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Deep and traditional machine learning models to predict pressure coefficients on low-rise building surfaces

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SUMMARY:
A 30’x45’x13’ (ST3) model with a small dataset from the NIST-UWO database was used to predict the external pressure coefficients using traditional machine learning (ML) models (RF and SVR) of which RF performed better. As the size of training data increases, the use of deep learning algorithms such as artificial neural networks (ANN) significantly increases the model performance over traditional ML models. In this study, a very large dataset of five different NIST-UWO models with plan dimensions of 80' x 125' and 40' x 62.5' and with varying eave heights, roof slopes, terrain exposures, and wind directions will be used to predict mean, rms, minimum and maximum pressure coefficients (both internal and external) using both deep learning and traditional ML models. This paper will further extend ML techniques to predict net pressures across building surfaces and global load effects (such as bending moments, base shears, etc.) by combining net pressures with the relevant influence coefficients.

Keywords: Deep learning, Low-rise building, Pressure coefficients

1. INTRODUCTION

Turbulence in the approaching wind, interactions with upstream structures, flow separation and vortex shedding all contribute to pressure fluctuations on bluff bodies immersed in an atmospheric boundary layer. These pressures on the building surfaces are typically expressed as pressure coefficients (Cp). Since precise analytical aerodynamic load predictions are limited by the complexity of wind-structure interactions, model tests of structures in simulated boundary-layer flows are the most effective methods of assessing such interactions (Kareem and Cermak, 1984). Many researchers have used wind tunnel model studies as well as full-scale test (Texas Tech Building) data to study the pressure distribution on buildings. Cóstola et al. (2009) classified Cp data sources into primary and secondary sources. Primary sources include wind tunnel model tests, full-scale tests, and computational fluid dynamics (CFD) simulations, whereas secondary sources include databases, codes, and analytical models to predict the Cp using primary data.

Despite full-scale tests being the most accurate to estimate pressure distributions on a building, they remain difficult, time-consuming and costly, and wind tunnel studies and CFD simulations are accepted approaches (Meddage et al., 2022). However, wind tunnel studies have similarity issues (Cermak, 1984) and CFD simulations have computational and scaling issues (Thordal et al., 2019). Since all these methods have costs and are expert- and facility-intensive (Meddage et al., 2022), it is imperative to seek more reasonable approaches to estimate pressure distributions economically and faster using fewer resources (expertise and facilities). When predicting wind pressure distributions on structures, machine learning (ML) models can effectively reduce reliance on experimental techniques (model and full-scale tests) and CFD simulations due to their capabilities to identify and analyze complex relationships between inputs and outputs (Kareem, 2020).

Machine learning can be broadly divided into traditional (shallow) and deep learning. Traditional ML models, such as decision trees (DT), random forest (RF), support vector machines (SVM), and so on have none or only one hidden layer which deal with shallow-structured data (small datasets) with limited complexities in variable relationships, however, deep learning (DL) models such as convolution neural network (CNN), deep reliability network (DBN), and so forth have multiple hidden layers, imitating a human neural network for data learning and have very good prediction/performance when the dataset is very large (Wang et al., 2021).

There has been a surge in the use of ML models in wind engineering. Meddage et al. (2022) used traditional ML to predict mean, rms, minimum, and maximum Cp using Tokyo Polytechnic University (TPU) database for flat roof. Chen et al. (2003) used an artificial neural network (ANN) to predict mean and rms Cp on the low-rise gable roof building surfaces using wind direction, location of pressure taps, and the building height. Gavalda et al. (2011) adopted ANN to interpolate pressure coefficients on low-rise buildings with varied plan dimensions and roof slopes. Bre et al. (2018) employed ANN to predict mean Cp on the surfaces of rectangular buildings with flat, gable, and hip roofs. Using deep neural networks (DNN), Huang et al. (2023) predicted mean and rms Cp of low-rise building using the NIST-UWO database for open country terrain exposure. Since previous work has been done only for open country exposure category using the NIST-UWO database, this paper will extend the approach to include suburban exposure and employ both traditional and deep learning algorithms to predict and compare Cp on the building surfaces (roof and walls).

2. DATA SOURCES

The NIST-UWO database (https://www.nist.gov/el/materials-and-structural-systems-division-73100/nist-aerodynamic-database/university-western-1) with 1:100 model scale data will be used to train and test the ML models. The models with the measurement of internal pressure due to distributed leakage will be chosen and corresponding internal Cp along with external Cp will be predicted. Table 1 represents the details of models that will be used in the analysis with different model dimensions, roof slopes, and terrain exposures (having ~ 1 million data/instances). Each model has pressure taps distributed uniformly on all surfaces. The Cp time history of each pressure tap is provided in the database for different wind directions (~37) which will be converted to mean, rms, minimum, and maximum Cp for further analysis.

Table 1. NIST-UWO model details for analysis.

Plan (ft)	Eave Height (ft)	Roof slope	Terrain Exposure
80x125	16, 24, 32, and 40	1:12 and 3:12	open country and suburban
80x125	12, 18, 24, 32, and 40	¼:12 and 6:12(not 32’ eave height)	open country and suburban
40x62.5	12, 18, 24, and 40	1:12	open country and suburban

3. METHODOLOGY

The input parameters are divided into two groups: i) geometric (3D coordinates of the pressure taps, wind angles, eave heights, roof slopes, and terrain exposures), and ii) pressure (Cp_mean, Cp_rms, Cp_min and Cp_max) as defined by Meddage et al. (2022). The following traditional and deep learning models will be utilized to predict each pressure parameter (mean, rms, min, and max Cp) individually from the geometric parameters.

3.1. Random forest (RF)

A random forest (traditional ML model) is a meta-estimator that employs averaging to increase predicted accuracy and reduce overfitting after fitting numerous classification decision trees to different dataset subsamples. A decision tree is a tree-like structure having several branches representing a choice between alternatives, and leaf nodes offering decisions until an outcome is achieved (Singh and Gupta, 2014).

3.2. Support vector regression (SVR)

SVR (traditional ML model) is a supervised learning algorithm that predicts discrete values by finding the best fit line to include the maximum number of points (instances) while limiting margin violations. SVR seeks to fit the best line within a certain threshold, in contrast to other regression models that aim to reduce the error between the real and predicted value. As SVR finds an appropriate line to fit the maximum data, some data still fall outside the boundary. We can fine-tune the model using hyperparameters minimizing such deviation as much as possible.

3.3. Artificial neural network (ANN)

ANN is a deep learning model composed of many input layers, several hidden layers of interconnected neurons, and outputs. The backpropagation algorithm that will be used in the analysis works in two stages: a) feed-forward (in which the input is passed to neurons along each layer through an activation/transfer function generating an output, and b) error backpropagation (in which the output error is backpropagated to the hidden neurons until the user-defined ML model performance is achieved) (Chen et al., 2003).

4. CASE STUDY

A case study was conducted for the ST3 model (exposure with roughness length 0.01m having 4,488 number of data/instances) from the NIST-UWO database using traditional ML models (RF and SVR). The model is a 1:100 scale flat roof (~1.19° roof slope) low-rise building with dimensions 30’x45’x13’ having 206 pressure taps on its surface providing Cp time history. The min and max Cp reported are obtained through the Lieblein-fitted Type I extreme value distribution by dividing the record into 10 parts and estimating the mean extreme from 10 individual peaks (Ho et al., 2005). Using geometric parameters (pressure tap coordinates and wind directions) and corresponding pressure parameters (mean, rms, min, and max Cp), the models were prepared (trained) for the prediction of each pressure parameter (external Cp) separately using 3,950 (80%) training data. The trained models were used to predict each pressure parameter using the (original wind tunnel data) testing data (20%) and corresponding R^2 and root-mean-square errors (RMSE) were computed between the predicted and testing data for each pressure parameter.

Table 2. Metrics computed for the prediction of RF and SVR for the testing data.

Metric	Cp_mean		Cp_rms		Cp_min		Cp_max	
	RF	SVR	RF	SVR	RF	SVR	RF	SVR
R^2	0.966	0.908	0.938	0.6	0.929	0.895	0.961	0.92
RMSE	0.068	0.113	0.022	0.056	0.24	0.293	0.121	0.174

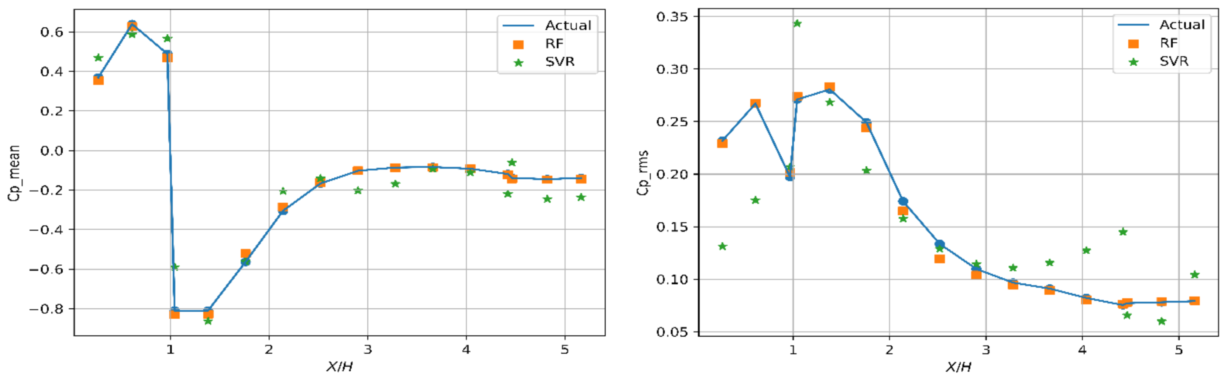

Figure 1. Comparison of pressure coefficients plotted along the center line of the building for 0° wind direction.

For RF, R^2 are higher, and RMSE are lower than SVR for the testing data of each pressure parameter (see Table 2). The predicted pressure parameters (mean and rms Cp) from RF and SVR along with actual data were plotted in the wind direction along the center line of the building for 0° wind angle to evaluate how well the model predicted local pressures (see Fig. 1). Fig. 1 shows that RF better predicted the pressure coefficients.

5. DISCUSSION

Using the 1:100 scale ST3 model (30'x45'x13') from the NIST-UWO database with a small dataset, mean, rms, min, and max Cp (external) were predicted with traditional ML models (RF and SVR). RF performed better than SVR in this case. This paper will employ deep learning along with traditional ML models to predict and compare the internal and external pressure coefficients for a very large dataset using five different NIST-UWO models (mentioned in Table 1) of plan dimensions 80'x125' and 40'x62.5' with varied eave heights, roof slopes, and wind directions and extend previous work to include different terrain exposures. This paper will also extend the ML approaches to predict net pressures across surfaces and global load effects (e.g., bending moments, base shears, etc…) by combining net pressures with appropriate influence coefficients.

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