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A prediction method of peak wind pressure on the building facade assisted by Convolutional Neural Networks

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SUMMARY:
From the perspective of wind-resistant design, it is essential to accurately estimate of the peak design load acting on glazed panels. Existing time-length-velocity (TVL) method is severely dependent on the selection of the TVL factors, which should be determined according to the wind pressure characteristics of the building surface. Hence, an alternative method is necessary to be proposed to guarantee the precision and robustness in estimation of the peak pressure. This study applied the Convolutional Neural Network (CNN) to reconstruct the super-resolution pressure distributions on the building facade from low-resolution pressure measurements. The high-fidelity pressure database from a wind tunnel test is employed to train the CNN model. The constraint represented by the pressure gradient are embedded in the loss function of the CNN to enable the model to generate realistic pressure distribution characteristics. By spatially averaging of the super-resolution distributions, the peak space-averaged pressure on the glazed panels could be predicted. The study aims to generate the CNN model that could be applicable to the peak pressure predictions at various wind pressure modes. The present method is expected to have higher precision and efficiency in the prediction of peak wind pressure than traditional TVL method.

Keywords: peak wind pressure, wind-resistant design, neural networks, pressure reconstruction, time-filtered

1. INTRODUCTION

Glazed panels or building roofs are often destroyed by local extreme wind loadings, especially for the high-rise buildings. It is important to accurately evaluate the peak loadings on the cladding panels, considering the balance between the safety and economy.

Two traditional ways exist. The first method is area averaging over a panel. However, due to the economic and technical limitations, sparse measurements were often installed in the previous field observations or wind-tunnel experiments, which resulted in the rough pressure estimations. For this reason, the second way is using time-filtering of pressure time series at a single pressure tap, which is called TVL approach. The moving-averaging window is determined by the TVL equation. An ambiguous parameter, K, is introduced in TVL equation. Many previous could not get the wide agreement of K values appropriate for corresponding wind pressure modes.

Convolutional neural network (CNN), as a representative of deep learning algorithms, has a good performance of capturing the value distribution features of measurements. It has applied to super-resolution of turbulent flow with the coarse field as input and the fine field as output (Fukami et al., 2021). Clearly, the CNN model owns the ability to consider the nonlinear spatial distributions.

Thus, the present study aims to examine the feasibility of CNN to reproduce high-resolution pressure field from given low-resolution measurements. After that, we could directly use the area-averaging method to estimate the peak pressure, which is thought to be more accurate. We are committed to generating the CNN model that could be applicable to the peak pressure predictions for different wind pressure modes. The gradient of the pressure is considered as constraint in the loss function of the CNN. We expect improvement of the accuracy and efficiency of extreme wind pressure estimation based on gradient-informed machine learning.

2. METHODS

For any machine learning, database is very crucial. The wind engineering group in Politecnico di Milano (PoliMi) conducted the very high spatial resolution pressure measurements in wind tunnel. The time series of pressure at various wind directions (α) were recorded at each measurement tap to build up a pressure database (Pomaranzi et al., 2022). The database gives us the chance to train the CNN model and evaluate it.

We focused on the region adjacent to the top corner of the building facade, as depicted in Fig. 1(a). The original experimental data is marked by the red stars. They are pooled to 3 time coarser field, indicated by the blue circles. The coarse fields are used for the input of CNN model.

Fig. 1(b) shows CNN architecture. It is simplified from the GAN model proposed by (Wang et al., 2019). The “Generator” is applied to generate super-resolution (SR) pressure distributions that approach to true high-resolution (HR) pressure fields, with the low-resolution inputs (LR). The loss function is calculated between the HR and SR fields. It is a combination of two different loss terms, as expressed in Eq. (1), where L_{MSE} is the pixel-based error of the reconstructed pressure fields, $L_{gradient}$ represents the error calculated from the pressure gradient and α is the coefficient used to balance the gradient term. Cao et al., 2022 reconstructed the pressure fields based on the CNN with only L_{MSE} and found that the distribution characteristics of local extreme pressure cannot be well reproduced. Therefore, in this study, we add $L_{gradient}$ to expect the gradient-guided CNN model to deal with the non-uniform measurement distribution in the facade tile, and to better capture local extreme pressure variations to improve the performance of peak pressure prediction.

$$L = L_{MSE} + \alpha L_{gradient} \tag{1}$$

The original data is split into training and testing set. The first 60000 time steps in different wind direction are extracted as the training set. Ten wind directions are selected with a 15° resolution. The training samples are selected at equal intervals of 10, 60 and 600 at each direction, generating three subsets with sample sizes of 60000, 10000 and 1000. While the last 90000 time steps in the analyzed wind direction are extracted as the testing set.

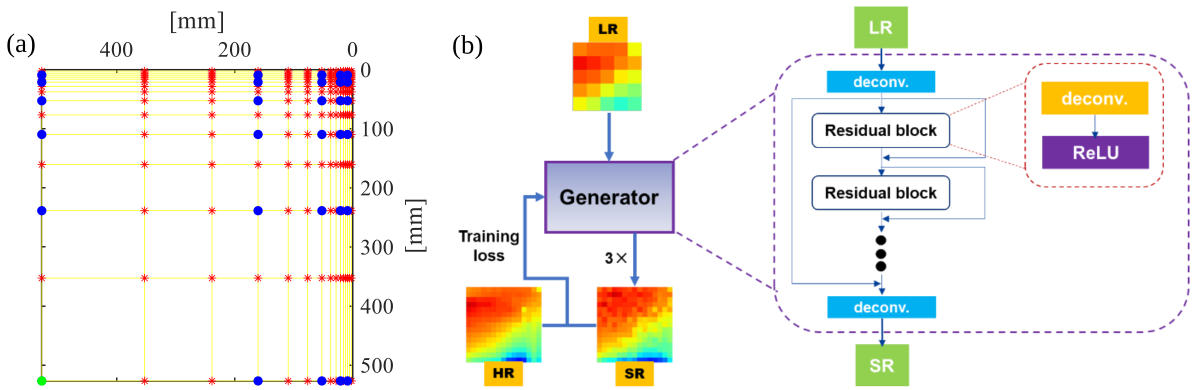

Figure 1. (a) High and low-resolution distributions of pressure taps in the database and (b) the CNN architecture.

3. RESULTS

After training, we can see the performance of SRCNN model. We first choose one wind directions prone to extreme suction events, i.e., at $\alpha = +10°$.

The root mean square error (RMSE) and accuracy R^2 are computed to check the statistical tendency of pressure distribution with sample number in Fig. 2. The curves show the reconstruction performance of CNN without $L_{gradient}$ informed. The higher sampling number improves the ability of instantaneous reconstruction. As the sample size is further increased beyond 10000, the reconstruction performances become convergent. The star signals denote the reconstruction errors and accuracies with CNN models constrained by $L_{gradient}$. They behave better than the models without the $L_{gradient}$ constraint at a certain sample number.

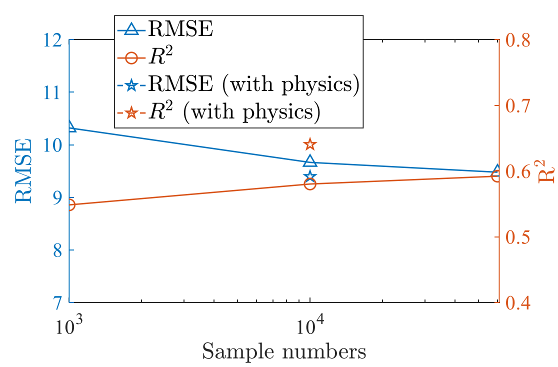

Figure 2. The errors and precisions of the instantaneous reconstructed pressure varied with the sample numbers.

Once the instantaneous pressure field has been predicted, the area-averaging method could be used to evaluate the peak pressures on glazed panel. Two sizes of square panels, i.e., 1.5 m × 1.5 m and 3 m × 3 m in full scale or 30 mm × 30 mm and 60 mm × 60 mm in model scale, are considered. The "true" area-averaged pressure coefficients are calculated from real measurements ($C_{p,\,AA}$). In order to assess the accuracy, the area-averaged peak pressure based on the low-resolution field ($C_{p,\,LR}$) and super-resolution CNN ones ($C_{p,\,SR}$). All these pressure coefficients are represented by $C_{p,\,Area}$ in Eq. (2). Indeed, the spatial resolutions differ by 3 times.

$$C_{p,Area}(t) = \frac{\sum_{i=1}^{M} C_{p,i}(t)A_i}{A} \quad (2)$$

We also compared the performance of CNN method with traditional TVL method. Pomaranzi et al., 2022 confirmed that taps at the center can predict representative pressure, and the TVL equation with $K \approx 3$ provides a good estimate for the peak pressure using for $\alpha = +10°$ at Tile A. Thus, when using TVL method, the pressure taps near the panel centers are checked with $K = 3$.

Table 1 shows mean relative errors between peaks of $C_{p,\,AA}$ and the predicted values. When 10000 sample number is used without the loss term of pressure gradient, the CNN predictions have much lower errors than the peak area-averaged pressure on the low-resolution field and the TVL estimations. When applying the same sample size with pressure gradient loss, the prediction errors decline further. This illustrates that the super-resolution method considered the gradient constraint predicts a more accurate area-averaged peak pressure.

Table 1. Mean relative errors of peak negative values of $C_{p,\,LR}$, $C_{p,\,SR}$ obtained from CNN without and with pressure gradient constraint and $C_{p,\,\tau}$ on individual pressure taps and with 10000 samples, in comparison with those of $C_{p,\,AA}$ on the panels of two sizes when α=+10°.

Panel	$C_{p,\,LR}$	$C_{p,\,\tau}$	$C_{p,\,SR}$ (without $L_{gradient}$)	$C_{p,\,SR}$ (with $L_{gradient}$)
1.5m×1.5m	17.01%	14.52%	7.88%	7.32%
3m×3m	10.55%	19.41%	5.71%	5.59%

4. CONCLUSIONS

CNN model is well trained by pressure data from various wind directions in this study. Although no pressure gradient loss embeds, it exhibits a better accuracy in peak pressure predictions of cladding panels when extreme suctions prevail, compared with the direct integration from the sparse pressure data and the TVL estimations with the appropriate K value. The CNN model constrained by the pressure gradient loss represents the true area-averaged peaks more adequately than the model without gradient loss. We expect the current model has ideal generalization performance in predicting peak wind pressure for cases of different wind directions, i.e., pressure distribution modes.

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