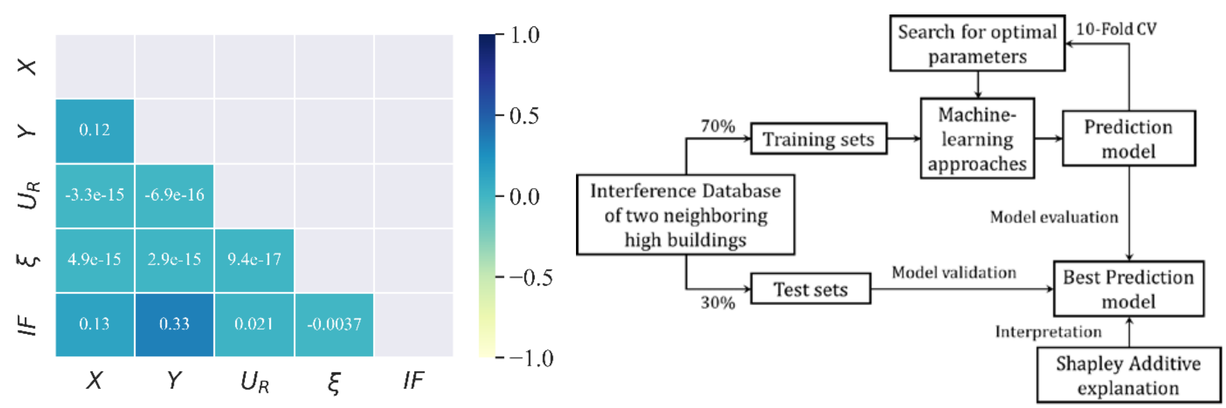
The dynamic interference factor is adopted as the IF in this study and is defined as follows:

$$IF = \frac{RMS\ across\text{–}wind\ acceleration\ response\ (interfering\ prism\ present)}{RMS\ across\text{–}wind\ acceleration\ response\ (isolated\ prism)} \tag{1}$$

Based on the measured across-wind aerodynamic forces of the principal building, the RMS across-wind acceleration responses of interfering cases and isolated case under different reduced wind speeds U_R (ranges from 3 to 15, with an increment of 0.5) and structural damping ratios ξ (ranges from 0.5% to 3%, with an increment of 0.1%) were calculated according to the random vibration theory (Chopra, 2007). The fundamental frequency was assumed as 0.1 Hz in prototype.

3.2. Selection of variables and implementation

The relative position (X and Y), U_R and ξ were selected as input variables. Fig. 2(a) shows the correlation coefficient matrix. No distinct correlations were observed between the variables. The whole implementations were operated by Python 3.9, and the calibration of hyperparameters was realized by the Scikit-learn platform. The flowchart of this study is shown in Fig.2(b).

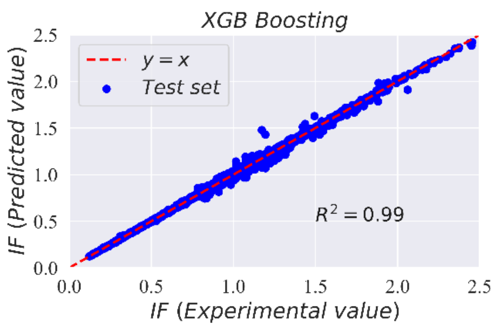


(a) Correlation matrix of input- and output-variables (b) Flowchart of the interpretable machine-learning-based prediction model.

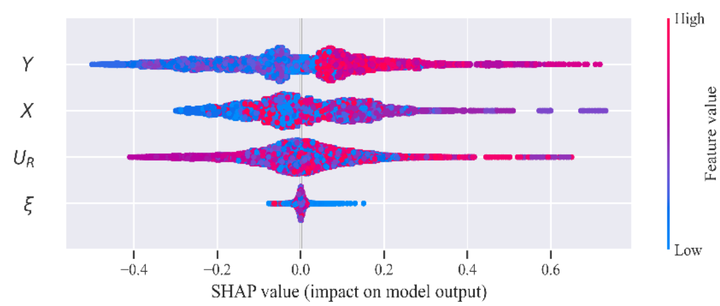
Figure 2. Workflow of the machine-learning-based predictive model.

4. MACHINE LEARNING BASED PREDICTION MODELS AND INTERPRETATIONS

Among different ML-based predictive models, XGB based model has the best performance in predicting IF. Due to the limited space, the predicted IF results by the XGB-based model are presented in Fig.3(a). It is worth noting that most of the predicted IF results are located around the diagonal line (y=x), showing good agreement with the experimental data ($R^2 = 0.99$). Fig.3(b) gives the summary plots for IF based on SHAP. It is revealed that the factors influencing the interference effects ordered by importance are Y, X, U_R and ξ, respectively. Specific position ranges (i.e., a specific range of X and Y coordinates) would remarkably amplify the IF. In contrast, the larger or lower X and Y coordinates have slight positive or negative effects on the IF. The relationship of U_R with the IF is relatively complicated. The smaller ξ would have a positive effect on the IF. The detailed variation laws of the features with IF will be given in the dependency figure in the full-length paper.



(a) Predicted IF results by XGB model.



(b) Global importance factors based on SHAP.

Figure 3. Machine-learning-based predictive model and interpretation.

6. CONCLUSIONS

ML-based techniques are adopted in this study to establish an accurate and reliable predictive model for IF. The predicted results show that all the ensemble methods have a good performance, while XGB performs best with the highest R^2 (0.99). It is noted that the relative positions have a greater influence on the IF than U_R or ξ, and the interference effects are more sensitive to the interfered buildings in the Y direction rather than in the X direction. Due to the limited space, further discussions of interference effects will be presented in the full-length paper.

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REFERENCES

Chopra, A.K., 2007. Dynamics of structures. Pearson Education India.

Hu, G., Liu, L., Tao, D., Song, J., Tse, K.T., Kwok, K.C.S., 2020. Deep learning-based investigation of wind pressures on tall building under interference effects. Journal of Wind Engineering and Industrial Aerodynamics 201, 104138.

Lin, P., Hu, G., Li, C., Li, L., Xiao, Y., Tse, K.T., Kwok, K.C.S., 2021. Machine learning-based prediction of crosswind vibrations of rectangular cylinders. Journal of Wind Engineering and Industrial Aerodynamics 211, 104549.

Lo, Y.-L., Li, Y.-C., Kim, Y.C., 2020. Downstream interference effect of low-Scruton-number high-rise buildings under turbulent boundary layer flow. Journal of Wind Engineering and Industrial Aerodynamics 198, 104101.

Xie, Z.N., Gu, M., 2007. Simplified formulas for evaluation of wind-induced interference effects among three tall buildings. Journal of Wind Engineering and Industrial Aerodynamics 95, 31–52.