Prediction of wind pressure coefficients in building energy simulation using machine learning

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Abstract

A common source of uncertainty for the airflow rate calculation in building energy simulation software is the use of surface-averaged generic wind pressure coefficients instead of local wind pressure coefficients for any building shape. This work explores the calculation of local wind pressure coefficients using artificial neural networks for a specific building shape. Results show that it is possible to approximate the local wind pressure coefficient using artificial neural networks with good agreement with the experimental data (up to 50% reduction in the error when compared to Air Infiltration and Ventilation Centre (AIVC) database Cp data). Subsequently, local wind pressure coefficients obtained from the neural networks are introduced to corresponded building energy simulation software. Simulations were performed for a case study in order to compare the performance obtained using data from (a) wind tunnel experiments (reference best practice), (b) surface-averaged generic wind pressure coefficient from AIVC and (c) artificial neural networks local wind pressure coefficient. Artificial neural network simulated air flow rates show significant improvement in accuracy when compared to AIVC.

Introduction

Natural Ventilation

Indoor thermal environment affects the health and productivity of occupants, therefore ventilation in buildings must be well incorporated into the design process. Natural ventilation approaches such as night-time ventilative cooling, atrium ventilation, wind towers and other similar techniques have been more widely adopted in recent years, in order to improve thermal comfort and indoor air quality conditions in buildings and reduce building energy consumption. Recent studies which have taken into consideration the behaviour of occupants towards window opening showed that the energy consumption and thermal comfort are relevant to the effects of window opening (Andersen, Fabi, & Corgnati, 2016; Chou & Ngo, 2016; Fabi, Andersen, & Corgnati, 2015; Firląg et al., 2015; Moghadam, Soncini, Fabi, & Corgnati, 2015; Sorgato, Melo, & Lamberts, 2016; Tahmasebi & Mahdavi, 2016; Zhang & Barrett, 2012).

Grilles and duct system and façade or roof openings/doors/windows are the means to achieve natural ventilation. Façade or roof openings can produce two configurations; single-sided ventilation (through one opening) or cross ventilation (multiple openings). Modelling single-sided ventilation is a complex process and is still widely debated since the 1980s. Unsteady parameters such as the variation in the pressure gradients induced by wind gusts and the wind turbulence heavily influence the single-sided ventilation model, therefore making it much more difficult to evaluate in contrast with the cross ventilation model (Oropeza-Perez et al., 2014).

In 1982, de Gids and Phaff presented the first natural single-sided ventilation in buildings model. Their approach was an empirical expression based on a) wind velocity, b) air temperature variation and c) opening area. It calculated the airflow in single-sided ventilation zones, produced by a unique window in a room. All investigations were conducted on the first floor of buildings located in urban areas and surrounded by buildings up to a maximum of 4 floors high (B.R. Hughes et at., 2012).

Nowadays, due to the high standard of existing hardware technology and advances in Computational Fluid Dynamics (CFD) software, more advanced analysis models have been developed for both single-sided ventilation and cross ventilation. Nevertheless, using a CFD approach is rather complex; for accurate modelling of the airflow around buildings, large computational area modelling is necessary. Therefore, for whole-building hydrothermal analyses, empirical expressions are still widely used (Roberto Z. Freire et al., 2013**)**. In this analysis, wind pressure is a major input as discussed below.

Wind pressure coefficient

Infiltration and ventilation largely depend on the wind in many aspects (Hagentoft C., 1996). Wind pressure distribution on building façades is a boundary condition for almost all the models currently used in Air Flow Network (AFN) and Building Energy Simulation (BES) programs. The wind pressure coefficient (Cp) is expressed using Equation 1 below.

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

where Px is the static pressure at a given point on the building facade (Pa), Po is the static reference pressure (Pa), Pd is the dynamic pressure (Pa), ρ is the air density (kg/m3) and Uh is the wind speed (m/s)

Sensitivity analysis research was carried out in the past to identify the impact Cp has on BES which concluded that Cp is the main source of uncertainty due to many building performance indicators like mould growth, thermal comfort and energy consumption which are largely dependent on the Cp values. The fact that these indicators depend on the air change rate as well results to the high Cp uncertainty. One of the very few ways to overcome this uncertainty in Cp was the use of wind-tunnel experiments and full-scale measurements which are quite costly. As stated by Tuomaala (2002) "there is no reliable and effective method for evaluating the value of wind pressure coefficients for complex cases." The statement above can be explained, as the influencing parameters of Cp data are of a large number and uncertainty increases. Some examples are the wind speed and direction, the building geometry and obstructions in the near vicinity of the building.

Artificial Neural Networks

Artificial Neural Networks (ANNs) are computational modelling tools that have recently emerged and found extensive acceptance in many disciplines for modelling complex real-world problems. ANNs may be defined as structures comprised of densely interconnected adaptive simple processing elements (called artificial neurons or nodes) that are capable of performing massively parallel computations for data processing and knowledge representation (Hecht-Nielsen, 1990 and Schalkoff 1997). The idea behind the ANNs is not the exact use and operation as in biological systems, but to use the functionality of them towards the solution of complex problems. Their ability to handle imprecise information and the fact that are capable to generalise the information are just two of their outstanding characteristics. Others are the high parallelism, fault and failure tolerance, robustness and high parallelism (Jain et al., 1996). ANN models possessing such characteristics are desirable because: (i) non-linearity allows better fit to the data, (ii) noise-insensitivity provides accurate prediction in the presence of uncertain data and measurement errors, (iii) high parallelism implies fast processing and hardware failure-tolerance, (iv) learning and adaptivity allow the system to update its internal structure in response to changing environment, and (v) generalization enables application of the model to unlearned data. The main objective of ANN-based computing (neurocomputing) is to develop mathematical algorithms that will enable ANNs to learn by mimicking information processing and knowledge acquisition in the human brain (Basheer at al., 2000)

Methodology

Wind Pressure Coefficients Database

The wind pressure coefficient database used in this case to train the ANN is the Tokyo Polytechnic University (TPU) database. This database includes data for low-rise and high-rise buildings in several configurations. This paper only explores two models of the database for low-rise unsheltered buildings.

Wind tunnel database – Model Geometric Parameters

Figures 1 and 2 show the 64 pressure tap locations on the model (x and y axis placed in the middle of each face).

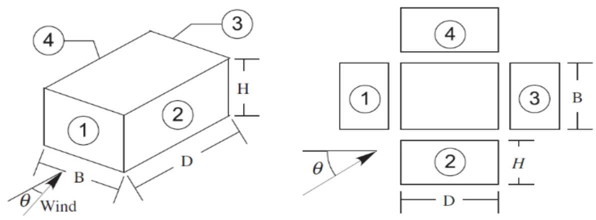

Figure 1: Building geometry identifying the building sides, the building dimensions and the wind angle

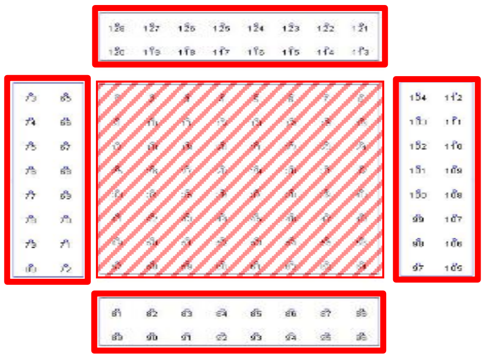

Figure 2: Model's pressure tap locations and numbers

The model has been analysed using the wind pressure coefficients across all the wind attack angles that have been tested during the wind tunnel experiment at Tokyo Polytechnic University. The results presented below have been divided into two sections; windward direction (0°-60° and 300°-360°) and leeward direction (75°-285°).

Figure 3 shows the distribution of the normalised Cp values across all sides of the model. As it can be seen from the graph, the Cp value varies across several values for each angle. This highlights the magnitude of simplifications adopted in surface-averaged Cp for a specific wind attack angle, as large amounts of Cp data are lost and never taken into consideration. The contour diagrams in Figure 4 show how the Cp value changes across the building when the wind attack angle changes as well.

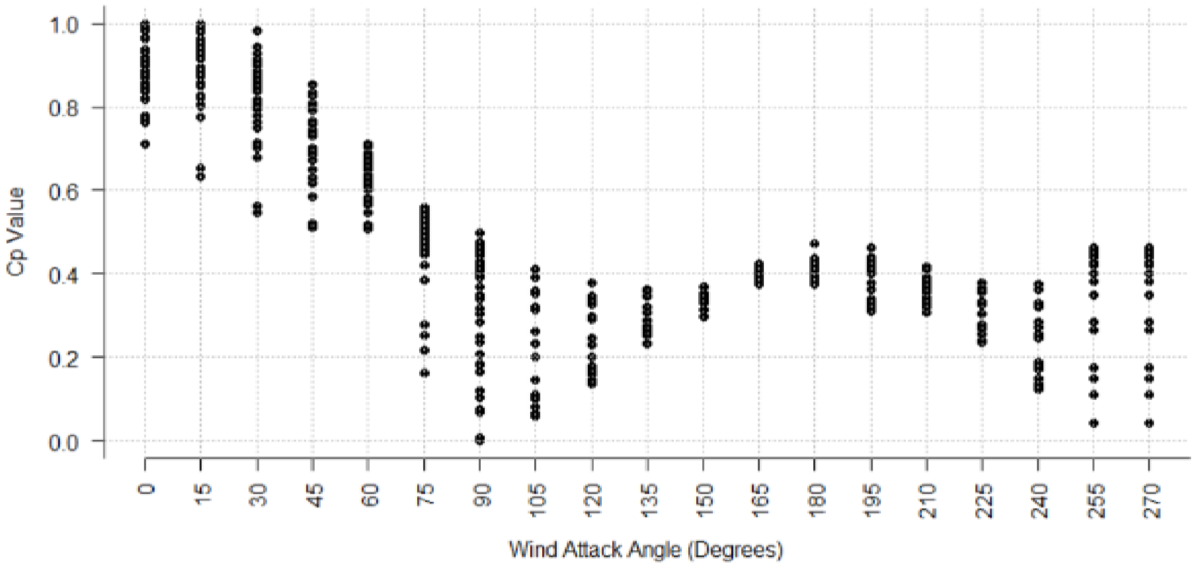

Figure 3: TPU Cp values against wind angle

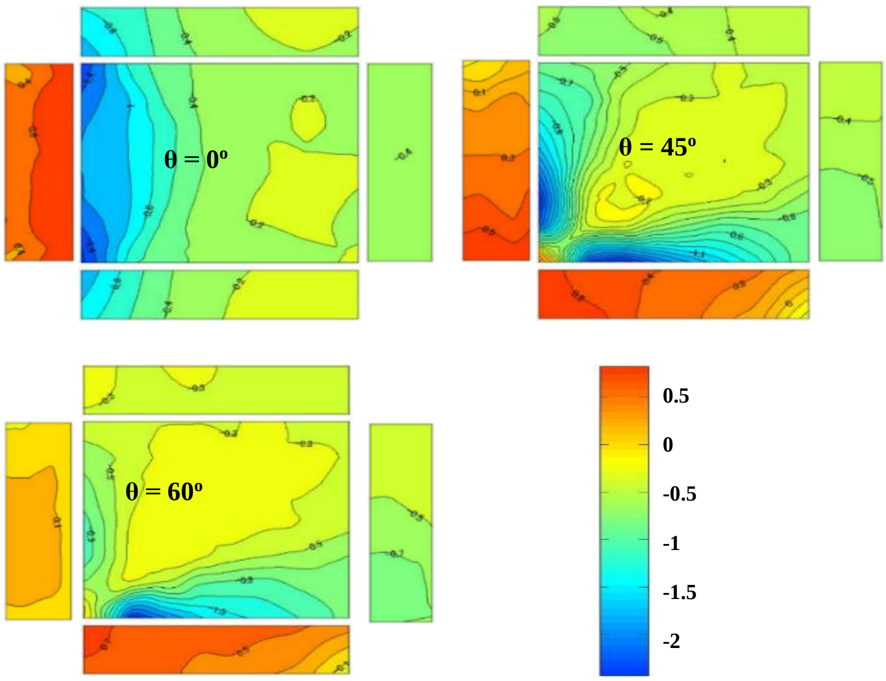

Figure 4: Mean wind pressure coefficients at wind angles 0º, 45º and 60º from TPU wind tunnel test (http://www.wind.arch.t-kougei.ac.jp/info_center/windpressure/lowrise/g080200.html).

Neural network modelling and configuration

Neural Network modelling for this paper was done using 'R statistical package' and more specific 'neuralnet' package which works mainly towards the training of the neural network using backpropagation. Tokyo wind pressure coefficients database was used towards the training of the ANN. The log sigmoid function (Eq. 4) has been used in every case in order that the output signal of each node is smooth.

$$s(x) = 1/(1 + e^{-x}) \qquad (4)$$

All the data regarding pressure tap location, wind pressure coefficient and wind attack angle taken from Tokyo Database have been imported into 'R'. For the training of the neural networks 80% of the data has been used, whereas the remaining 20% of the data was used for their production. The number of inputs for the creation of the neural network are the x and y value of the pressure tap location and the wind attack angle ending to the outcome node of the Cp. The training process of the artificial neural network in this case is to complete as many steps as possible and this process stops when all partial derivatives of the error function were smaller than 0.1. Using the 'compute' function in 'neuralnet' package, which is a function that calculates and summarises the output of each neuron, the new wind pressure coefficients have been calculated based on the outcome of the trained neural network.

Using the calculated weighting factors and biases, results for an ANN with one hidden layer and one output node can also be calculated according to the following equation (Melo et al., 2014,):

$$\mathrm{Cp} = \mathrm{Cp_{MIN}} + (\mathrm{Cp_{MAX}} - \mathrm{Cp_{MIN}}) \times [1/(1 + \mathrm{e}^{\mathrm{NETinput}})] \qquad (2)$$

$$NETinput = \sum_{n=1}^{H} \left\{ \left[1/\left(1 + e^{-\left\{ \sum_{i=1}^{X} \left[\left(\frac{x_j - x_{MIN\,j}}{x_{MAX\,i} - x_{MIN\,i}} \right) \times W_{i,n} \right] + b_n \right\}} \right) \right] \times W_{n,S} \right\} + b_S \qquad (3)$$

Cp is the wind pressure coefficient, Cp_{min} and Cp_{max} are the minimum and maximum values used in the artificial neural network. H is the number of nodes in the hidden layer, X is the number of input nodes, x_i is the input values for the calculation, $x_{max\,i,}$ and x_{min} are the maximum and minimum values for the input used in the ANN training, $W_{i,\,n}$, and $W_{n,s}$ are the weighted values for each pair of nodes and b_n , and b_S are the biases of the hidden nodes and the output ones.

BES modelling and airflow rate error

The energy modelling of the project will be done in ESP-r software, in order to compare the new results with the default ones in ESP-r. This software has 27 different datasets of wind pressure coefficient taken from the Air Infiltration and Ventilation Centre (AIVC) Handbook for a basic case scenario. Due to this particular project's needs, two new datasets have been added; the first one resulting from the existing Tokyo database and the second one from the ANNs. This will enable us to evaluate whether the previous work carried out for wind pressure coefficient was somewhat accurate towards the energy consumption of a building. Reflecting back to the overall aim of the project, where local Cp values will be used for the simulation rather than surface-averaged ones, the new databases added to BES program have local Cp values. A model has been created with the same dimensions as the one used for the wind tunnel test, at Tokyo Polytechnic University, to compare the results after inputting all three different wind pressure coefficients.

The relative airflow rate error for the same pair openings is defined as:

$$r = \frac{\Phi_{LOC} - \Phi_{AV}}{\Phi_{AV}} = \frac{\Phi_{LOC}}{\Phi_{AV}} - 1 \qquad (5)$$

where Φ_{LOC} is the airflow rate calculated from Cp_{-LOC} and Φ_{AV} is the airflow rate calculated from Cp_{-AV}.

BES Modelling – Model Geometric Parameters

A model has been created for the energy modelling of the results, with two openings, one on wall 1 and the other one on wall 3 (Figure 5). The openings represent the points where the new wind pressure coefficient values will be inserted.

Having said that, the ESP-r model is of the same dimensions as the model used for the wind tunnel. The ESP-r model has the following geometric parameters:

- Height = 4.0 m
- Depth = 16.0 m
- Width = 16.0 m
- Volume = 1020 m^3
- Cd = 0.6 (orifice discharge coefficient)

The airflow network has been created between zone 1, which is the internal area of the building, and the two openings in order to find the mass flow rate between them, and therefore the impact to the total energy consumption.

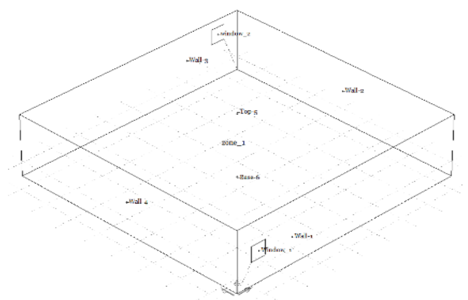

Figure 5: BES simulation model

ANN Results Analysis

The ANN results are presented below; these results have been derived using the low – rise data from Tokyo Polytechnic University database as mentioned in the methodology section. The neural network produced from the data consists from three inputs (wind attack angle, x - coordinate and y - coordinate), one hidden layer with 7 nodes and the Cp as the output. Tables 1 and 2 include all the weights, biases together with the maximum and minimum values used for the training of the ANNs.

Table 1: Weights and biases of the ANN

Hidden Nodes	Weight Input			Bias	Weight Output
	angle	x	y		Cp
1	0.093	-0.533	-0.401	1.160	-0.840
2	-0.005	-0.234	0.011	-1.469	-2.686
3	0.058	0.557	-0.456	-4.077	-0.825
4	-0.051	-0.131	0.057	3.058	1.384
5	-0.063	-0.063	0.039	3.022	-0.874
6	0.122	0.568	-0.902	-2.988	-0.640
7	-0.077	0.033	-0.196	3.741	0.713
Cp				2.071	

Table 2: Maximum and Minimum values for the input and output nodes

Nodes	minimum	maximum
Angle	0	360
x coordinate	-21	21
y coordinate	-13	13
Cp	0.980	0.804

The outcome (i.e. weights and biases) of the neural network has been then used to input the exact same numbers for angle, x and y and compute its own Cp value. A histogram has been drawn to present these new results, which can be seen in Figure 6. The histogram shows that the majority of the difference in values is in the range of ±0.1.

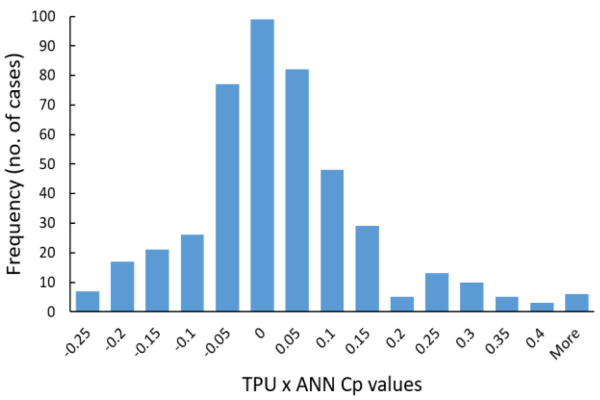

Figure 6: Histogram of the frequency of the error against the error value of the model

A further break down of the results has been made taking this time into account only the windward direction rather than all four sides of the model. Windward direction as mentioned earlier is between 0º and 60º. Figure 7 shows a symmetry plot for windward data, where a large amount of the points fall on or near the red line of equality. In order to prove the difference between selecting a surface-averaged and a local Cp, the root mean square error and the confidence interval for 95% of the cases have been calculated using the new Cp values computed from the ANN. The results are summarised in the Table 3 and as it can be seen, the local Cp has nearly 55% more accuracy for the wind pressure coefficient.

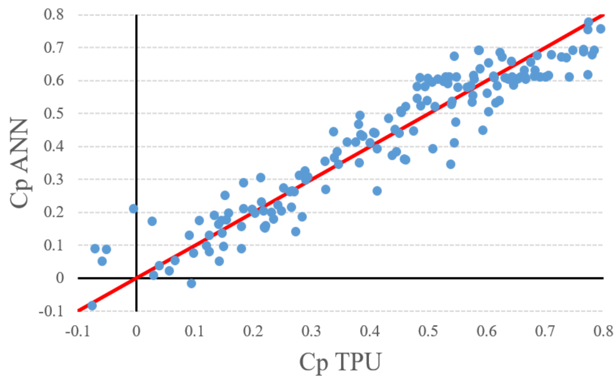

Figure 7: Symmetry plot for windward direction

Table 3: ANN error values comparing local and surface-averaged Cp for windward direction

	Local Cp	Surface-averaged Cp
Mean bias	0.23	0.23
Root mean square	0.08	0.17
Confidence interval (95%)	0.15	0.33

Leeward direction results of the model are shown below in Figure 8. Unlike windward direction results, the ANN did not functioned as expected. Even though some results are close to equality line others are way apart and especially from -0.5 up to -1 on the Cp TPU axis they constantly give a result of around -0.45 on the Cp ANN axis. Table 4 below summarises the results of the leeward direction. Again, in this case the local Cp has a higher confidence interval by almost 10% than the surface-averaged Cp.

Table 4: ANN error values comparing local and surface-averaged Cp for leeward direction

	Local Cp	Surface-averaged Cp
Mean bias	0.21	0.21
Root mean square	0.12	0.22
Confidence interval (95%)	0.24	0.44

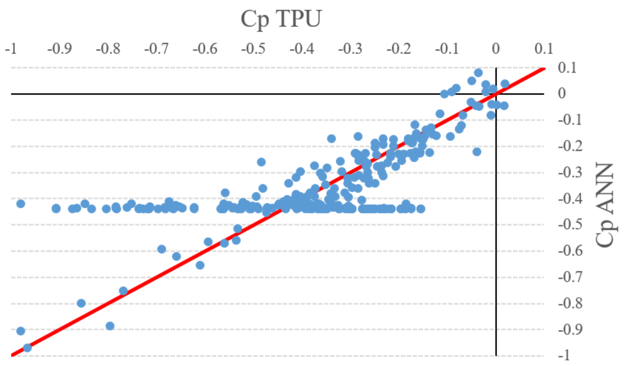

Figure 8: Symmetry plot for leeward direction

BES simulation results using Cp from ANN

The energy modelling results are presented in the following graphs, concluding the whole idea of this project which is the relation of wind pressure coefficients with energy consumption and how inaccurate surface-averaged Cp are, compared to local ones.

Figure 9 shows the difference in pressure coefficient values between the three databases used. The AIVC, which is the one utilised in ESP-r, Tokyo Database where the ANNs were based for training and the new results from ANNs. As can be seen on the graph, there is a lot of difference between the pressure coefficients. More specifically in terms of numbers, there is a nearly 40% difference between AIVC and TPU and 60% difference between AIVC and ANN. This difference will definitely have an impact in the ventilation of the building, and therefore the model created in ESP-r has been simulated using all three different databases.

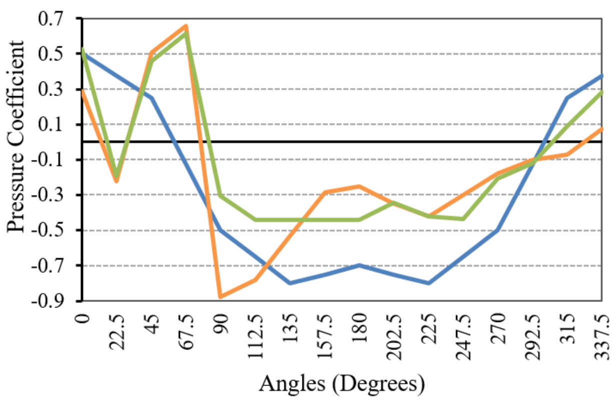

Figure 9: Pressure Coefficients for — AIVC, — TPU and — ANN

The simulation results can be seen in Figure 10 over the period of one week between 9 and 15 of January. The AIVC line as seen on the graph has more fluctuations with much higher peak values than TPU and ANN. This is demonstrated better in Figure 11 where the error of AIVC and ANN compared to TPU is plotted.

The ANN error from Figure 11 is accounted to be an average of 0.0054 whereas the AIVC error is -0.054, i.e. simulations based on ANN results have error 10 times smaller than simulations using AIVC data. The wind direction and speed during the simulation period is detailed in the appendix. A further calculation was carried out with the wind pressure coefficients of the AIVC and ANN databases between 0° and 180°; the positions of the two windows according to wind direction. The outcome of that was a percentage difference of 25% which indicates the extra ventilation required within the building to meet at least the minimum indoor air quality requirements.

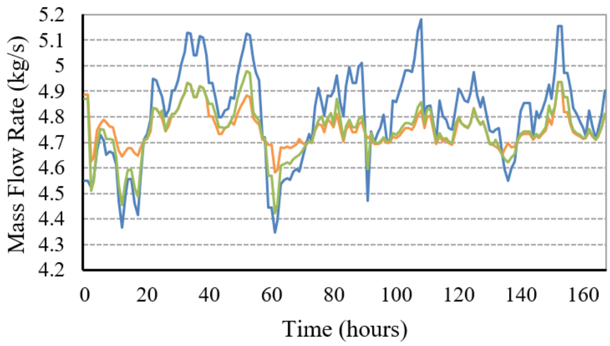

Figure 10: Mass flow rate for — AIVC, — TPU and — ANN

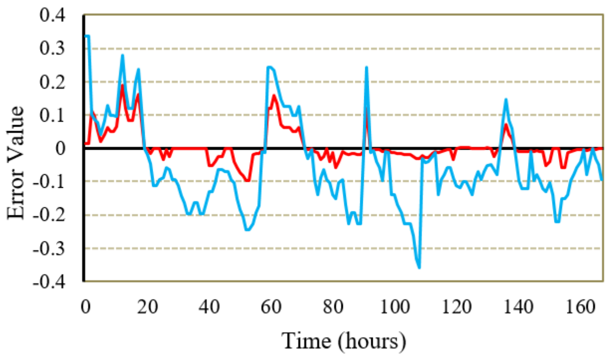

Figure 11: Mass flow error of — AIVC and — ANN compared to TPU

Discussion

Ventilation and infiltration of a building play a key role in the performance of it in terms of thermal comfort, energy consumption and indoor air quality. Limited amount of Cp data is used from building energy simulation programs and in all cases is the surface-averaged Cp. In this work, as the first step, an artificial neural network with three input nodes, one hidden layer with seven nodes and one output node was created for the training of it. The developed artificial neural network was used to obtain new local Cp values. The second part of this project was to use the artificial neural network results for the building simulation. All the data of the model regarding angles, x-coordinates, y-coordinates and Cp values were ready and used towards the creation and training of the artificial neural network.

The method of comparison and verification between the Tokyo database and the ANN results was mainly the difference between the surface-averaged Cp and local Cp. Thus, the error and confidence interval of 95% between them could be easily compared. The confidence interval of 95% for local Cp is as low as 0.15 whereas surface-averaged Cp is 0.33.
This work has two main limitations which are briefly explained below:

- Only one ANN was created for the model. More targeted ANNs in terms of angles or building sides are required to conclude in more accurate results for wind pressure coefficients and therefore airflow rate.
- Concerning the energy modelling, the number of openings is limited to two because of the methodology followed. More openings could have been added to the model and obtain results for different number of openings.

The implications of the above results and according to Melo et al. (2014), the use of artificial neural networks can potentially improve the prediction of the local wind pressure coefficient. This is confirmed by the model's ANN results. Regarding the airflow simulation results there is an agreement that surface-averaged pressure coefficients are less accurate than local wind pressure coefficients.

Specifically, in this work an absolute minimum reduction was calculated for the simulation error (absolute ANN error – absolute AIVC error, Figure 11) of 0.08. The mode of the absolute error reduction is likely more representative with a value of 0.09 and standard deviation of the absolute error reduction is 0.06. This result is especially crucial to wind attack angles where Cp exhibits the smallest variability (angles 105° to 180°, Figure 3). In this wind attack angle region, the variability of Cp is at the order of 0.5 hence a change of 0.09 is associated to a change in the order of 20%.

Conclusions

Neural networks improve significantly the prediction of Cp which can be used as input in relevant simulations of wind flow modelling in buildings. ANN results showed an overall good agreement with the experimental TPU output. When inputted in a building energy simulation software (ESP-r) the local Cp showed an error 10 times smaller than results obtained based on AIVC data for Cp A reduction of the mean absolute error of 0.08 (mode 0.09) was observed when compared to values calculated with the technique of surface-averaged Cp. Both, surface-averaged Cp and ANN Cp were compared to the experimental data of TPU. The further calculation of Cp value between AIVC and ANN indicated a 25% difference between them, meaning that 25% more ventilation is required to meet indoor air quality standards.

In the future two aspects of the above calculations can be improved. The first aspect is the improvement of the approximated local Cp using ANNs. More complex ANNs can be used as well as preliminary statistical analysis for the identification of possible key factors that affect Cp.

The second aspect concerns the improvement of the wind flow simulation corresponding software. More complex situation scenarios can be implemented which can include zoning of the wind flow distribution as well as specific building features that will complicate the turbulent airflow inside the building.

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