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Machine learning-based prediction and optimization of wind effects on high-rise buildings: Review

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SUMMARY:
Machine learning (ML) has been gradually applied in structural wind engineering. This study introduces the popular methodology and data source, then presents the four main applications of ML in wind engineering. ML helps us predict wind speed, wind pressure pattern recognition on the building surface, and wind-induced building responses. ML can help us to conduct aerodynamic optimization procedures. While most of the treatments mostly are passive configuration control. Thus, dynamic adaptive optimization in the real-time condition via deep reinforcement learning is proposed, which means the building can adjust the configuration based on the real-time environment.

Keywords: *machine learning, wind loads, high-rise buildings, prediction, optimization*

1. INTRODUCTION

Machine learning (ML) has been widely applied in different fields of society, including wind engineering. With the aid of ML, some redundant wind tunnel tests can be eliminated. They possess multiple functions, like doing the prediction work and optimizing the procedures to handle the work better. This study introduces the popular methodology and data source, then presents the main applications of ML in wind engineering.

2. METHODOLOGY AND DATASET SOURCE

2.1. Methodology

Machine learning methods applied in wind engineering can be generally divided into three categories. The first category is general linear-separatable regression, including linear regression, logistic regression, and support vector machine (SVM). The next category contains the decision tree (DT) algorithm and the ensemble methods, including random forest, gradient boosting decision tree (GBDT), and Light gradient boosting machine (LGTM). The last category consists of deep learning-based neural network methods, including artificial neural network (ANN), convolutional neural network (CNN), and recurrent neural network (RNN).

2.2. Dataset source

For any AI algorithm, the quantity and quality of the data is the paramount issue when implementing the models. Generally, the dataset can be obtained from three different means. The most reliable data comes from wind tunnel tests or filed testament. Besides this, some massive data may also be accumulated from numerical simulation in computational fluid dynamics (CFD). To achieve the enormous quantity and quality of data, many researchers have also chosen the public database or collected and combined the data from previous studies.

3. RELATED WORK OF ML APPLICATIONS IN WIND ENGINEERING

Four main categories of machine learning applications exist in wind engineering. The first is predicting wind speed or field in a particular location. Furthermore, the next is the prediction and pattern recognition of pressure on the building surface. The third category consists of the prediction and optimization of wind-induced responses of the building. The aerodynamic optimization refers to the passive configuration choice by default. The last is adaptive configuration optimization, which means the building can adjust the configuration based on the real-time environment via deep reinforcement learning.

3.1. Wind speed and field prediction

Wind speed is directly related to the wind loads of high-rise buildings. There are many studies investigating the prediction of wind speeds or wind fields. Mercer and Dyer (2014) predicted the daily peak wind gusts by a support vector regression algorithm. The method was applied in ten cities highly impacted by wind hazards and achieved outstanding social contributions. Equally, Liu et al. 2014) forecast the wind speed by applying the wavelet transform and SVM. The parameters in SVM were optimized by genetic algorithm to achieve better performance. Li and Shi (2010) investigated three kinds of ANN to predict wind speed. The relative distinction in some evaluation indices, like mean absolute error, can be up to 20%, suggesting a robust algorithm is necessary. Liu et al. (2012) utilized two hybrid approaches (ARIMA-ANN and ARIMA-Kalman) to predict the non-stationary wind speed.

3.2. Optimization of hyper-parameters of the LGBM model

The wind load of a building is not only related to wind speed but also directly connected to the pressure on its surface. Hu and Kwok (2020) utilized three ML algorithms, including decision tree (DT), random forest (RF), and gradient-based decision tree (GBDT), to predict the mean and fluctuating pressure coefficients on the surface. They also found that the GBRT better predicts the pressure coefficients in the studied Reynolds number (*Re*) and Turbulence Intensity (*Ti*) range. In addition, Hu et al. (2021) applied four ML models, including DT, RF, XGBoost, and GAN (generative adversarial network), to predict the wind pressures on the tall building surface under interference effects. They concluded that 70% of the wind tunnel test could be saved via the application of the GAN model. Likewise, Kim et al. (2021) also proposed the generative adversarial imputation network to predict the wind pressure in case of some failure tap test conditions. Kim et al. (2021) used the unsupervised machine learning algorithm clustering to recognize the pressure distribution pattern. Chen et al. (2022) examined three ML models, including back-propagation neural network (BPNN), genetic algorithm back-propagation neural network (GA-BP), and Wavelet Neural Network (WNN). The WNN showed the best performance predicting wind pressure characteristics in both the time and frequency domains.

3.3 Wind-induced responses prediction and optimization

The pressure characteristics are focused on the local part. More studies have emphasized the wind loads or wind-induced responses of the structure. Many factors impact the wind loads, like wind speed, aspect ratio, side ratio, terrain exposure, and building shape detail configurations. With the aid of machine learning, much effort can be saved. Nikose et al. (2018) obtained the data from the Indian code consisting of the *H*, *B*, *L*, *V*, and terrain category parameters to calculate the dynamic wind-induced base forces via the ANN algorithm. Oh et al. (2019) explored the top floor displacements and velocity to obtain the floor strains utilizing CNN. Lin et al. (2021) collected massive amounts of data from previous studies to investigate the cross-wind vibration changing law due to terrain intensity, side ratio, and Scruton number parameters. They implemented DT), RF, KNN, and GBDT algorithms. They concluded that the GBDT has the best performance in predicting cross-wind vibration. Likewise, Lin et al. (2022) also utilized the data from WERC database-TU to explore the terrain exposure, side ratio, and aspect ratio impact on the cross-wind spectrum characteristics. The light gradient boosting machine (LGBM) was employed in the process, demonstrating high accuracy and low time cost.

The wind-induced responses rely on the general outline shape and terrain exposure environment and significantly correlate with the building configuration details. Due to the flow separation and reattachment around bluff bodies, wind effects on buildings are sensitive to the external shape details and façade configurations. In the design stage, to choose an optimal shape, Elshaer et al. (2017) presented building corner aerodynamic optimization procedures to mitigate the wind loads by coupling an optimization algorithm, large eddy simulation (LES), and an artificial neural network. Similarly, Abdelaziz et al. (2021) presented a control system composed of plates that utilize genetic algorithm optimization to determine the optimum plate angle. They obtained data from numerical simulation and chose the optimal configuration from the calculated cases.

3.4 Self-adaptive optimization

Nonetheless, the wind environment is changing all the time. The self-adaptive dynamic optimization is also proposed in recent studies accordingly. Ding and Kareem (2018) suggested an appealing approach to designing a building that can adapt its form to changing complex wind. However, the cost increase associated with complex dynamic façade design and construction can be substantial. Xie and Yang (2019) proposed an innovative "Wind-Adaptable Design" concept. It is to take temporarily adjustable measures like utilizing wind fairings to modify the building's shape in extreme conditions while keeping the original shape in average weather conditions. Elhawary [(2020) employed deep reinforcement learning (DRL) agents to train ANN via the numerical simulation data to control the active flow around a 2D cylinder. He illustrated that mean velocity magnitude and velocity fluctuations have a significant reduction. Correspondingly, Rabault et al. (2020) also concluded that DRL implementation could solve problems like nonlinearity, high dimensionality, and non-convexity. Furthermore, Wang et al. (2022) developed an open-source platform DRLinFluids based on OPEN FOAM, which significantly accelerates the efficiency in computational fluid dynamics applications. The machine learning-based optimization of wind-induced responses on tall buildings with flexible façade configurations has aroused more and more concern in the community.

4. CONCLUSIONS

Overall, machine learning techniques are powerful tools to be implemented in the field of wind engineering. ML helps us predict wind speed, wind pressure pattern recognition on the building surface, and wind-induced building responses. Furthermore, ML can help us to optimize the configurations and conduct dynamic adaptive optimization in the real-time environment via deep reinforcement learning.

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