Predicting Transient Wind Pressure Over A Tall Building Using Machine Learning

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ABSTRACT

Over the past decade, machine learning (ML) has drawn much interest in wind engineering applications. Previous machine learning-based studies for wind load predictions for tall buildings have mostly been restricted to time history or static pressure without considering the spatial coordinate system. ML models need to predict both the spatial distribution and transient wind flow to design wind-sensitive tall buildings. Thus, utilising a three-dimensional (3D) spatial coordinate system, this study employed ML to predict the transient wind pressure on a tall building. Transient pressure data on building surfaces were obtained through computational fluid dynamic simulations, which were validated using wind tunnel data. The extreme gradient boosting (XGB) model was chosen as the machine learning model, and it obtained good prediction accuracy in both training and testing. Furthermore, over the building surfaces, unique flow phenomena such as flow separation, and steep pressure gradients have been well predicted by the XGB model. As a result, this work demonstrates how machine learning may be used to predict wind loads on tall buildings and capture important flow characteristics.

INTRODUCTION

Tall buildings are quite sensitive to wind forces and wind-induced vibrations, posing challenges to their structural integrity and serviceability. Therefore, accurate wind pressure estimation is crucial for ensuring the safe and cost-effective design of tall buildings (Hu et al., 2020). Generally, wind tunnel experiments and computational fluid dynamics (CFD) simulations are employed to investigate the wind loads occurring on tall buildings. Although wind tunnel experiments are highly reliable, they are resource-intensive, costly, and require time and expertise. On the other hand, numerical methods like CFD modelling may require high computational resources depending on the simulation and also need expertise and time. Considering these limitations in both approaches, the wind engineering community has turned to data-driven methods, such as machine learning (ML), to predict the wind loads on tall buildings.
Machine learning (ML) is generally used to learn from data and identify patterns within it. For this reason, it is increasingly being applied in civil, structural, and wind engineering applications (Kareem, 2020). The importance of machine learning in the wind engineering domain holds several advantages. ML can learn from data and predict patterns more time-efficiently compared to numerical and experimental methods (Brunton et al., 2020). Moreover, once a machine learning model is properly trained, obtaining its predictions requires no significant expertise or computational expense. With such advantages, machine learning-based predictive models can be used in wind engineering as a complementary tool to numerical and experimental methods.

Recent advancements in ML, including artificial neural networks (ANNs) and tree-based models like random forest (RF) and extreme gradient boosting (XGB) have been applied successfully to predict wind pressures of buildings. For example, Dongmei et al. (2017) used an ANN model to predict static wind pressure on a tall building (490 m) with a square cross-section of 57 m x 57 m. Similar work was conducted by Shruti et al. (2021) to predict the static wind pressure on a square-shaped tall building with a height of 160 m. Hu et al. (2020) used tree-based models, including RF and XGB, as well as a generative adversarial network (GAN), to predict the static pressure on a tall building (280 m). All these studies suggested that neural network methods and tree-based models are effective in capturing variations in static wind pressure on tall buildings.

However, machine learning methods have been rarely employed for transient wind pressure predictions. Recently, Chen et al. (2022) used a wavelet neural network to successfully predict transient wind pressure on a rectangular tall building. Their models achieved a Pearson correlation (R) of 0.99 for the transient pressure predictions and highlighted the need for further research. Despite their model's accuracy, they did not consider the spatial coordinates of the pressure taps as inputs for the ML model. Including both spatial and temporal behaviour (changes over time) in a ML model to predict transient pressure on a tall building is both important and challenging. ML models need to be able to predict transient wind pressure on a tall building while maintaining spatial correlations in the predictions. Such analysis would demonstrate the ability of ML models to identify special flow features and localised variations on building surfaces that change over time.

In consideration of this, the present study uses machine learning to model transient wind pressures on the CAARC tall building by incorporating three-dimensional spatial coordinates as additional inputs. This approach utilises a combination of wind tunnel data and computational fluid dynamics (CFD) simulations to train the ML models, allowing for more accurate predictions of complex wind interactions on building structures.By integrating ML with validated CFD models, the study offers a fast, reliable, and cost-effective method for predicting wind pressures, which can serve as a complementary predictive tool.

WIND TUNNEL EXPERIMENT

This section describes the experimental setup and methodology used to assess wind pressures on the CAARC tall building, a commonly used structure in wind engineering research. The building model was scaled down to a 1:300 ratio, and the wind tunnel tests were conducted at the boundary layer wind tunnel (BLWT) at the University of Sydney. The model was fabricated from plywood to ensure a smooth finish that matches the surface texture used in numerical modelling. The dimensions of the model were 600 mm in height, 150 mm in length, and 100 mm in breadth, maintaining a blockage ratio of 1.2%. Figure 1.a shows the setup used for the wind tunnel experiment at BLWT at the University of Sydney.

Initially, the tests were conducted without the building model to establish velocity and turbulence profiles according to the TCIII terrain specifications as defined in AS/NZS 1170.2:2011. After achieving the required velocity and turbulence profiles, tests with the building model involved measurements of surface pressures. These measurements were taken using 198 pressure taps distributed across the building's facade, with data collected at 2 kHz to capture transient wind pressures. The freestream velocity was maintained at 12 m/s and the Reynolds number measured at the top of the building was 4.4×10^5.

NUMERICAL MODELLING

Following the wind tunnel experiment, the experimental setup was modelled in ANSYS FLUENT 2023 as a rigid building in a rectangular domain as shown in Figure 1.b. The mesh of the domain was converted into 1.56 million polyhedral elements which can result higher accuracy and reduced computational time compared to typical tetrahedral mesh. A finer mesh was used near the building and a coarser mesh in the outer regions. Twelve prism layers with a growth ratio of 1.1 were introduced to capture the boundary layer around the building, maintaining the dimensionless wall distance (y^+) < 5. A no-slip boundary condition was applied to the ground and building walls, with pressure-velocity coupling handled by the Semi-Implicit Method for Pressure-Linked Equations Consistent (SIMPLEC).

First, the empty domain (without CAARC building) was validated by using wind tunnel data for mean velocity profile U(z), turbulent kinetic energy (TKE), and specific dissipation rate (SDR). The k-ω model was initially used for the Reynolds averaged Navier Stokes (RANS) simulations to achieve steady state convergence (1×10^{-6}) before large eddy simulations (LES). Next, the empty domain was simulated using Large Eddy Simulation (LES) for 10 s with a time step of 5×10^{-4} s. During this time, velocity time histories at 0.6 m upstream of the building were extracted to calculate turbulence intensity, velocity profiles, and turbulent power spectrum profiles. These profiles were validated using corresponding data obtained from wind tunnel experiments. Subsequently, the validated profiles were applied to the domain containing the building, and Reynolds-Averaged Navier-Stokes (RANS) simulations were executed until convergence at a tolerance of 10^{-6}. LES was commenced with velocity fluctuations applied through the vortex method at the inlet. Using monitor points on the building surface, transient pressure at each time step was extracted. Transient simulations ran for 10 s with a 5×10^{-4} s time step, matching the wind tunnel experiment's sampling frequency (2000 Hz). The simulations, executed on 32 cores, took 164 hours and were conducted for a single wind direction (θ=0°).

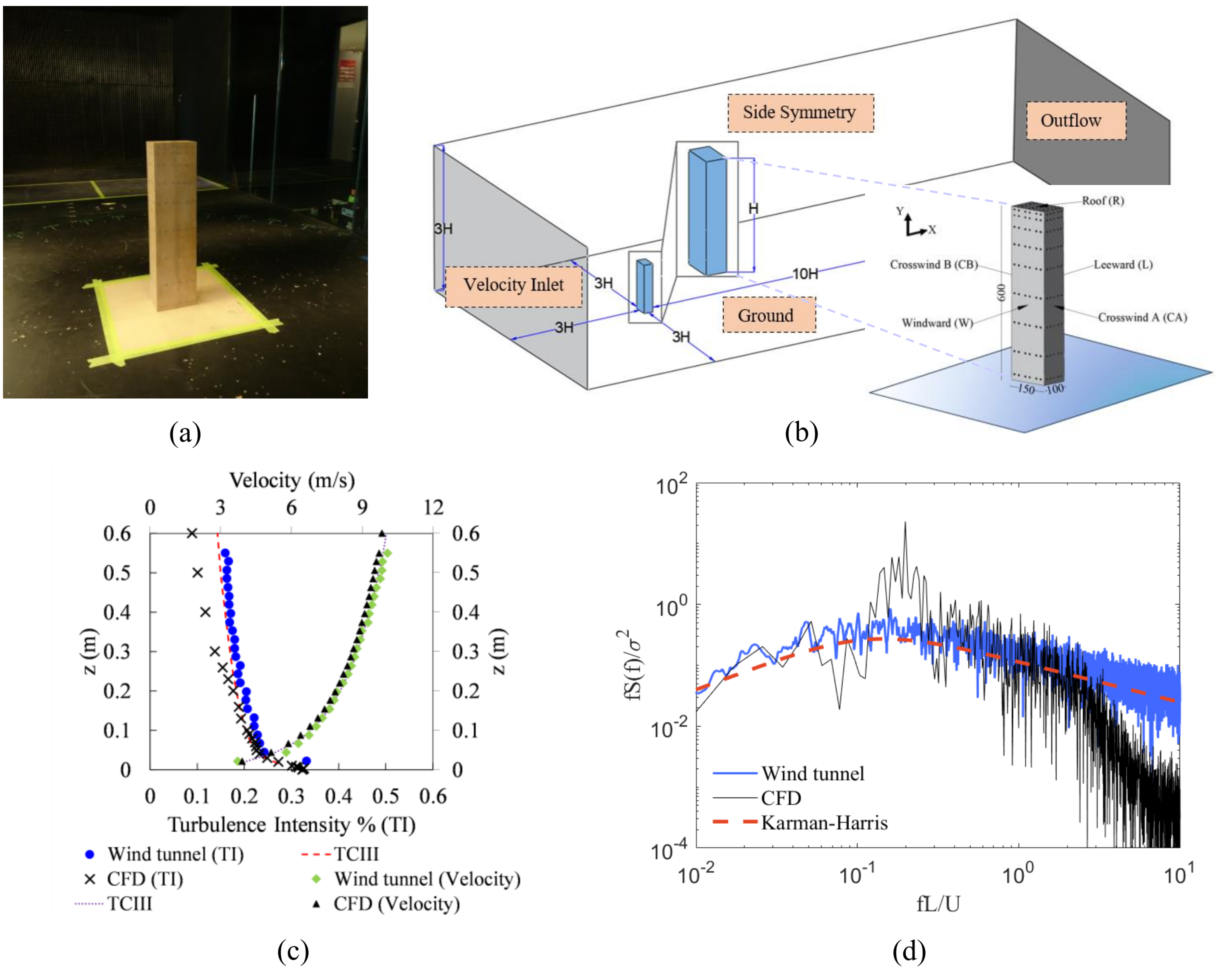


Figure 1: (a) Wind tunnel experiment setup (b) Numerical model of the building (c) Validation of velocity and tubulence intensity profiles (d) Turbulence power spectrum

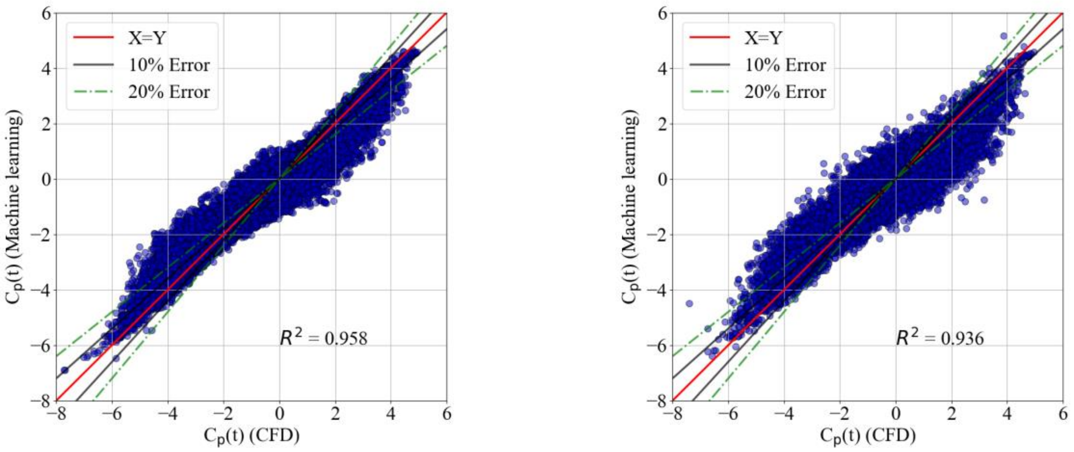
Transient pressure records were structured into a data frame by specifying the 3D spatial coordinates of each point on the building (x,y,z), surface and the flowtime as the input parameters whereas time-dependent pressure coefficient, $C_p(t)$ was the dependent parameter for the machine learning model. The total dataset consisted of 4.56 million data points.

MACHINE LEARNING MODEL

The popular tree-based model, extreme gradient boosting (XGB), was used to predict transient pressure using the dataset obtained from numerical modelling. XGB is a state-of-the-art model that has been successfully applied in wind engineering research applications. It operates through multiple decision trees and can learn complex hidden patterns within a dataset. To train the XGB model, 70% of the data was used, with the remaining 30% reserved to test the model's ability to generalise to unseen data. The XGB model was optimised using a grid search method available in the Sci-kit learn library, focusing on critical model parameters such as tree depth, number of estimators, and learning rate. The optimised settings included a tree depth of 16, 100 trees, and a learning rate of 0.2. These parameters helped the model achieve its optimised predictive performance.

RESULTS AND DISCUSSION

Figure 2 shows the overall training and testing accuracies of the XGB predictions compared to the numerical results. The training accuracy of XGB predictions reached R^2 of 0.958, while the testing accuracy was $R^2 = 0.936$. The XGB model accurately predicted extreme suction pressure ($-8 < C_p(t) < -6$) and higher $C_p(t)$ values (> 4) within a 10% margin of error. Overall, the predictions are reliable for wind engineering applications related to tall buildings.



(a) Triaining set (b) Test set

Figure 2: Comparison of XGB models' transient wind pressure predictions

It is noteworthy that the five surfaces of the building have different aerodynamic flow characteristics. The windward wall mainly experiences positive pressure whereas the crosswind and root surfaces undergo intense negative pressure and intermittent vortex formation as a result of flow separation. The leeward wall faces the flow-recirculating wake region with negative pressures.

Based on these flow characteristics, the predictions were evaluated for each building surface, as shown in Table 1. During the training phase, the highest correlation (R) between predictions and numerical results was on the roof (R = 0.976) while the lowest correlation was observed for the windward and crosswind A walls (R = 0.970). Despite its lower correlation, the windward wall had the lowest mean absolute error (MAE = 0.095) and root mean square error (RMSE = 0.168). This is because the windward wall mostly experiences positive pressures with lower magnitudes, resulting in smaller prediction errors compared to the magnitude of negative $C_p(t)$ values on remaining surfaces.

Table 1: Analysis of statistical indices of XGB predictions compared to CFD results

Surface	Correlation (R)	MAE	RMSE

Windward wall	0.970	**0.095**	**0.168**
Leeward Wall	0.972	0.145	0.236
Crosswind A wall	0.970	0.139	0.222
Crosswind B wall	0.972	0.134	0.212
Roof	**0.976**	0.121	0.190

Surface	Correlation (R)	MAE	RMSE
Windward wall	0.945	**0.140**	0.253
Leeward Wall	0.963	0.165	0.269
Crosswind A wall	0.955	0.165	0.266
Crosswind B wall	0.956	0.161	0.257
Roof	**0.965**	0.141	**0.220**

In contrast, remaining surfaces like the roof and crosswind walls are subjected to extreme negative pressures due to intense flow separation. Also near the leading edges of these walls, the turbulence is higher which can result in higher fluctuations in the wind pressure. Therefore, in those regions, the model predictions can have minor deviations, resulting in slightly higher MAE and RMSE values compared to the windward wall predictions. During XGB testing, similar trends in the $C_P(t)$ predictions were observed. The $C_p(t)$ predictions on the roof attained the highest correlation (R = 0.965) and the lowest RMSE (0.220) while the windward wall predictions had the lowest MAE (0.140). These results demonstrate the XGB model's ability to predict transient pressure values accurately, especially on surfaces with different wind flow characteristics and higher fluctuations.

It is also important to observe the pressure contours generated by the ML to determine the consistency of the prediction over the building surface. Figure 3 shows the variation of $C_p(t)$ at a flow-time of 7.9805 seconds for both CFD and ML models.

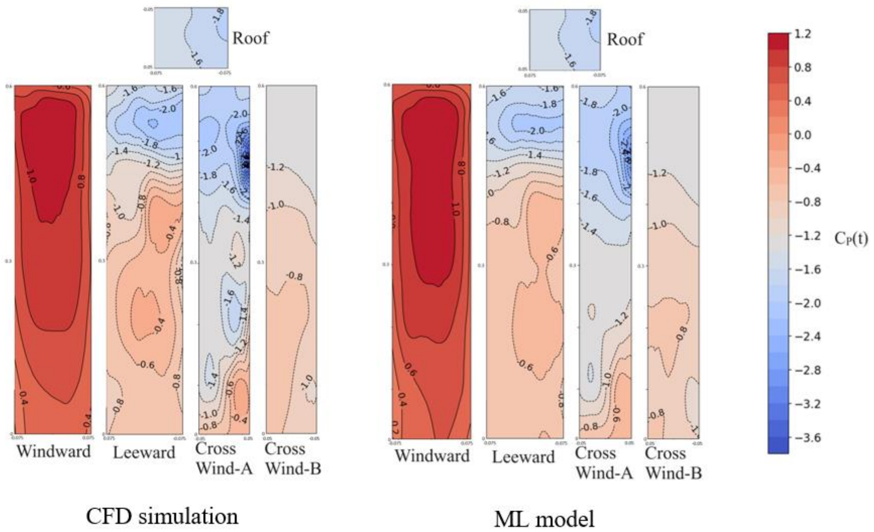


Figure 3: Comparison of wind pressure contours on the building at flowtime = 7.9805 s

On the windward wall, the positive pressure region with $C_p(t)$ = 1 is present in the top third in the CFD simulation and it extends to the middle third in the ML predictions. Both models agree on the pressure variation near the windward wall's leading edges. The ML model predicted a region with $C_p(t)$ = 0.6 near the ground level of the windward face, whereas the CFD model showed a lower value of 0.4 in the same area. The deviations can be explained by the tendency of the ML model to smooth out sudden changes in positive pressure observed in CFD results. On the leeward wall, a steep pressure gradient in the upper third region was accurately predicted by the ML model. The ML pressure distribution shows a large portion of the leeward wall with $C_p(t)$ = -0.6, which is slightly different from the CFD simulations. The minimum pressure observed on the crosswind wall was -3.6 in the numerical simulations, while the ML model predicted around -3. Despite minor deviations, the overall flow features are comparable between both models. Crosswind wall B shows good agreement between the pressure profiles from CFD and ML models at the same flow time. The roof pressure was also accurately modelled. In general, the ML model achieved a good accuracy and effectively predicted important flow features that change with time. Overall, the ML model is competent in modelling and accurately reconstructing pressure profiles obtained from numerical simulations.

In terms of computational efficiency, large eddy simulations (LES) took 164 hours to run a 10-second simulation, while the trained XGB model required only 4 seconds to produce wind pressure predictions. This highlights the potential of ML models in wind engineering as a complementary tool to support practicing engineers. It is important to note that these ML models cannot replace numerical simulations or wind tunnel experiments rather they can be used for wind pressure predictions on tall buildings as a complimentary tool. These ML models can be further improved by including different-shaped tall buildings, various surrounding conditions and terrain categories to develop a more generalised predictive tool for tall buildings.

CONCLUSION

This study successfully applied machine learning to simulate transient wind pressures on the CAARC tall building with an along-wind attack angle ($\theta = 0°$). The machine learning (ML) model demonstrated high accuracy in predicting transient wind pressures, especially in areas with flow separation and high building-induced turbulence. While there were minor deviations, these predictions were within acceptable limits for wind engineering applications. The ML model accurately reconstructed complex flow features such as flow separation and steep pressure gradients, demonstrating its ability to capture dynamic flow characteristics over the building surfaces. Given its efficiency and accuracy, ML has the potential as a surrogate modelling tool in wind engineering. It offers a faster, less resource-intensive alternative for predicting time-dependent pressures on buildings, which is crucial for design and analysis.

REFERENCES

Brunton, S. L., Hemati, M. S., & Taira, K. (2020). Special issue on machine learning and data-driven methods in fluid dynamics. *Theoretical and Computational Fluid Dynamics*, *34*(4), 333-337.

Chen, F., Wang, X., Li, X., Shu, Z., & Zhou, K. (2022). Prediction of wind pressures on tall buildings using wavelet neural network. *Journal of Building Engineering*, *46*, 103674.

Dongmei, H., Shiqing, H., Xuhui, H., & Xue, Z. (2017). Prediction of wind loads on high-rise building using a BP neural network combined with POD. *Journal of wind engineering and industrial aerodynamics*, *170*, 1-17.

Hu, G., Liu, L., Tao, D., Song, J., Tse, K. T., & Kwok, K. C. (2020). Deep learning-based investigation of wind pressures on tall building under interference effects. *Journal of wind engineering and industrial aerodynamics*, *201*, 104138.

Kareem, A. (2020). Emerging frontiers in wind engineering: Computing, stochastics, machine learning and beyond. *Journal of wind engineering and industrial aerodynamics*, *206*, 104320.

Shruti, K., Govindray, S. R., Rajasekharan, S. G., & Rao, P. N. (2021). Artificial neural network-based prediction of wind pressure coefficients on buildings. *Journal of The Institution of Engineers (India): Series A*, *102*, 403-409.