PREDICTING LOCAL WIND PRESSURE COEFFICIENTS FOR OBSTRUCTED BUILDINGS USING MACHINE LEARNING TECHNIQUES

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ABSTRACT

Wind pressure coefficients (Cp) are important elements in the simulation of natural ventilation in urban environments, where it tends to be less effective. Cp values can be obtained by wind tunnel experiments or CFD simulations, but these methods are not always available to building simulators due to cost and time constraints. Cp values also can be obtained by inexpensive methods, such as databases and analytical models, but these values are usually surface-averaged and introduce major errors in the calculation. This paper reports early results on the use of machine learning techniques to derive more accurate models for obstructed buildings with the potential use for urban stock modelling. Artificial neural networks (ANN) were applied to the empirical data from wind tunnel experiment in order to predict local (non surface-averaged) values of Cp. The cases used were obstructed, flat-roofed buildings with different area density values and surrounding buildings' height. One ANN was developed per wind attack angle using the statistical package R and consists of 5 inputs, three hidden layers and the output. Results obtained indicate than an ANN can predict the local Cp in obstructed buildings with uncertainty of ± 0.05 for a confidence level of 95%. This paper demonstrates promising results in the use of machine learning techniques to model complex input required by urban building performance simulation. Cp values by ANN show major improvements when compared to current practice sources.

INTRODUCTION

Predictions indicate that, by 2030, almost 80% of the world population will be loving in cities increasing from 50% where it currently is. Cities use a large amount of energy resources and account for over 70% of global carbon emissions (Luederitz, Lang and Von Wehrden, 2013; Vega-Azamar et al., 2013). In order to manage the use energy of the built environment in a sustainable way and to minimise harmful emissions, the performance of the city in sectors or 'as a whole' must be considered. For sustainable urban planning there is a need to consider large number of buildings at the same time. This will have an impact to the natural ventilation of buildings when not considered to be isolated. An accurate coefficient of wind pressure on a building's façade would result in a more accurate calculation of natural ventilation. This work proposes the prediction of wind pressure coefficient (Cp) of obstructed buildings through the use of machine learning.

Wind is a key factor affecting infiltration and ventilation in buildings (Hens et al., 1996; Ramponi, Angelotti and Blocken, 2014). Energy use of buildings, air quality and indoor and outdoor thermal comfort are directly affected by the air flow around the buildings. Wind pressure difference and pressure fluctuations around the building, inducing internal air flows, are one of the most essential driving forces of power for indoor natural ventilation. Thus, the arrangement of surrounding buildings in relation to wind direction fully impacts natural ventilation. Natural ventilation occurs due to pressure difference between in and out of the building allows the air to move through it (Zhang, Gao and Zhang, 2005). In the majority of Air Flow Network (AFN) modelling and Building Energy Simulation (BES) programmes, wind interaction with building is addressed using Cp on building facades as a boundary condition (Clarke, 2001; Sahal and Lacasse, 2005). Cp has been used in a variety of contexts, from calculating ventilation in standard buildings (Kalogirou, Eftekhari and Marjanovic, 2003; Guan et al., 2016), to evaluating ventilation in greenhouses (Kwon et al., 2016; Kim et al., 2017; Kuroyanagi, 2017), impact of microclimate in air flow rates (Charisi, Waszczuk and Thiis, 2017), performance of solar panels (Stathopoulos, Zisis and Xypnitou, 2014), and relation between ventilation and building shapes/sizes (Jendzelovsky, Antal and Konecna, 2017; Zhao and He, 2017). Cp is defined as:

$$C_p = \frac{Px - Po}{Pd} \, , P_d = \frac{\rho \cdot U_h^2}{2} \qquad\qquad (1)$$

where P_x is the static pressure at a given point on the building facade (P_a), P_o is the static reference pressure (P_a), P_d is the dynamic pressure (P_a), ρ is the air density (kg/m3) and Uh is the wind speed (m/s).

Secondary sources are largely used to obtain Cp data, as they are straightforward and inexpensive when compared to more accurate sources such as custom wind tunnel experiments or computational fluid dynamic simulations (Cóstola, Blocken and Hensen, 2009). The most widely used secondary source for Cp data is the regression model proposed by Swami and Chandra (S&C) (Cóstola, Blocken and Hensen, 2009). In this model, there are two different equations for low-rise and high-rise unobstructed buildings with rectangular floor plans (Swami and Chandra, 1987). The correlation coefficient of the low-rise equation is 0.8 and the model has only two input parameters: building floor plan aspect ratio and wind direction (Cóstola, Blocken and Hensen, 2009). The S&C model calculates surface-averaged Cp, as it assumes that cracks are evenly distributed over the building facades (Wiren, 1985) and (Knoll B, Phaff JC, 1995). The use of surface-averaged Cp has major limitations and may incur significant errors error in the calculated airflow rate (Cóstola *et al.*, 2010). Other widely used data sources of Cp, the Air Infiltration and Ventilation Centre (AIVC) database, also adopts surface-averaged Cp values (Liddament, 1986).

Wirén (Wiren, 1985) examined a Swedish single-family building and the possible effects on pressure distributions from the surrounded identical buildings in various arrays. The magnitude and distribution of the wind pressure on the test building is affected by the density of the surrounding buildings. A similar study done by Tsutsumi et al.(Tsutsumi, Katayama and Nishida, 1992) which modelled some blocks in order to find out the wind pressure on groups of buildings mainly discussed the relationship of the various layouts and the average wind pressure coefficient. Different geometries and wind directions were examined and concluded that these two factors are very important in terms of natural ventilation.

Artificial Neural Networks (ANN) has shown success results in a variety of fields, such as banking (Tavana *et al.*, 2017), solid state physics (Carrillo *et al.*, 2017), ocean engineering (Seyedashraf, Rezaei and Akhtari, 2017), microelectronics (Khera and Khan, 2017), human science (Aram *et al.*, 2017), archaeology (Burry *et al.*, 2017), agriculture(Elnesr and Alazba, 2017), thermal comfort (von Grabe, 2016) and particularly on applications related to building performance (Kumar, Aggarwal and Sharma, 2013; Melo *et al.*, 2014; Jovanović, Sretenović and Živković, 2015; Li *et al.*, 2015; Deb *et al.*, 2016; Magalhães, Leal and Horta, 2017). ANN has been recently used to predict surface-averaged Cp (Bre, Gimeneza and Fachinottia, 2018). In terms of Cp data, Tokyo Polytechnic University (TPU) provides a considerable amount of high-quality data for various building configurations (Tokyo Polytechnic University, 2017b). The present paper describes an investigation on the modelling local Cp for obstructed buildings using ANN and the TPU database.

METHODOLOGY

This work adopts the box-shape flat-roof models of the TPU wind tunnel database for low-rise obstructed buildings (Tokyo Polytechnic University, 2017a). Data from these models was used for the training and validation of ANNs. Cp data has been analysed across all wind attack angles for each facade (0°-338°) using the different geometric parameters of these flat-roof models in a scale of 1:100 and Figure 1 shows the aspect ratios of the target model and surrounding identical models. TPU database consists of 30 models, tested for 5 wind directions (0°, 23°, 45°, 68° and 90°) and 8 different area densities (C_A) (from 0.1 to 0.6) resulting in a total of 23,281 entries (corresponding to a given model / wind direction / pressure tapping position on the façade/ area density). The chosen arrangement type of models is the simplest in the TPU database, the regular one as shown in Figure 2, which can be compared to the building stock of Barcelona.
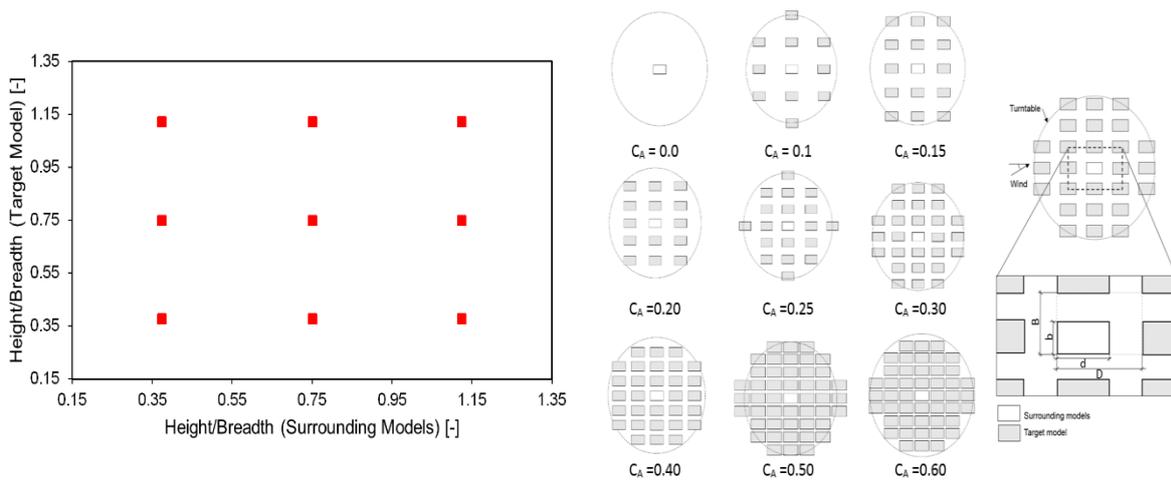
Figure 1: Aspect ratios of target model and surrounding models of box-shape flat-roof obstructed TPU models

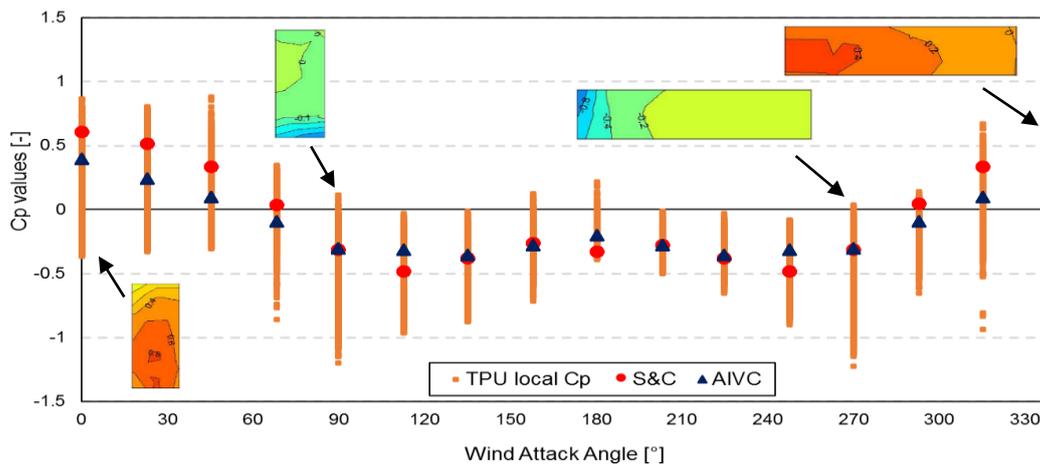*Figure 2: Different area densities of surrounding buildings*

Figure 3: Wind pressure coefficient values of the models compared to TPU local Cp and surface-averaged of S&C and AIVC (with samples of Cp distribution over some facades for wind attack angles 0°, 90°, 270° and 338°).

As S&C and AIVC are the most common sources of Cp data, it is useful to provide an evaluation of the difference between their predictions and actual local Cp data obtained in wind tunnel experiments. Figure 3 shows a sample of local Cp data from TPU for different wind attack angles when compared to surface-averaged data from S&C and AIVC. The figure shows that such methods oversimplify the wide distribution of values seen in wind tunnel experiments. While the figure is informative, it is useful to quantify the difference between S&C and AIVC when compared to TPU. Such quantification was performed by comparing each one of the 23,281 local Cp data entries to the prediction of S&C and AIVC. The absolute errors were analysed both using histograms and using the root-mean squared error (RMSE) to create confidence intervals for S&C and AIVC predictions. The confidence intervals were based on a confidence level (95%) and assumed that errors were normally distributed. These confidence intervals provide a reference point to quantify the improvement in accuracy obtained by the ANN model for local Cp.

The modelling of the neural networks for this work has been done using the statistical package R and 'neuralnet' package (Fritsch *et al.*, 2016). The neural networks in this package are feed-forward trained and focuses on multi-layer perceptrons (MLP) (Günther and Fritsch, 2010). The training and validation data was randomly separated by R to 80% and 20% respectively. Five input parameters were used for the creation of the neural network: the x coordinate, the y coordinate of the pressure tapping on the facade of the model, the aspect ratio of the surface, the surrounding models' height in relation to the target model and the area density. Several configurations of ANN were investigated to define the best number of hidden layers and neurons in each layer and the final one is shown Figure 4. The log sigmoid function (Eq. 2) has been used in all configurations of the ANN to ensure that the output signal of each node is smooth and as stated by Duch and Jankowski (Duch and Jankowski, 1999) and Widrow and Lehr (Widrow and Lehr, 1990) ensuring it was appropriate for the application.

$$s(x) = 1/(1 + e^{-x}) \tag{2}$$

Where x corresponds to the sum of the weighted input of each previous node plus the bias of the node itself.

The input and output data associated with the ANN was normalised within the same boundaries as the activation function, i.e. the sigmoid function, giving a value between 0 and 1 (Guoqiang Zhang, B. Eddy Patuwo and Michael Y. Hu, 1998). Validation is a critical aspect of any model construction and therefore only the validation results were included in the graphs of ANN predictions compared to TPU database values (Figure 6a). The comparison between the TPU Cp values data and the ANN results was analysed based on the RMSE, which was used to calculate confidence intervals based on the same criterion and assumptions listed in the following sections. The frequency of errors between the TPU database and the neural network results was also analysed using histograms.
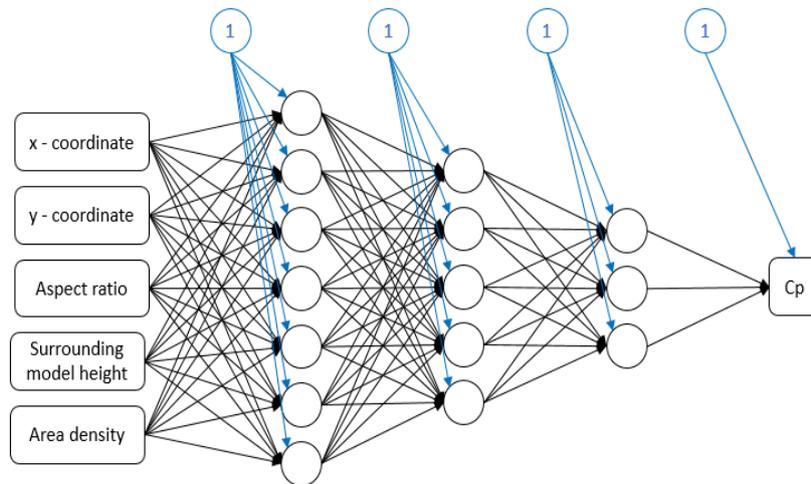

Figure 4: ANN configuration for obstructed low-rise buildings

RESULTS AND DISCUSSION

Figure 5a and 5b show a comparison for each data entry between the local Cp from TPU database and the surface-averaged Cp of the two existing data sources typically used in energy and airflow simulations (S&C and AIVC). These figures show symmetry plots where wind tunnel data from TPU is on x-axis and the S&C and AIVC data on the y-axis. In both cases, the surface-averaged data assumes discreet values that fail to capture the complexity of local wind pressure distribution in the models. This can be better quantified through the histograms in Figure 5c which shows the frequency of errors as described in a previous section. Errors are comparable for both data sources and vary from -1.0 to +0.8, which are if the same order of magnitude as Cp itself (which varies from -1.3 to 0.9 in this dataset). Assuming a normal distribution of errors, the calculated confidence intervals of AIVC and S&C Cp data are ±0.45 and ±0.58 respectively for a confidence level of 95%. These results are in agreement with

the large uncertainties reported in the literature, (Cóstola *et al.*, 2010), which result from the surface-averaging of Cp.

Results in Figure 6a show the comparison between the ANNs predictions for the validation data and the local Cp data from the TPU database. The ANN results show good agreement, particularly in comparison to data in Figure 5 (which represents the best practice in terms of Cp data using secondary sources). The best configuration identified for the ANN comprises three hidden layers with 7, 5 and 3 nodes respectively and the strategy of using one ANN per wind attack angle proved to deliver good results. The frequency of error (calculated based on the method outlined in methodology) is shown in the histogram in Figure 6(b). The histogram captures all the errors, even though it cannot be clearly seen due to the fact that the frequency is small compared to the columns shown. For the present application, predictions made using the ANN gave a confidence interval of ±0.05 (RMSE=0.025) for a confidence level of 95%.
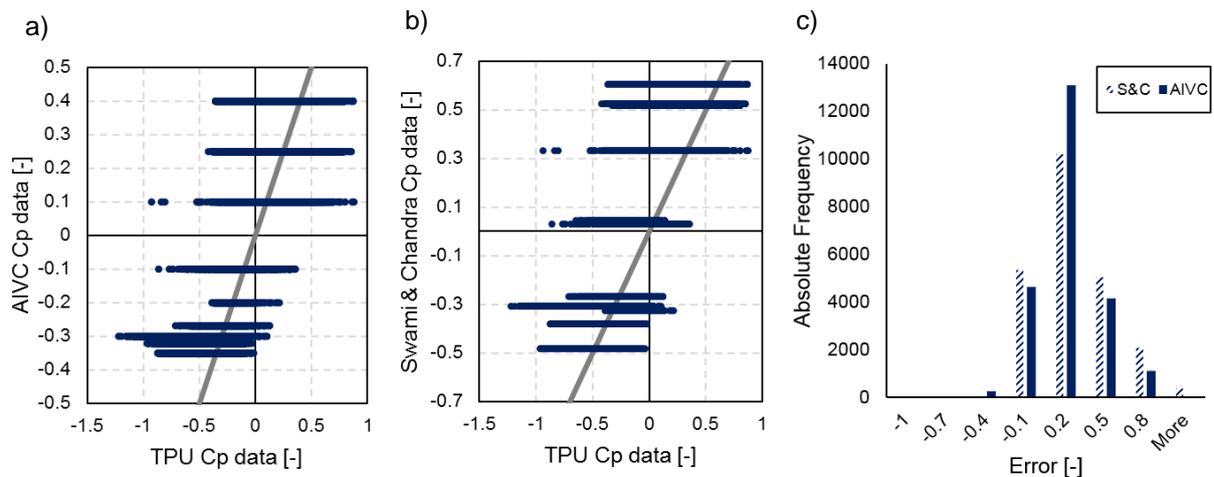

Figure 5: Comparison between TPU wind pressure coefficients and data from S&C and AIVC: (a) symmetry plot of AIVC, (b) symmetry plot of S&C and (c) histogram of errors in Cp calculations
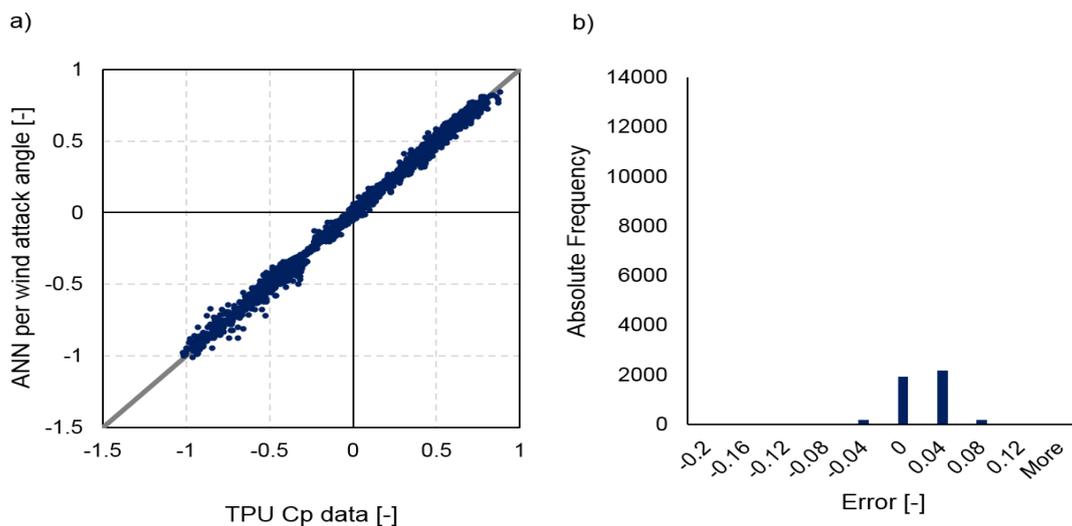

Figure 6: Reference data of TPU compared to ANN per angle predictions: (a) symmetry plot and (b) histogram of errors in ANN calculations.

The results obtained in this study are in line with previous studies and demonstrate the ability of ANN to handle complex relations between input and output data. These results provide a promising perspective towards the future application of ANNs in the prediction of local Cp in obstructed buildings

with more complex geometry and/or in sheltered of partially sheltered environments. There are many other promising applications for ANNs in relation to building simulation.

CONCLUSIONS

This work described the development of artificial neural networks for the prediction of local wind pressure coefficients in box-shape obstructed building facades. The conclusions drawn based on the results presented are:

- The most widely used sources for wind pressure coefficients of Swami and Chandra and AIVC database provide the surface-averaged wind pressure coefficient that fail to describe the variation of pressure seen in building facades. Swami and Chandra and AIVC models have a confidence interval of ±0.58 and ±0.45 respectively for a confidence level of 95%.
- The trained and tested artificial neural networks using Tokyo Polytechnic University wind pressure database showed that local wind pressure coefficients can be predicted with ±0.05 confidence interval for a confidence level of 95%.
- One artificial neural network per wind attack angle with three hidden layers with 7, 5 and 3 nodes respectively showed the best results when compared to other ANN configurations.
- This model can be used for the accurate prediction of wind pressure coefficient for a large number of building types, geometries, and different wind angles, supporting high-resolution stock models addressing naturally ventilated buildings. Further work can be focused on embedding this ANN into building energy simulation software.

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