

Wind pressure prediction on low-rise buildings based on an image method

Youqin Huang^a, Zhiwei Wu^a

^aGuangzhou University, Guangzhou, Guangdong, China, yqhuang@gzhu.edu.cn

^aGuangzhou University, Guangzhou, Guangdong, China, wzw@e.gzhu.edu.cn

SUMMARY

Prediction of wind pressure distribution on buildings based on limited wind tunnel testing data is an effective way to provide wind load information for all nodes in structural wind-resistant design, and the main methods are based on artificial neural networks (ANNs). Wind pressure distribution is very sensitive to structural shape, but the conventional methods only considered the shape of building by several geometrical parameters, such as eave height and slope of gable roof, so they cannot be used for complicated modern roofs. This paper proposes an image method to predict the wind pressure distribution on the gable roof of low-rise building and can be applied to complicated roofs. The study shows that, by adopting the image sample in place of the tap sample, the accuracy and efficiency of wind pressure prediction are eminently improved, and the image method can be used for predicting the aerodynamic forces on complicated roofs.

Keywords: wind pressure prediction; low-rise buildings, machine learning, image method, pressure statistics

1. INSTRUCTIONS

Prediction of wind pressure distribution on buildings based on limited data from wind tunnel tests is an important topic in structural wind engineering, which could provide sufficient wind load information for all loaded finite element nodes in structural wind-resistant design, since the number of nodes is much more than the number of measuring taps in wind tunnel tests. The main methods for wind pressure prediction are based on the machine learning (ML) models, most of which are artificial neural networks (ANNs).

However, the existing studies mainly focused on the aspect of spatial interpolation of wind load, that is, predicted the wind load on the unmeasured locations of the building in wind tunnel tests. **For the engineering application of these methods, the wind tunnel tests are still need to be carried out, and no cost will be saved. The wind pressure prediction for totally untested buildings was seldom been paid attention to, which could essentially save the testing cost** (Huang et al., 2023a, b, 2024). Even several developed models have considered the geometric parameters of buildings as the prediction parameters, but basically only a single type of geometric parameter has been included, which is insufficient to describe the shape of a building. The difficulty for the conventional ML models to predict wind pressure distribution on a whole building is that, these models use several geometric feature parameters to represent the shape of buildings, but a limited number of parameters are hard to describe a modern roof with complicated architecture.

Consequently, this paper proposes an image method to realize the wind pressure prediction on a roof which could be complex. Even though the method is explained and applied in a typical gable roof low-rise building, it can be applied to more complicated roofs with modern architecture, such as stadium or terminal roofs. The shape of roof is input into the ML model as an image in place of several parameters. By the image input, all the shape information of building can be sent into the

model. Accordingly, the output of the model is the spatial distribution of wind pressure on the whole roof, not several values in some predicted locations in the conventional methods.

2. METHODS

Figure 1 demonstrates the structure of the proposed image-CNN based model for wind pressure prediction. The input data of the model are not parameters but 3 kinds of geometric feature images of the roof. In order to more accurately and conveniently extract the features of complex roofs, this study does not directly use the height as shape indicators, and instead of introducing a geometric feature index system that is more sensitive and comprehensive in capturing shape changes. Inspired by the spherical coordinate system, this work introduces a comprehensive geometric index system corresponding to the radius, azimuth, and polar angle. By a series of convolutional and pooling operations, the shape feature of the roof is related to the wind pressure output on 96 taps.

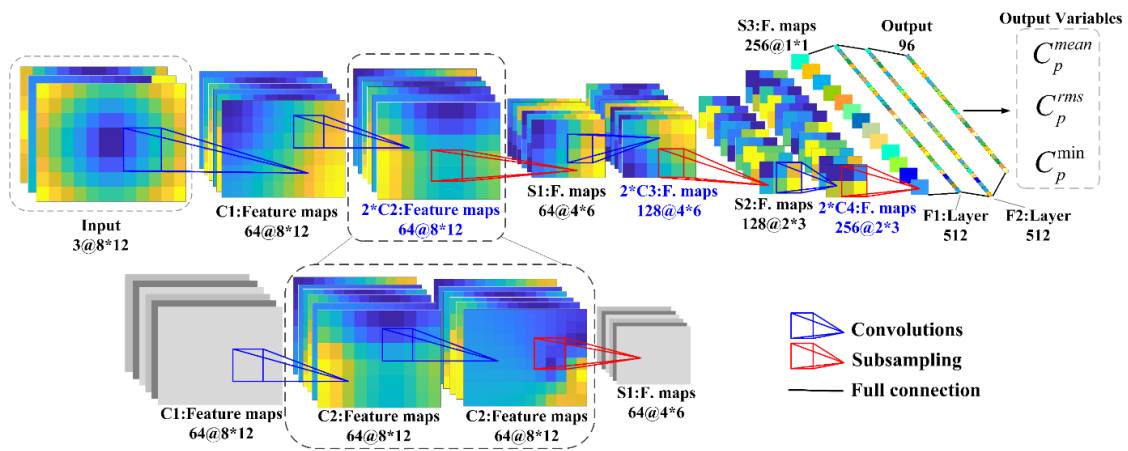


Figure 1: Structure of the image-CNN model for wind pressure prediction.

3. RESULTS AND DISCUSSIONS

Using the trained image-CNN model, the prediction accuracy is validated based on 4 test buildings, as shown in Figure 2, comparing the prediction results with those of a traditional DNN model. It can be observed that for any building and all wind directions of 0° – 90° , the R^2 values of the image-CNN model are higher than those of the DNN model, with significant differences under certain wind directions. Therefore, the image-CNN model significantly improves the accuracy of wind pressure predictions. Even for buildings with high eaves or steep slopes, the accuracy of the image-CNN model remains relatively stable.

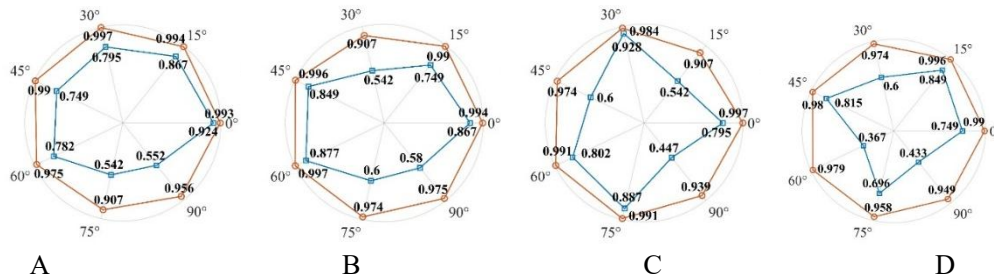


Figure 2: R^2 of mean wind pressure coefficients for various test buildings.

For error metrics such as RMSE, MAE, and MAPE, the results of CNN across all wind directions are also significantly lower than those of DNN. For example, for test building B, the maximum RMSE, MAE, and MAPE are 0.226, 0.176, and 31%, respectively, from DNN, while those of CNN are only 0.102, 0.073, and 10%, respectively (Figure 3). Therefore, when evaluating errors across all measurement points under various wind directions—whether in terms of root mean square absolute error, mean absolute error, or mean relative error—the prediction accuracy of CNN is consistently higher than that of DNN.

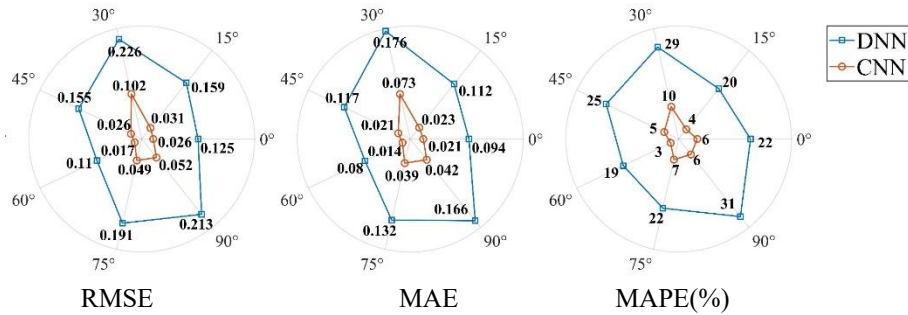


Figure 3: Different error metrics of building B.

Further observation and comparison of the prediction accuracy at each measurement point (Figure 4) reveal that, across all wind directions, the variation of CNN-predicted values with measurement point numbers closely matches the true values, whereas the DNN results exhibit significant deviations at numerous measurement points.

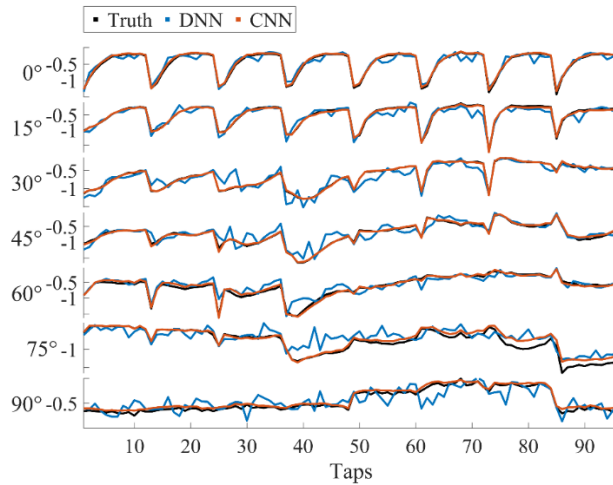
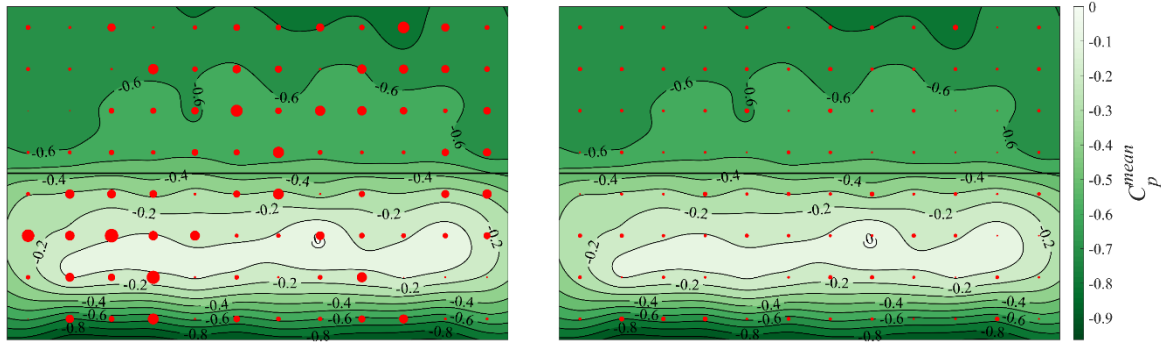


Figure 4: Variation of predicted values of CNN and DNN in tap number under all wind directions (building A).

By comparing the spatial distribution of absolute errors at all taps from the two models (Figure 5, larger dots indicate greater absolute errors), it can be observed that the wind pressure at each tap generated by CNN is basically closer to the true values than DNN. Even in regions with significant flow separation where wind pressure is high, the absolute error of CNN remains notably smaller.



(a) DNN (b) CNN
 Figure 5: Spatial distribution of absolute errors for building A under 90° wind direction.

4. CONCLUSIONS

An image method based on the 2D-CNN model is proposed to realize the easy and accurate feature extraction of building appearance. Thereby, the appearance prediction is achieved for wind pressure prediction. The advances of the new method in precision and efficiency are proved by the sample data from the TPU database for low-rise gable-roof buildings.

ACKNOWLEDGEMENTS

This work was jointly supported by National Natural Science Foundation Project of China (No. 52578569) and Guangzhou Municipal Education Bureau Project (2024312337). Special thanks are also given to the TPU database for supplying the aerodynamic datasets for deep learning and a Chinese Government Scholarship from China Scholarship Council.

REFERENCES

- Huang, Y., Ou, G., Fu, J., Zhang, H. 2023a. Prediction of mean and RMS wind pressure coefficients for low-rise buildings using deep neural networks. *Eng. Struct.* 274, 115149. <https://doi.org/10.1016/j.engstruct.2022.115149>.
- Huang, Y., Ou, G., Fu, J., Wu, H. 2023b. Prediction of skewness and kurtosis of pressure coefficients on a low-rise building by deep learning. *Wind Struct.* 36(6), 393-404. <https://doi.org/10.12989/was.2023.36.6.393>.
- Huang, Y., Wu, H., Fu, J., Zhang, H. 2024. Convolutional neural network-based wind pressure prediction on low-rise buildings. *Eng. Struct.* 309, 118078. <https://doi.org/10.1016/j.engstruct.2024.118078>.