Accuracy of a neural network for the prediction of wind pressure coefficient

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ABSTRACT

The objective of this paper is to evaluate the usefulness and the accuracy of an artificial neural network (ANN) as a prediction tool of the wind pressure coefficient (Cp). The ANN is applied to predict the Cp for rectangular buildings. The Cp values obtained by wind tunnel experiments are approximated by using a Cascade-Correlation Learning Network model to make a prediction, and the performance of three kinds of residential ventilation systems depending on the wind effect is evaluated by using both of the predicted Cp and the Cp experimentally obtained. The results of the approximation for the rectangular buildings of three different heights suggest that the ANN has a promising potential as a prediction tool for the Cp with sufficient accuracy. The performance of the ventilation systems is evaluated of their total ventilation rates and fulfilment of ventilation requirements in multiple rooms represented by "Overall Supply Rate Fulfilment" values. In the performance evaluation, similar result is obtained even when the predicted Cp is used in the network simulation.

1. INTRODUCTION

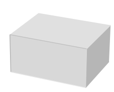
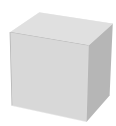
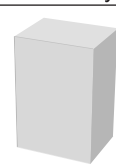
The wind pressure coefficient (Cp) has been used for the design and the evaluation of building ventilation systems. Thus, the accuracy of the Cp values affects the design and the evaluation, and it is recommended to do the wind tunnel experiment individually. On the other hands, more practical and economical method to determine the Cp has been searched for and there have been some trials, in which the database of the Cp and any algorithm are utilised (Swami et al. 1988, Knoll et al. 1995). However, it is still considered that any simpler estimation techniques are needed, if they can give accurate Cp values. This paper is intended to evaluate the accuracy of the approximation of the Cp for rectangular buildings by the artificial neural network (ANN). Even for a limited shape of buildings, for example for rectangular buildings, there are variety of the proportion among their height, width and depth. Moreover, it is impossible to carry out the wind tunnel experiments for every degree of wind direction. Therefore, any method to interpolate the Cp taking those conditions into consideration is needed. The effect of surrounding buildings is not dealt with in this paper, but it will be tried in the next step of this research.

2. METHOD

2.1 Methodology
This investigation is carried out by the following steps.
(1) Cp values of three types of buildings, which were measured by the wind tunnel experiments, are learned by an ANN model.
(2) The Cp values predicted by the ANN are compared with the Cp directly measured by the wind tunnel experiments.
(3) Network simulations are executed by using the both kinds of the Cp values, and those results are compared.
(4) The approximation accuracy of the Cp is evaluated from the view point of the prediction accuracy of whole house ventilation performance.

2.2 Training Cp Data
The reference data, which were measured in an Eiffel-type wind tunnel, consists of the Cp data for three 1/250 scale building models (Table 1) with simulated roughness adjusted to α=0.27 as described in the literature (Maruta 2004). The models had three different heights with the same width and depth. Three fourth of the data consisted of input and output parameters (described in 2.3) were used as training data. At the same time, the other data were used as checking data to detect over learning.

Table1: Scale models to be measured of their Cp values in the wind tunnel experiments

Type	L 5-storey	M 10-storey	H 15-storey
Height	 15m	 30m	 45m
Width	30m		
Depth	12.5m		
Measurement points	40	64	80
Wind directions	0°, 11.25°, 22.5°, 33.75°, 45°, 56.25°, 67.5°, 78.75°, 90°		

2.3 Neural Network Model

A Cascade-Correlation Learning Network model, which can determine its hidden layer's topology dynamically, was applied to learn the training data. The input and output parameters are shown in table2. The definition of wind direction and the facade are shown in Figure1. The wind direction was represented by sine and cosine functions. These input parameters were selected after several trial runs with the neural network model.

Table2: Input and output parameters for the neural network model

Input Parameters	I_1 Wind direction in cosθ
	I_2 Wind direction in sinθ
	I_3 Normalised horizontal position on facade
	I_4 Normalised vertical position on facade
	I_5 Height of building
Output Parameters	O_1 Cp value on Facade N
	O_2 Cp value on Facade S

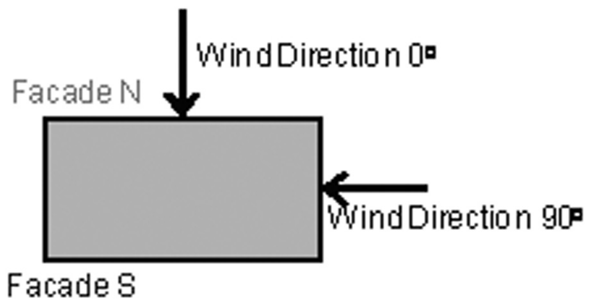
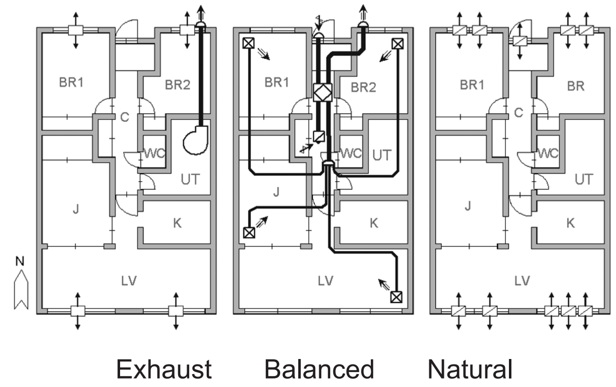


Figure1: definition of wind direction and facade

2.4 Ventilation Calculations

Ventilation network simulations were carried out in order to estimate the approximation accuracy of the ANN. The VENTSIM, which is a multi-zone network simulation program, was developed by BRI and NILIM, was used for the simulations. The air flow rates among zones and the index of "Supply Rate Fulfilment" (Sawachi, 1998) of each room were calculated for three different ventilation systems (Figure 2) with the Standard Expanded AMeDAS (Automated Meteorological Data Acquisition System) weather data of Tokyo as a meteorological data. The meteorological data contains hourly data through the standard year. Hourly total ventilation rates and hourly "Overall Supply Rate Fulfilment (OSRF)" were used as the indices of the ventilation performance, when estimating the approximation accuracy of the ANN. The OSRF is a geometric mean of each room's Supply Rate Fulfilment, which is defined as the ratio of effective supply rate to substantial fresh air requirement. Therefore, the OSRF represents whole house ventilation performance.

The three whole house ventilation systems for a unit of the multi-family buildings were assumed in the simulation. The exhaust ventilation system and the balanced ventilation system employ fans, of which total capacity is 90m^3/h. On the other hands, a natural ventilation system employs openings (see Figure 3), which have self regulating dumper inside, on the external wall.



- Total floor area of the unit: 72m^2
- Air tightness of the unit in n50: 0.7
- Capacity of mechanical ventilation: 0.5ACH = 90m^3/h
- Required fresh air supply rate of each rooms
  - LV+J+K: 50 m^3/h
  - BR1, BR2: 20 m^3/h

Figure 2: Ventilation systems in each residential unit to be simulated by a multi-zone network model, VENTSIM

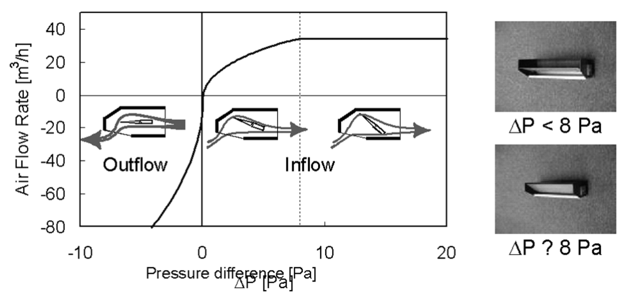


Figure 3: ΔP-Q Characteristics of natural ventilation opening

3. RESULTS AND DISCUSSION

3.1 Results of Approximation of the Cp Values by the Artificial Neural Network

The approximation results by the ANN are shown in Figure 4 for the building model type-H. The distributions of approximated Cp for three wind directions are in good agreement with those of reference Cp. The approximation errors are shown in the table 2, and they are small. The standard error and the root mean squared error are about 0.001 and 0.05, respectively.

Table 3: Approximation errors

	Building	Facade N	Facade S	total
SE	L	0.002	0.003	0.002
	M	0.002	0.002	0.001
	H	0.002	0.001	0.001
	All	0.001	0.001	0.001

RMS	L	0.045	0.057	0.051
	M	0.054	0.046	0.050
	H	0.056	0.039	0.048
	All	0.053	0.046	0.050

SE: Standard Error

RMS: Root Mean Squared error

3.2 Conditions and Results of Net work Simulation for Ventilation Systems

The network simulation was done for one unit in the building model Type-H. The unit was selected by choosing the unit, for which the discrepancy between the reference Cp and the predicted Cp was the maximum. The Cp difference between north and south facades, $\Delta Cp_{N\text{-}S}$, depending on the wind direction is shown in Fogure5. In the Figure5, the reference Cp (measured by the wind tunnel experiments), is plotted with three different Cp, which were made artificially to have larger RMS's, 0.2(Cp_{01}), 0.3(Cp_{02}) and 0.5(Cp_{03}). The effects of the error in the prediction of the Cp were checked by comparing the results of the network simulation.

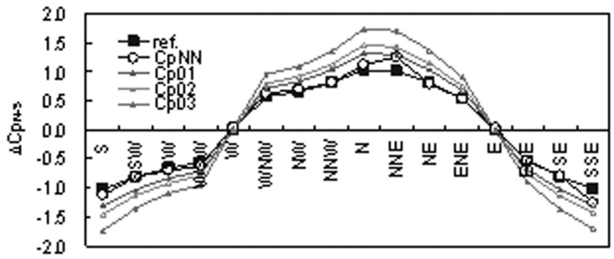


Figure 5: ΔCp values used for the ventilation calculations

Table 4: Root mean squared errors of the each Cp set

	RMS error	note
ref.	0	Reference data
Cp_{NN}	0.10	Neural network
Cp_{01}	0.20	Comparative data
Cp_{02}	0.30	Comparative data
Cp_{03}	0.50	Comparative data

Firstly, scatter diagrams of the hourly total ventilation rate and the hourly OSRF value, which is based on the reference Cp (Cp_{ref}) and the approximated Cp (Cp_{NN}), are shown in Figure 6, 7 and 8. Box-plot diagrams of the

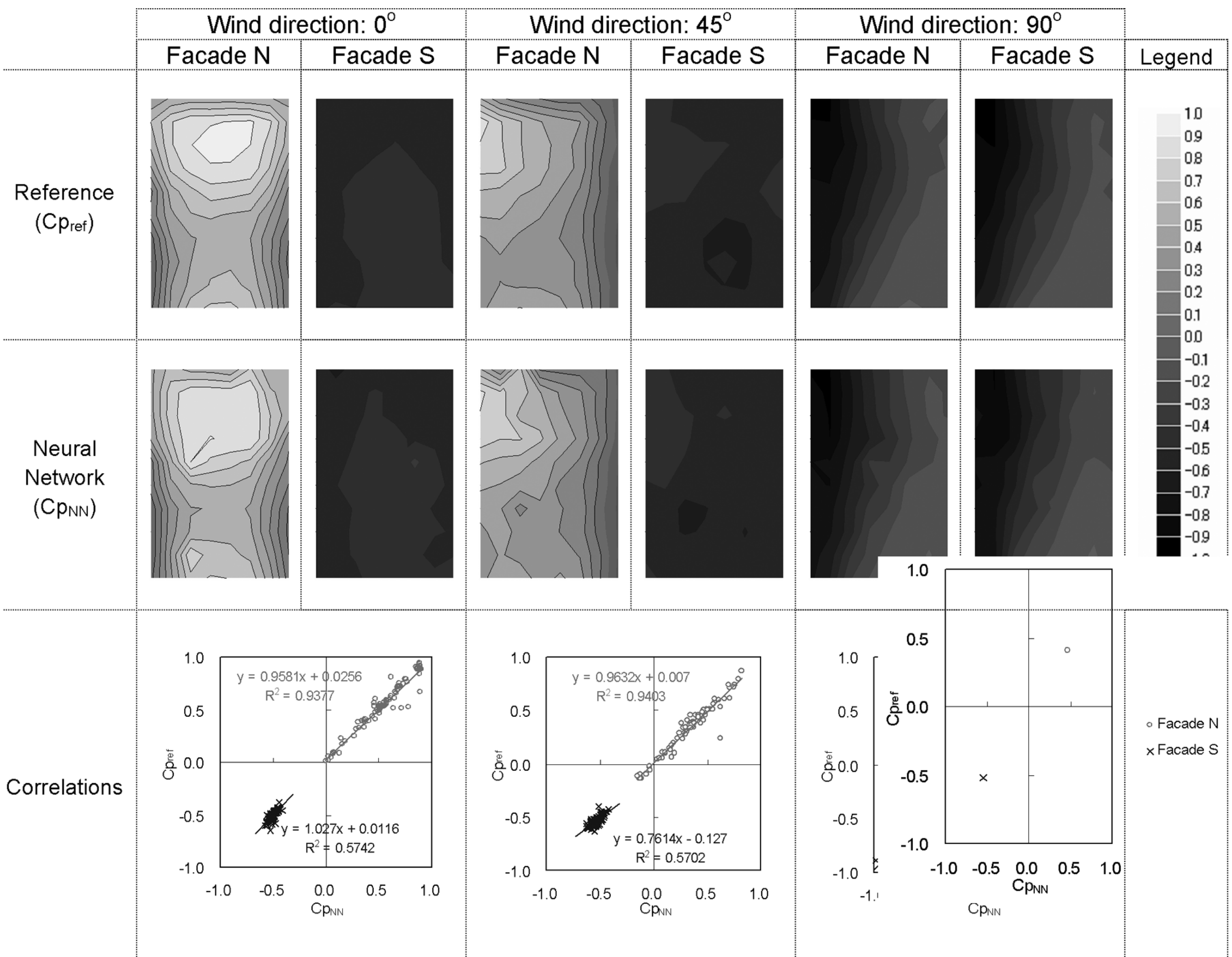


Figure 4: Comparison of the Cp values between reference (measured) data and determined data by using neural network

errors for each ventilation system are shown in Figure 9, 10 and 11. Referring to the Figure 6, 7 and 8, the total ventilation rate predicted by the Cp_{NN} has rather high accuracy. The OSRF value also shows good agreement even for the natural ventilation system. Not only for mechanical ventilation systems but also for the natural ventilation system, which is more sensitive to the wind pressure, the accuracy of the performance evaluation can be satisfactory even by using the approximated Cp values by the ANN instead of the measured value. The comparison for mechanical ventilation systems shows that the average error of total ventilation rate can be estimated within only a few cubic meters per hour, when the root mean squared error is less than 0.3 (when using Cp_{NN}, Cp_{01} and Cp_{02}). At the same time, the result for the natural ventilation system shows that the average error of total ventilation rate is 10 m^3/h or more when the Cp values' root mean squared error is greater than 0.2 (when using Cp_{01}, Cp_{02} and Cp_{03}). These results indicate that natural ventilation calculation requires more accurate Cp values, at least the root mean squared error is less than 0.2. On the other hands, the average error of the OSRF value is negligible, when the root mean square is 0.1 (when using Cp_{NN}).

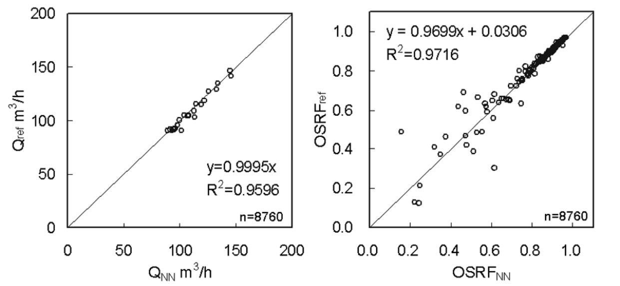


Figure 6: Comparison of calculation results of total ventilation rate Q and OSRF with Cp_{NN} & Cp_{ref} (Exhaust ventilation system)

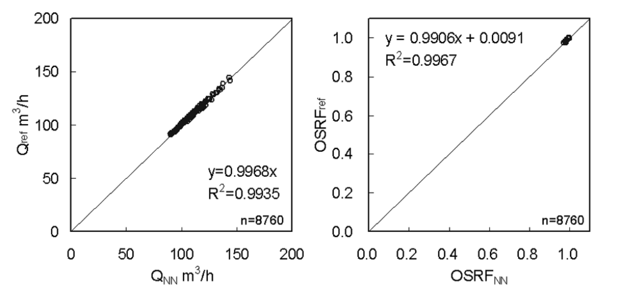


Figure 7: Comparison of calculation results of total ventilation rate Q and OSRF with Cp_{NN} & Cp_{ref} (Balanced ventilation system)

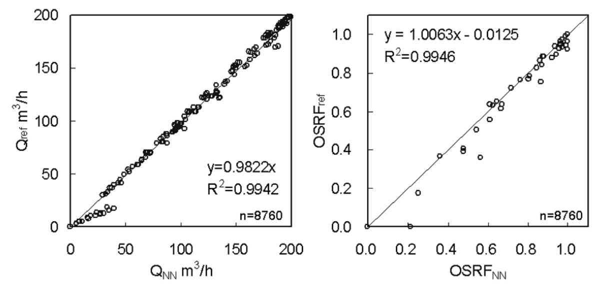


Figure 8: Comparison of calculation results of total ventilation rate Q and OSRF with Cp_{NN} & Cp_{ref} (Natural ventilation system)

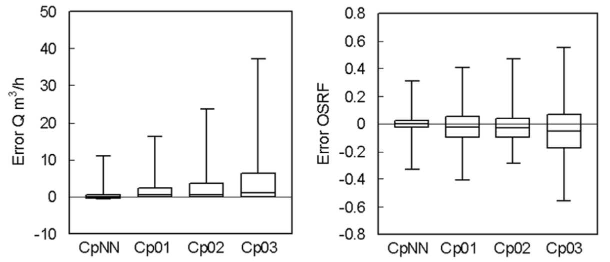


Figure 9: Errors of calculation results of total ventilation rate Q and OSRF with various Cp values (Exhaust ventilation system)

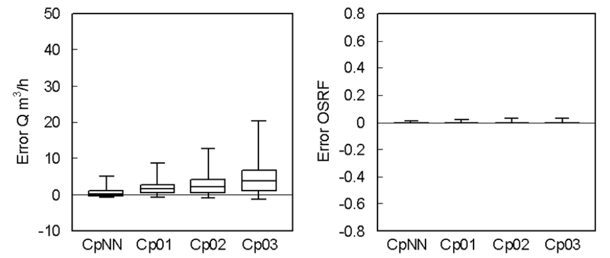


Figure 10: Errors of calculation results of total ventilation rate Q and OSRF with various Cp values (Balanced ventilation system)

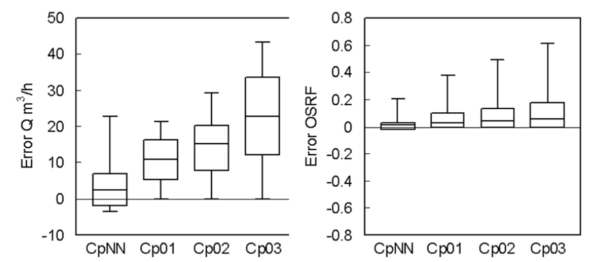
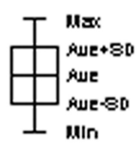


Figure 11: Errors of calculation results of total ventilation rate Q and OSRF with various Cp values (Natural ventilation system)



Legend (Figure 9 -11)

4. CONCLUSION

In this study, firstly, a Cascade-Correlation Learning Network model was used to approximate Cp values obtained by wind tunnel experiments, and the accuracy of the model was checked. Approximation results for three kind of rectangular buildings, of which height were different to each other, were compared with the experimental Cp data, and it was suggested that the artificial neural network has learned Cp values with promising accuracy. Secondly, the approximated Cp by the artificial neural network was applied to the network simulation of two kinds of mechanical ventilation systems and a natural ventilation system installed in a multi-family building. The results of the simulation to evaluate the ventilation performance of those ventilation systems were summarized by the total ventilation rate and the Overall Supply Rate Fulfilment values. It was indicated that the evaluation of the performance by using the Cp produced by the artificial neural network was almost in accordance with the evaluation by using the measured Cp values. Not only for mechanical ventilation systems but also for natural ventilation system, of which performance is more depend on the wind pressure condition, there is a potential to be able use the artificial neural network method in order to reproduce or predict the wind pressure coefficient with satisfactory accuracy, from the view point of whole house ventilation performance. However, it is only the possibility that the artificial neural network can be used for the prediction of the Cp, and further detailed validation is indispensable in the next step.

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