Deep Learning-Based Estimation of Peak Wind Pressures on Buildings from Short Duration Measurements

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This project presents a **deep learning model** to predict **peak wind pressures** experienced on building surfaces from **short durations** of data. The model serves as a viable solution to **reducing required computation.**

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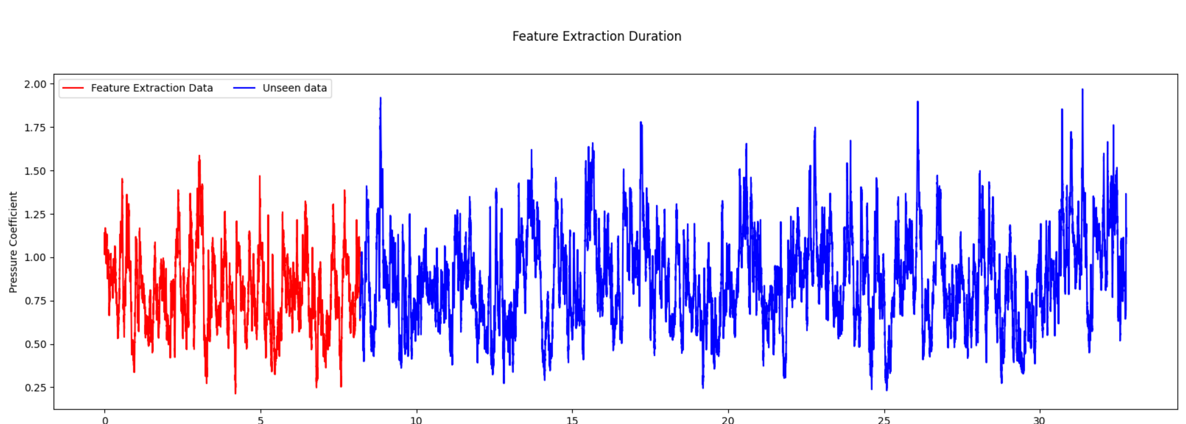
Introduction

- Peak wind pressures need to be determined for building feature design (cladding, windows, doors)
- BLWT experiments and CFD simulations can be expensive computationally, economically, and timewise
- Machine learning (ML) models can learn from wind data to determine pressure coefficients in a more efficient manner
- Previous studies have not determined peak pressures from short duration data

Methods

A multi-layer perceptron model was created to determine peak pressure coefficients from statistical features extracted from short durations (8 seconds) of pressure coefficient time series data. The model was trained on BLWT data considering wind angles from 0-90 degrees.



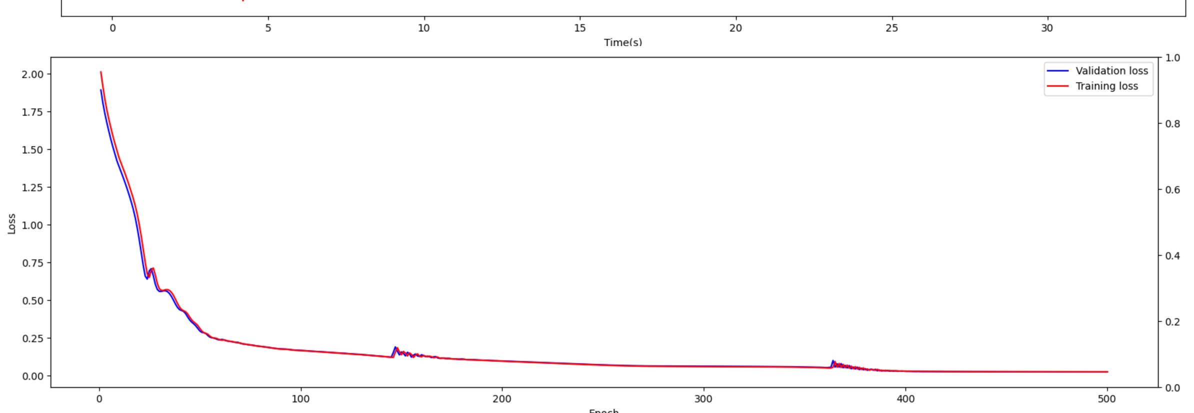


Fig. 1. Feature extraction data

Fig. 2. Training process plot

The final architecture contained 8 total layers and 10 neurons per hidden layer. Inputs were mean, standard deviation, kurtosis, skewness, minimum, maximum, and range (all extracted from 25% of each pressure coefficient time log for the 510 sensors at each wind angle). The two outputs being predicted were positive and negative fitted peak pressure coefficient.

Next Steps

- Hyperparameter tuning
- Alternative deep learning models
- PINNs with governing fluid dynamics equations
- Finite-Element PINN

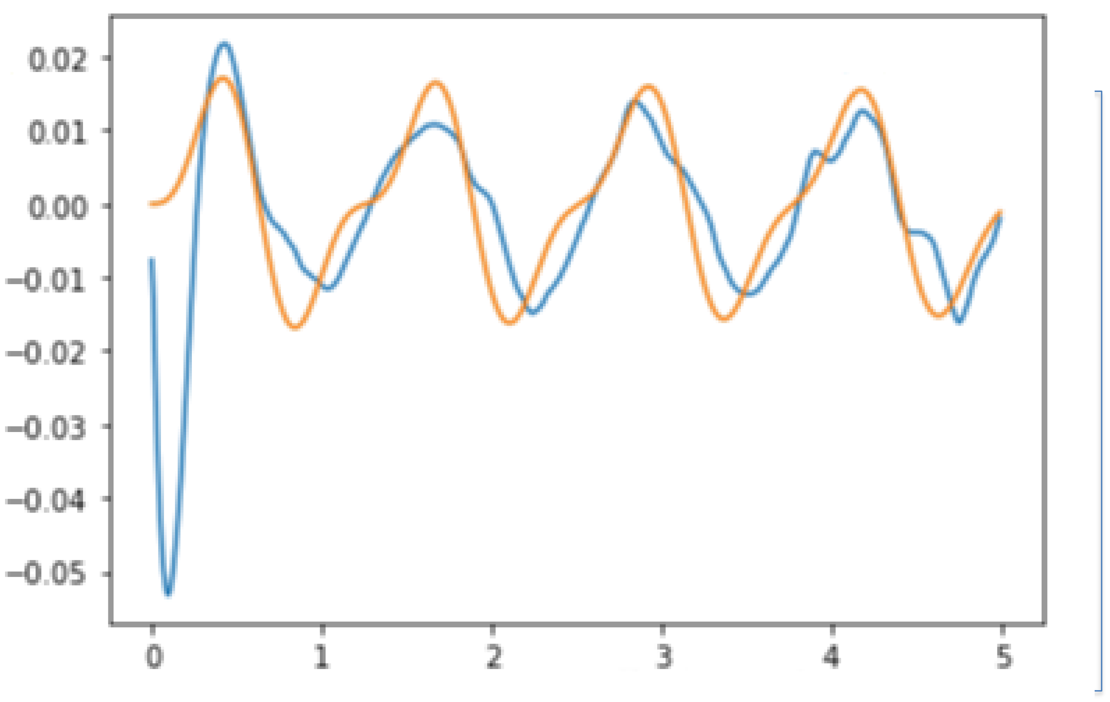


Fig. 5. 1-DOF finite-element PINN preliminary results

Results

- Positive peak prediction:

Average percent error = 2.78%

- Negative peak prediction:

Average percent error = 3.47%

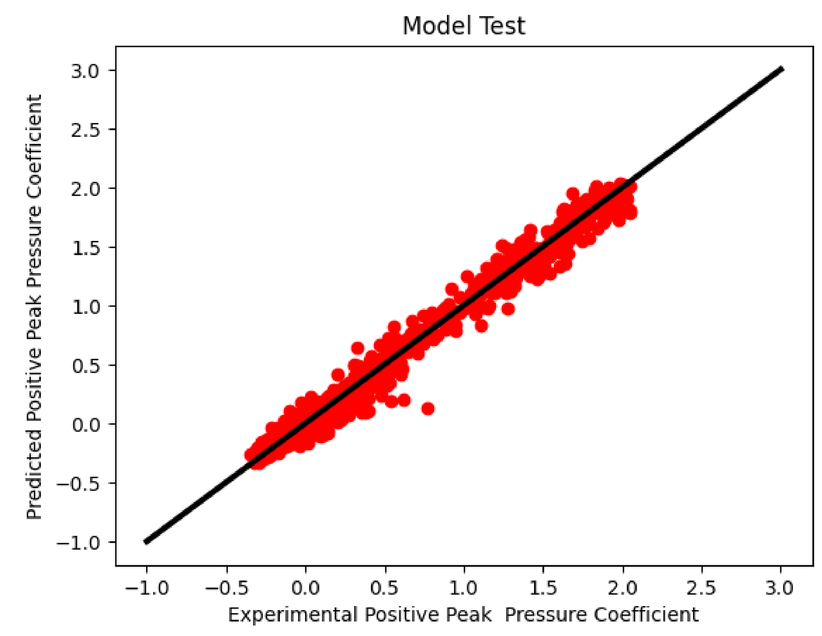


Fig. 3. Predicted versus experimental positive peak pressure coefficient

Fig. 4. Predicted versus experimental negative peak pressure coefficient

Conclusions

- The MLP model yields low percent error in predicting peak pressure coefficients while being trained on only short durations of data
- This model can be tested on CFD simulation data to expand its applications

References

Chen, Y., G. A. Kopp, and D. Surry, 2002. "Interpolation of wind-induced pressure time series with an artificial neural network." *J. Wind. Eng. Ind*. 90(6), 589–615. https://doi.org/10.1016/S0167-6105(02)00155-1.

Chen, Y., G. A. Kopp, and D. Surry, 2003. "Prediction of pressure coefficients on roofs of low buildings using artificial neural networks." *J. Wind. Eng. Ind*. 91(3), 423–441. https://doi.org/10.1016/S0167-6105(02)00381-1.

Fu, J. Y., S. G. Liang, and Q. S. Li, 2007. "Prediction of wind-induced pressures on a large gymnasium roof using artificial neural networks." *Computers & Structures*, 85(3–4), 179–192. https://doi.org/10.1016/j.compstruc.2006.08.070.

Gardner, M. W., and , S. R. Dorling 1998. "Artificial Neural Networks (the multilayer perceptron)—a review of applications in the Atmospheric Sciences." *Atmospheric Environment*. 32(14–15), 2627–2636. https://doi.org/10.1016/S1352-2310(97)00447-0

Tian, J., K.R. Gurley, M.T. Diaz, P.L. Fernández-Cabán, F.J. Masters, and R. Fang, 2020. "Low-rise gable roof buildings pressure prediction using deep neural networks." *J. Wind. Eng. Ind*. 196, 104026. https://doi.org/10.1016/j.jweia.2019.104026.

Wind.arch.t. (n.d.). http://www.wind.arch.t-kougei.ac.jp/info_center/windpressure/highrise/Homepage/select_T215_4.html

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