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Prediction of wind loads on buildings with non-rectangular plans based on Machine Learning regression models

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SUMMARY:
Wind loads on buildings with non-rectangular plans were investigated through limited experimental and computational Fluid Dynamics (CFD) studies. Therefore, the wind design of non-rectangular buildings is described through short guidance in the current building codes and standards. This paper predicts wind loads on roofs and walls of non-rectangular buildings using Ensemble Machine Learning (EML) technique. The EML combines predictions of several regressors, such as Gradient Boost (GB) and Multi-Layer Perceptron (MLP), and results in predictions more accurate than the outputs of a single regressor. Numerous tests were performed at the wind tunnel for building models with plan shapes of L, T, X, and U to create a dataset for the Machine Learning (ML). An exhaustive Grid Search with K-fold Cross Validation was used for hyperparameters optimization. The Ensemble Machine Learning models predicted wind pressure coefficients with minimal Mean Squared Error (MSE) and coefficients of determination (R-squared) of up to 0.98.

Keywords: Non-rectangular buildings, wind tunnel, machine learning

1. MOTIVATION

The wind design of buildings with rectangular plans is well-described in wind codes and standards. On the other hand, wind design of buildings with irregular (non-rectangular) plans is available through insufficient and short guides in wind provisions. Several wind studies investigated wind loads on non-rectangular buildings in wind tunnels and through CFD, (e.g., Cook, 1990; Jamieson et al., 1992; Stathopoulos and Zhou, 1993; Morse, 2003; Gomez et al., 2005; Amin and Ahuja, 2011; Bandi et al., 2013; Raj and Ahuja, 2013; Bhattacharyya et al., 2014; Chakraborty et al., 2014; Mukherjee et al., 2014; Paul and Dalui, 2016; Shao et al., 2019; and Bhattacharyya and Dalui, 2020; Meena et al., 2022). However, the past studies are limited; for instance, most of these studies did not include peak wind loads and reported only mean wind pressures. Machine Learning is a powerful tool for performing multiple and multivariate regression of complex data. ML has been implemented in wind engineering to predict wind loads and wind speeds (e.g., Bre et al., 2018; Higgins and Stathopoulos, 2021; Sang et al., 2021).

This paper uses a wind tunnel data-ML pipeline to predict wind loads on irregular buildings. Wind tunnel data were collected at Concordia University for L-, T-, X-, and U-shaped models to measure pressures on limited irregular shapes. The experimental data were used as training and testing sets for ML to predict wind loads on irregular buildings.

2. METHODOLOGY

As WT models are difficult to make, it was decided to assemble all irregular configurations using four basic models and wooden dummy models. The basic models were constructed using a length scale of 1:200 and equipped with taps on roofs and walls, they represent four buildings, three triangular buildings, and one trapezoidal building, the four basic models form a rectangular model when they are assembled as shown in Fig. 1.a (dimensions in meters, Full-scale), the roof is equipped with 193 taps. Fig. 1.b presents the basic and dummy models combined to form an L-shaped (configuration: L1). In this study, 12 configurations of L, T, X, and U shapes were tested in the wind tunnel. Each shape was tested for three different plans and a height of 10 m, and two L-shaped configurations were tested for three heights: 5, 10, and 20 m. In addition, 72 wind directions were considered for the L-shaped configurations (0° to 355° at a step of 5°); and for the rest of the shapes, the tests were performed for 36 wind directions (0° to 350° at a step of 10°). Testing was conducted in a simulated open country exposure with a power-law exponent, α, of 0.14. All pressure coefficients in the study represent pressures normalized by hourly averaged dynamic velocity pressure at roof height.

For ML, a technique called Ensemble Learning was implemented for wind load predictions; this technique selects the best prediction by combining the predictions of a group of regressors such as Random Forest (RF), Gradient Boosting (GB), Extra Trees (ET), and Artificial Neural Network (ANN). The implementation of ML in this paper starts with data preprocessing which includes One-hot-Encoding of the categorical features and features scaling (normalizing the features from 0 to 1) for the entire dataset, which is then randomly split into training and testing sets using a ratio of 7:3. Afterwards, the training set is fed into the regression algorithms for training, and the unseen testing set is used as a validation set of the ML models. Regressors such as RF, ET, and GB are based on decision trees (weak learners); in other words, those regressors are effective learners and use ensembles of weak learners. A multi-layer perceptron (MLP), an ANN, was also used for the predictions of wind loads. Eventually, the predictions of the best regressors are combined using a Voting regressor to result in more effective outcomes. Hyperparameter tuning for ML models was done using an exhaustive Grid Search with K-fold Cross Validation. Data preprocessing and ML models training and validation were implemented in Python using the Scikit-Learn library (Pedregosa et al. 2011).

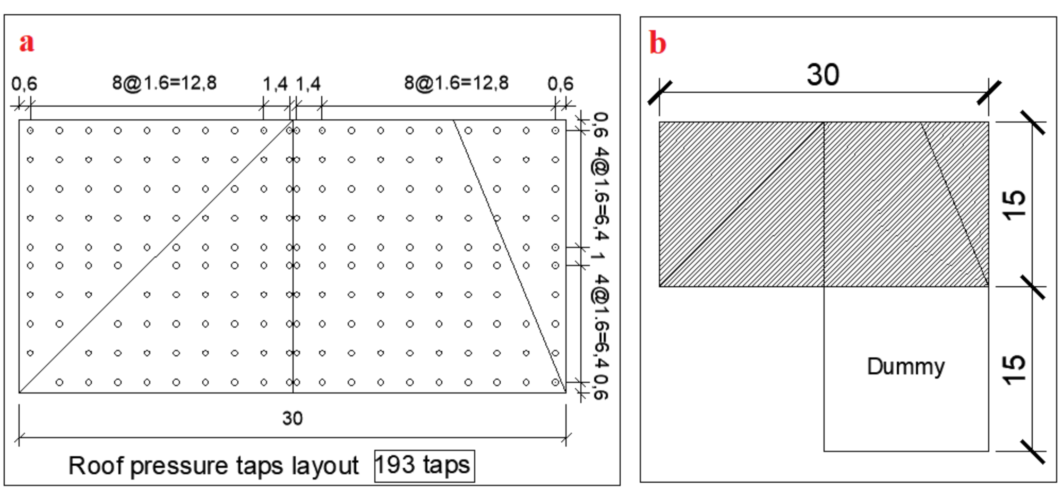

Figure 1. a.) Basic models and roof pressure tap layout, b.) L-shaped model.

3. RESULTS

Testing of the configuration L1 (shown in Fig. 1.b) produced a dataset of 13,896 instances (72 wind directions x 193 taps), which was divided into a training set (70%) and a testing set (30%). The ensemble method was implemented to train the ML models. Fig. 2 presents ML predictions of local mean Cp on the testing (unseen) set compared with the measured (WT) local mean Cp of six regressors for the L-shaped configuration (L1), height is 10 m.

Among the six models, predictions of RF have the maximum MSE (0.004) and the Lowest R-squared (0.960). On the other hand, MPL and ET models have R-squared values of 0.979 and 0.974, respectively, and outperform RF. Although the GB model has a relatively lower R-squared than MPL and ET, it did better in the predictions of Cp around -2. The best two models, MLP and ET have more or less the same accuracy, and therefore, they were added up with equal weights using a voting regressor that takes the average predictions of ET and MLP, in other words, the voting regressor ensembles MLP and ET. Voting regressor 1 is more effective than MLP or ET and outputs better results; the R-squared is 0.981. Predictions of GB, RT, and MLP were also combined in another voting regressor, Voting regressor 2. The ensemble of GB, ET, and MLP output predictions with slightly lower MSE than the ensemble of ET and predicted mean Cp more effectively around -2; however, Voting regressor 1 is more accurate for the predictions of mean Cp around -1. Ensemble Machine learning was also utilized to predict local peak pressure coefficients; the models' outputs are strongly correlated to the measured peaks with R-squared values comparable to those obtained for the mean Cp. In summary, Ensemble Learning is an effective tool for the predictions of wind loads on irregular buildings.

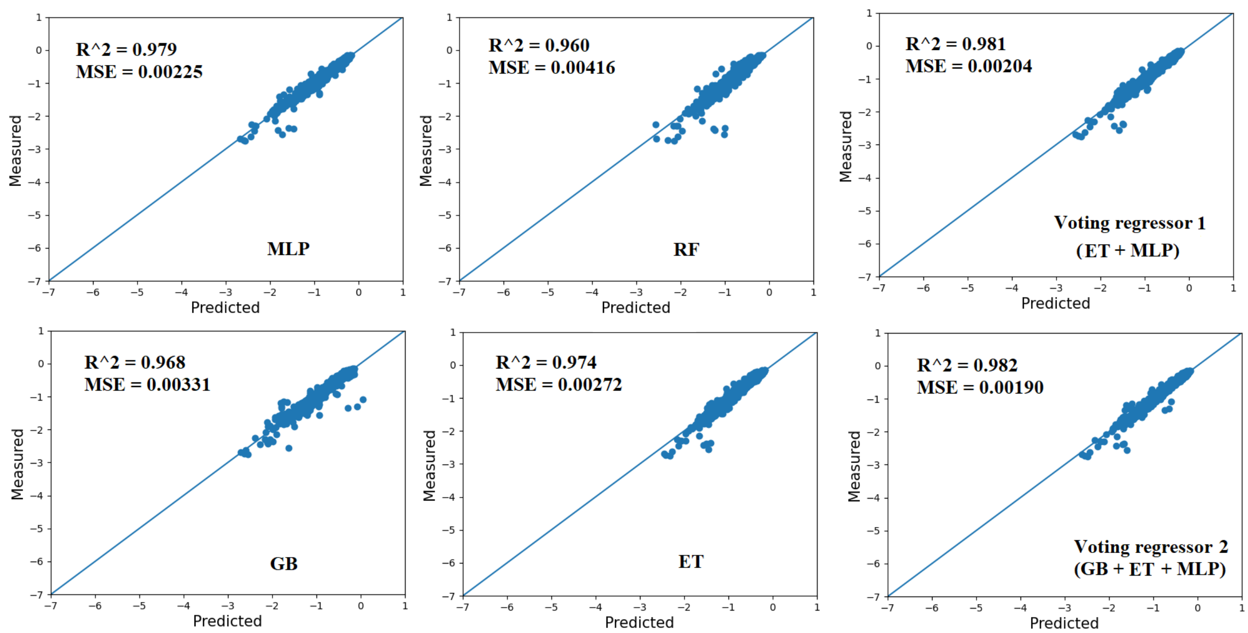

Figure 2. a.) Comparison of predicted and measured mean Cp of six regressors, testing set.

4. CONCLUSIONS

Wind loads were scanned on walls and roofs of 12 irregular (non-rectangular) building configurations in the wind tunnel to create a dataset for ML. Ensemble ML was implemented to predict wind loads on irregular buildings using the experimental results as training and testing tests. The ML models were tested, and it was found that predictions are strongly correlated to the measured data with a coefficient of determination of up to 0.98. The ML model will be validated with different cases from the literature, i.e., other than those used for training, to generally inspect its ability to estimate wind loads on irregular buildings.

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