Predicting pressure coefficients on low-rise buildings using deep neural networks

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SUMMARY:
Prediction of wind pressure on buildings is a very important topic in wind engineering. The Artificial Neural Network (ANN) model is the principal method used for pressure prediction since the traditional analytical regression approaches are not effective for such a multivariate nonlinear problem. However, the prediction accuracy is still unsatisfactory in the areas with flow separation, owing to the limited learning capacity of ANNs which have only less than two hidden layers. In the progress of computer hardware and algorithms, the deep neural networks (DNNs) with more than two nonlinear layers have been proposed and applied in many fields of science and technology. Therefore, the DNNs are introduced in this study to predict wind pressure on low-rise buildings. In order to compare the prediction accuracy with the literature and facilitate the precision comparison of further studies, the aerodynamic data used for machine learning are extracted from the internationally open database, i.e. the NIST-UWO database. Also, the prediction results of all taps on the roof are presented by various error metrics. The study demonstrates that in the areas of roof ridge and corner bay, the DNNs model obtains better accuracy than the ANNs model in the literature. For the mean or RMS coefficients, their correlation coefficients between predicted and experimental results exceeds 0.997, and the mean-square-error (MSE) is less than 5%.

Keywords: Deep neural networks, wind pressure prediction, low-rise buildings

1. THE AERODYNAMIC DATABASE AND THE DNNs MODEL

The NIST-UWO database setup by National Institute of Standards and Technology of America and University of Western Ontario in Canada, provides the wind pressure data of low-rise buildings with various plan dimensions, heights, roof slopes and terrain conditions (NIST, 2003). The work of wind pressure prediction using the open database is limited. Chen et al. (2003) employed the data of ss20-test 1 to predict the mean and RMS pressure coefficients on the roof under untrained wind directions. Therefore, the same data packages are used and the same prediction cases are conducted in the present study for comparing the prediction results with Chen et al. (2003). The studied building has the plan dimensions of 80ft×125ft, roof slope β of 1:12, and heights H of 24ft, 32ft and 40ft. The numbering of pressure taps on the roof and the definition of wind directions α

is shown in Fig. 1. The training set consists of the data from the wind directions between 270° and 360° (with increment of 5°) except 300°, 320° and 340° under various roof heights, and the testing set includes the data of wind directions 300°, 320° and 340°.

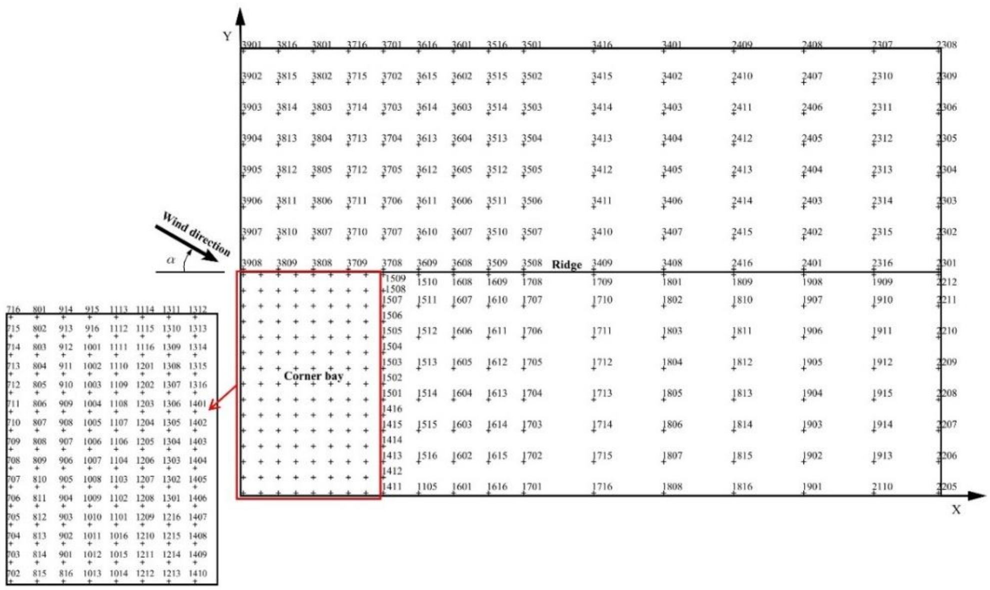


Figure 1. Pressure tap layout on the roof

The typical deep neural network used in this study is shown in Fig. 2. In comparison with the ANNs model, more hidden layers can be effectively included in DNNs after Hinton and Salakhutdinov (Hinton and Salakhutdinov, 2006) developed a layer-wise pretraining procedure for training multiple-layer neural networks. For fixing the suitable number of hidden layers (HLs) in the DNNs model, five models with 1, 2, 3, 4 or 5 HLs are built, and it is found that the correlation coefficient generally increases with the number of HLs while the best prediction is obtained when there are 3 HLs, so the number of HLs is set as 3 in this study, and the number of neurons in each HL and other optimum hyper parameters such as learning rate and batch size are determined by the Bayesian Optimization (BO). Moreover, in order to further improve the prediction in the corner zone with flow separation, a nested DNNs model as shown in Fig. 3 is further proposed by adding the mean coefficients as the inputs of the network according to the strong correlation between the mean and RMS pressure coefficients.

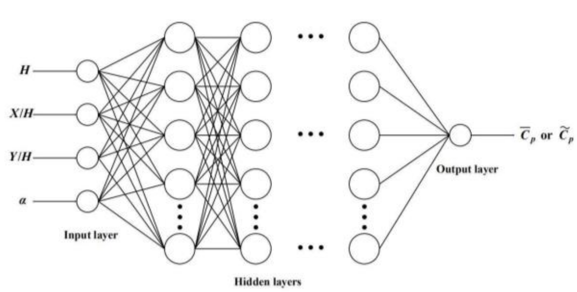


Figure 2. Architecture of deep neural network

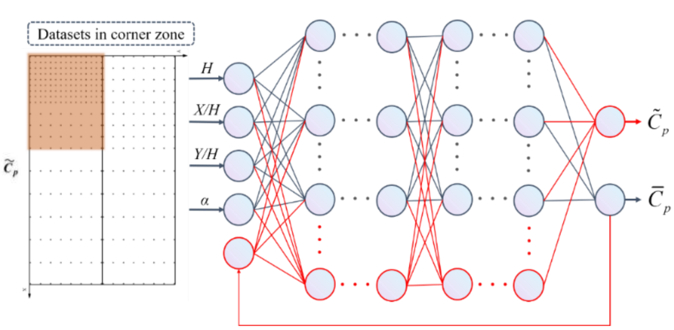


Figure 3. The nested DNNs model for predicting corner zone

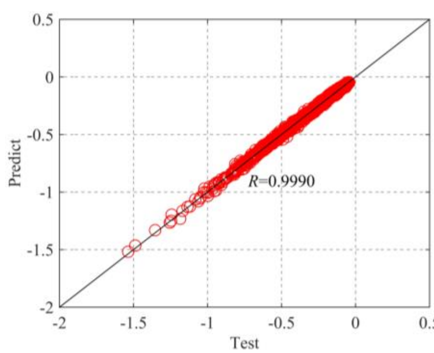
2. RESULTS AND DISCUSSIONS

By comparing the predicted results on the corner tap and the corner bay with the literature results (Table 1), it can be seen that this work presents better accuracy than Chen et al. (2003).

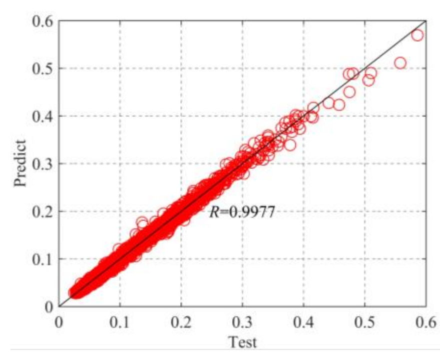
Table 1. Comparison of RMS pressure coefficients

H (ft)	*α*		Corner tap			MSE of corner
			Real	Prediction	Error (%)	bay (%)
24	300°	DNN	0.308	0.327	5.9	8.2
		ANN		0.289	-6.2	10.3
	320°	DNN	0.212	0.213	0.0	7.3
		ANN		0.230	8.5	9.3
	340°	DNN	0.299	0.293	-2.8	7.5
		ANN		0.331	10.7	9.0
32	300°	DNN	0.352	0.350	-1.1	9.2
		ANN		0.346	-1.7	11.3
	320°	DNN	0.254	0.252	-1.0	11.8
		ANN		0.287	13.0	9.1
	340°	DNN	0.341	0.344	0.1	5.5
		ANN		0.366	7.3	5.3
40	300°	DNN	0.410	0.381	-7.5	5.3
		ANN		0.378	-7.8	9.7
	320°	DNN	0.292	0.300	2.3	8.9
		ANN		0.317	8.6	11.8
	340°	DNN	0.384	0.379	-2.0	8.1
		ANN		0.387	0.8	9.5

The correlation coefficients between the averaged results of 10 runs and the experimental results are 0.999 and 0.997 for the mean and RMS coefficients respectively (Fig. 4). MSEs of all the 3015 samples under all predicted wind directions and roof heights are about 4.5% and 4.8% for the mean and RMS coefficients respectively.



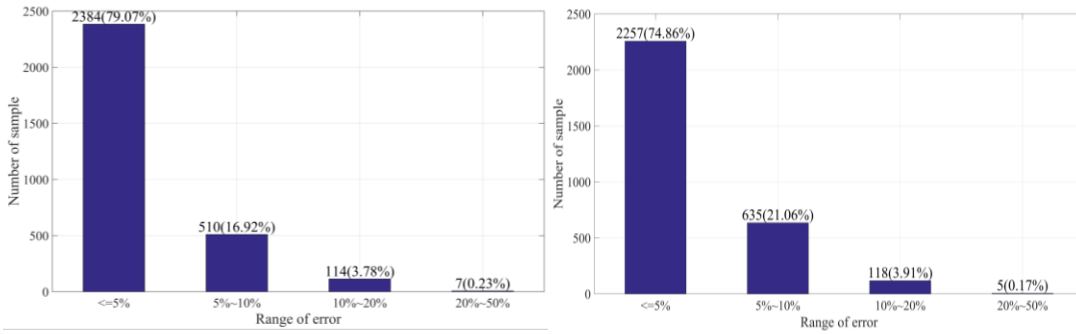
(a) Mean



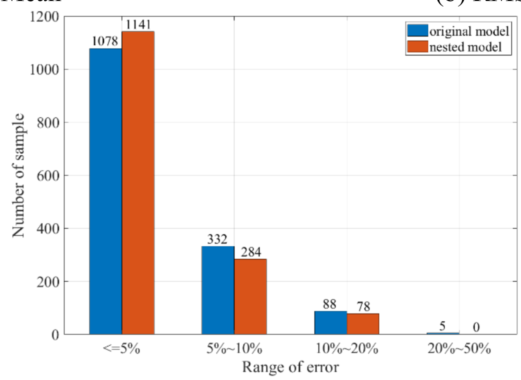
(b) RMS

Figure 4. Comparison between predicted and experimental pressure coefficients

The statistics of relative errors are shown in Fig. 5. It is indicated that more than 95% samples having error < 10%. There are about 0.3% samples produce errors > 20% but the pressure coefficients of these samples are very small and they are less significant for the wind effect. Moreover, the errors of 20% are further eliminated by constructing the nested network.



(a) Mean (b) RMS



(c) Results of the nested network (RMS)

Figure 5. Statistics of errors for pressure coefficients

3. CONCLUSIONS

The DNNs models obviously improve the prediction accuracy on the roof in comparison with the results of ANNs from the literature. The predictions are robust with the correlation coefficients exceeding 0.99 and the MSEs less than 5% for all predicted cases under various wind directions and roof heights. More than 95% samples have errors < 10% and the errors > 20% are further removed by the method of nested DNNs.

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