Artificial Neural Networks for Predicting the Pressure Coefficients in a Naturally Ventilated Test Room

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ABSTRACT

The objective of this work is to investigate the possibility of using artificial neural networks for the prediction of air pressure coefficients across the openings in a light weight single-sided naturally ventilated test room. Experimental values have been used for the training of the network. The outside local temperature, wind velocity and direction are monitored. The pressure coefficients at the top and bottom of the openings have been estimated from the recorded data of air pressures and velocities across the openings together with indoor air temperatures. The collected data together with the air heater load and a factor indicating whether the opening is in the windward (1) or leeward (0) direction are used as input to the neural network and the estimated pressure coefficients as the output. A general regression neural network (GRNN) was employed with one hidden slab. The training was performed with satisfactory accuracy and correlation coefficients of 0.9539 and 0.9325 have been obtained for the two coefficients respectively. Satisfactory results have been obtained when unknown data were used as input to the network with correlation coefficients of 0.9575 and 0.9320 respectively.

1. INTRODUCTION

Natural ventilation is becoming an increasingly important design strategy for non-domestic buildings. The main reason is that the primary energy consumption in buildings is reduced which consequently results in reduced CO_2 emissions. To achieve thermal comfort in naturally ventilated buildings it is important to predict the airflow inside the building due to both stack and wind effects. Matthews and Rousseau (1994 a, b) used a flow network model which took account of both wind and buoyancy forces. It was found that the changes in air temperature along the flow path were not easy to predict and that empirical room air temperature profiles were necessary for the evaluation of thermal comfort. Also recent experimental studies at Loughborough University (Eftekhari and Pinnock, 1998) demonstrated that airflow is dependent on the direction of the wind and it is difficult to predict in a single-sided naturally ventilated office.

When designing a naturally ventilated building, knowledge of wind pressures on the external openings is often required to allow prediction of ventilation performance. The ability to effectively predict the combined wind and stack effects would considerably enhance the performance of natural ventilation in buildings.

The British Standard Method (BS 5925, 1980) proposes formulae for the calculation of the airflow in single sided and cross ventilation configurations. The method assumes two-dimensional flow through a building and ignores all internal partitions. Another simplified method for single-sided ventilation with openings at different levels or the same height is proposed by Santamouris and Asimakopoulos (1994). The current guidelines on the design of natural ventilation (CIBSE, 1997) are incomprehensive and more models and data are required. These simplified models have limited application and cannot be considered of general validity; they should always be used within the limits of their applicability (Limam and Allard, 1996).

One method to predict the airflow is artificial neural networks, which can estimate input-output functions, without a mathematical model of how output depends on input. They are model-free estimators and learn from experience with numerical sample data (Swingler, 1996).

Neural networks are widely accepted as a technology offering an alternative way to tackle complex and ill-defined problems. They can learn from examples, are fault tolerant in the sense that they are able to handle noisy and incomplete data, are able to deal with non-linear problems, and once trained can perform prediction at very high speed. The power of neural networks in modelling complex mappings and in system identification has been demonstrated (Kohonen, 1984; Narendra and Parthasarathi, 1990; Ito, 1992). This work encouraged many researchers to explore the possibility of using neural network models in real world applications such as in control systems, in classification, and modelling complex process transformations (Kah *et al.*, 1995; Kreider and Wang, 1995; Pattichis *et al.*, 1995; Curtis *et al.*, 1995; Chong *et al.*, 2000).

Successful application of neural networks in different areas has been reported extensively (Kalogirou *et al.*, 1996; 1997). Kindangen (1996) reported the use of artificial neural networks in naturally ventilated buildings, where the effect of opening configurations was investigated. It was shown that this method provides reliable results in the cases where many parameters were taken into account. In another work of the authors neural networks have been used to predict the air flow and temperature distribution inside the same single-sided naturally ventilated test room used here (Kalogirou *et al.*, 1999).

The objective of this research is to use neural networks to predict the pressure coefficients inside a single-sided naturally ventilated test room**.** This is considered as an important parameter for the determination of airflow into the test cell as a result of its natural ventilation. The room is a portable cabin (Portakabin, 1994) with a volume of 22.2 m^3 located in a sheltered area. The ventilation rate into the room was controlled by adjusting four sets of louvres. The local outside air temperature and wind velocity and direction are monitored. To investigate airflow inside the room, the air pressures and velocities across the openings together with indoor air temperature and velocity at four locations and six different levels are measured. From these data the required pressure coefficients at the top and bottom of the openings are estimated.

2. EXPERIMENTAL TECHNIQUE

2.1 Test Room

An existing portable cabin of light mass is used as a test room for natural ventilation at Loughborough University, which is fitted with four sets of horizontal slats metal louvres. Each unit had overall dimensions of 125 cm wide, 80 cm high and 20 cm deep and contained 5 of 12 cm wide adjustable louvre blades. Relative to the internal dimensions the louvres covered just over 60% of the bulkhead area with a capability, when fully open, to provide an aperture equivalent to approximately 28% of the bulkhead area. The adjustable louvres were fitted to ensure that significant ventilation entered the test room.

In order to accurately regulate the degree of opening of the louvre blades while controlling each louvre unit or bank individually to any configuration a motor actuator was required for each unit. The motors were driven by a 24 V d.c. supply with a positioning signal ranging from 0 to 10 volts. The motors provided a return signal ranging from 2 to 10 volts to indicate their position. In the set up used 2 volts represented fully open and 10 volts fully closed. It also incorporated a 0 to 10 volt voltmeter that could be switched between the motors to measure the return signal and, hence, allowed the motor to position accurately and consistently.

To measure the indoor air flow distribution the room was divided into four zones and for each zone the temperature and velocity stratification were measured. During summer the internal heat loads inside the room were three computers, one multichannel flow analyser and two 58 W fluorescent luminaires. Over the winter period additional 2kW or 4 kW heaters were used. Due to the sheltered position of the test room there was no solar gain into the room. During the experiments the size of the opening at the top and bottom was 0.07 m^2 and 0.12 m^2 respectively with a 1.25 m distance between the centre of the openings. This area, i.e., the specific louvre position, was constant throughout the experiments. Details of the U-values and the thermal capacity of the test room are described fully elsewhere (Eftekari, 1998).

2.2 Instrumentation and data acquisition

Due to the sheltered nature of the test room, the external environmental weather conditions local to the test room were measured. Weather station sensors were mounted locally, which measured the wind velocity, direction, outside air temperature, and other parameters like humidity and pressure, which are not used in the present study. Inside the room, the air velocity through the louvre opening, air pressure and temperature across the room were measured. The direction and airflow at the openings were measured using four ultrasonic air flow meters. The total pressure at top and bottom levels inside and outside across the louvres was recorded using low pressure differential transducers manufactured by Furness type FC044. The reference pressure for all pressure measurements was the static pressure inside the room taken at approximately 1m from the floor. Type 54N10 multichannel flow analyser was used for the measurements of the inside air temperature and velocity at four locations and six levels above the floor. The positioning of indoor sensors is shown in Figure 1.

The ultrasonic anemometers that were used are the BIRAL 3-axis logging type. The logging ultrasonic anemometer consists of a sensing head with six ultrasonic transducers arranged in three pairs, surmounting a cylindrical electronic base housing. The onboard electronics provide all ultrasonic processing and vector computations required to calculate wind data.

The measurement characteristics for the time period and range of measured data are:

- Wind speed accuracy: ±3%
- Wind speed offset: ±0.02 m/s
- Direction accuracy: ±3°

The ultrasonics were used to measure the direction of the airflow into/out of the room.

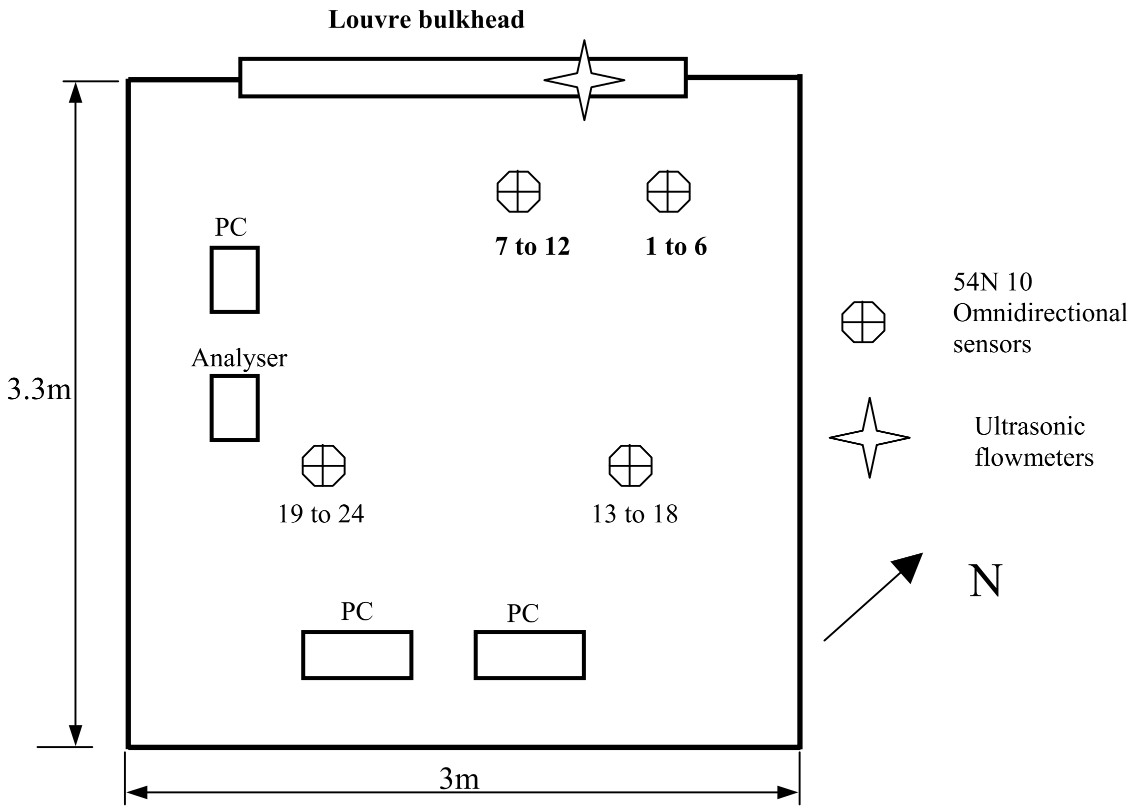

Figure 1. Location of the sensors inside the test room.

2.3 Experimental Pressure Coefficient (C_p)

The wind pressure distribution on a building envelope is usually described by dimensionless pressure coefficient – the ratio of the surface dynamic pressure to the dynamic pressure in the undisturbed flow pattern measured at a reference height, caused by impinging wind on the specific building surface. The pressure coefficient at any point K(x,y,z) with the reference dynamic pressure p_{dyn} corresponding to the height z_{ref} for a given wind direction ϕ can be described by:

$$C_{p_K}(z_{ref},\phi) = \frac{p_K - p_o(z)}{p_{dyn}(z_{ref})} \qquad (1)$$

where $p_o(z)$ is the outside pressure at height z (Pa).

The dynamic pressure corresponding to reference height is given by:

$$p_{dyn}(z_{ref}) = \frac{1}{2}\rho_o \cdot v^2(z_{ref}) \qquad (2)$$

If Equation (2) is substituted in Equation (1), the final form for pressure coefficient equation can be obtained.

$$C_{p_K}(z_{ref}, \phi) = \frac{p_K - p_o(z)}{\frac{1}{2}\rho_o \cdot v^2(z_{ref})} \qquad (3)$$

where v is the wind speed (m/s).

The C_p values for both tests were determined according to the equation (3) based on the measured wind speed and pressure values.

3. DATA COLLECTION AND PRE-PROCESSING

Experimental values have been used for the training of the network. The outside local temperature, wind velocity and direction were monitored. The air pressures and velocities across the openings together with indoor air temperature and velocity at four locations and six different levels were measured. From the measured data (pressures and wind velocity) at the top and bottom of the openings the pressure coefficients were estimated. These data together with the air heater load, ambient temperature and a factor indicating whether the opening is in the windward (1) or leeward (0) direction were used as input to the neural network and the estimated pressure coefficients as the output. Seven tests of 5-6 hours duration have been performed in total. Readings were taken every 1-2 minute for the whole testing period. A total of 1791 patterns were available in total. From these, 1289 patterns were used for training and 322 patterns for testing the network whereas 10% of the data (180 patterns) were randomly selected and used for validation.

4. ARTIFICIAL NEURAL NETWORK

According to Haykin (1994) a neural network is a massively parallel distributed processor that has a natural propensity for storing experiential knowledge and making it available for use. It resembles the human brain in two respects: the knowledge is acquired by the network through a learning process, and inter-neuron connection strengths known as synaptic weights are associated with the knowledge. Instead of complex rules and mathematical routines, ANN's are able to learn the key information patterns within a multidimensional information domain. In addition, inherently noisy data does not seem to present a problem, since they are neglected.

ANN models represent a new method in system prediction. An ANN operates like a "black box" model, requiring no detailed information about the system. Instead, they learn the relationship between the input parameters and the controlled and uncontrolled variables by studying previously recorded data, similar to the way in which a non-linear regression might perform. An advantage of using ANNs is their ability to handle large and complex systems with many interrelated parameters.

Various network architectures have been investigated to find the one that could provide the best overall performance. The architecture, among those tested, that gave the best results and was adopted for the present work is shown in Figure 2. It is a general regression neural network architecture, which has one hidden slab.

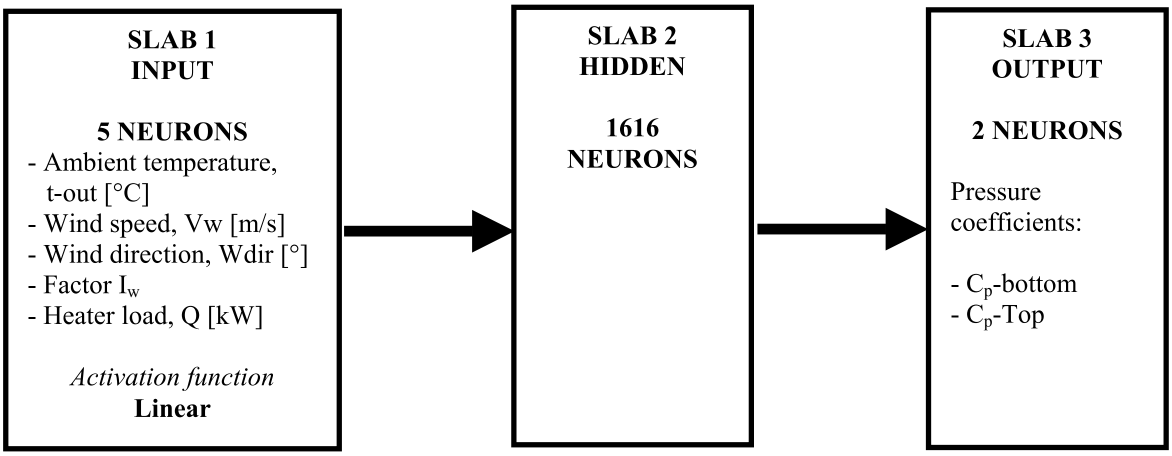

Figure 2. Neural network architecture employed.

General Regression Neural Networks (GRNN) are known for the ability to train quickly on sparse data sets. In numerous tests it was found that GRNN responds much better than backpropagation to many types of problems, although this is not a rule. It is especially useful for continuous function approximation. GRNN can have multidimensional input, and it will fit multidimensional surfaces through data.

A GRNN network is a three-layer network that contains one hidden neuron for each training pattern (see Figure 2). There are no training parameters such as learning rate and momentum as there are in Backpropagation networks, but there is a smoothing factor that is applied after the network is trained. The smoothing factor determines how tightly the network matches its predictions to the data in the training patterns.

If more than 2000 patterns are available in the training data set, then GRNN may become too slow to be feasible unless a very fast machine is available. The reason is that applying a GRNN network requires a comparison between the new pattern and each of the training patterns.

For GRNN networks, the number of neurons in the hidden layer slab is usually the number of patterns in the training set because the hidden layer consists of one neuron for each pattern in the training set. This number can be made larger if one may want to add more patterns, but it cannot be made smaller. The number of neurons in the input layer (Slab 1) is the number of inputs corresponding to the ambient temperature, wind speed and direction, factor I_w indicating whether the opening is in the windward or leeward direction and the heater load. The number of neurons in the output layer (Slab 3) corresponds to the number of outputs, i.e., the pressure coefficients C_p at the top and bottom of the opening.

The smoothing factor for each link, shown by the thick arrows in Figure 2, can be modified. Different smoothing factors can be used in order to find which works best. For the present work the same smoothing factor was applied to all links and the factor obtained after training is equal to 0.09929.

The GRNN is trained using a genetic algorithm (GA). Genetic algorithms use a "fitness" measure to determine which of the individuals in the population survive and reproduce. Thus, survival of the fittest causes good solutions to evolve. A genetic algorithm works by selective breeding of a population of "individuals", each of which is a potential solution to the problem. In this case, a potential solution is a set of smoothing factors, and the genetic algorithm is seeking to breed an individual that minimizes the mean squared error of the test set. The larger the breeding pool size, the greater the potential of it producing a better individual. However, the networks produced by every individual must be applied to the test set on every reproductive cycle, so larger breeding pools take longer. After testing all of the individuals in the pool, a new "generation" of individuals is produced for testing. Unlike Backpropagation networks which propagate training patterns through the network many times seeking a lower mean squared error between the network's output and the actual output or answer, GRNN training patterns are only presented to the network one time.

The input smoothing factor is an adjustment used to modify the overall smoothing to provide a new value for each input. At the end of training, the individual smoothing factors may be used as a sensitivity analysis tool; the larger the factor for a given input, the more important that input is to the model, at least as far as the test set is concerned. Inputs with low smoothing factors are candidates for removal for a later trial.

Individual smoothing factors are unique to each network. The numbers are relative to each other within a given network and they cannot be used to compare inputs from different networks.

If the number of input, output, or hidden neurons, is changed however, the network must be retrained. This may occur when more training patterns are added because GRNN networks require one hidden neuron for each training pattern.

All the data sets used to the neural network are scaled from their numeric range into the numeric range that the neural network deals with efficiently. In the present case all the data were scaled from –1 to 1. For the GRNN an activation function is only required in the input layer slab. The activation function used is linear.

The training was performed with satisfactory accuracy and correlation coefficients of 0.9539 and 0.9325 have been obtained for the pressure coefficients at the bottom and top of the openings respectively. The closer these values are to unity the better is the mapping of the patterns of the training data set.

The contribution factors of the various input parameters are shown in Figure 3. These factors are estimated from the smoothing factors and indicate the contribution of each input parameter to the learning of the neural network and are estimated by the network. It is of interest to note that the parameter with the greatest contribution is the wind speed. The second most important parameter is the wind direction (see Figure 3). These findings although agree with theory are estimated by the network which doesn't know the importance of each input parameter.

5. RESULTS / VALIDATION

Once a satisfactory degree of input-output mapping has been achieved, the network training is frozen and a set of completely unknown test data was applied for verification. The validation data sets comprise data completely unknown to the network. The correlation coefficients were equal to 0.9575 and 0.9320 for the two pressure coefficients respective; both values are close to unity indicating a high degree of prediction accuracy.

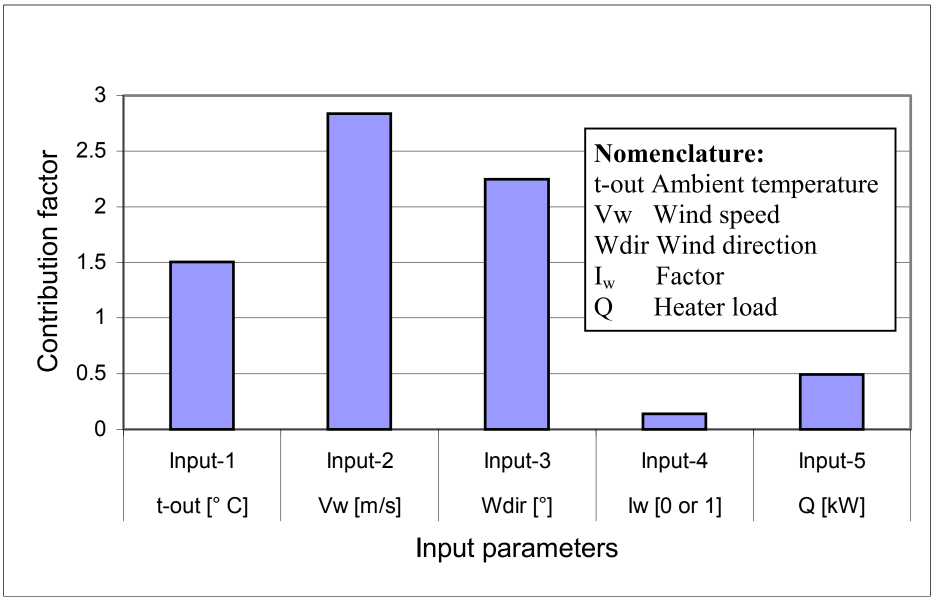

Figure 3. Contribution factors of the various input parameters.

A comparison of the predicted results with the actual values for the pressure coefficients at the bottom and top of the opening is shown in Figures 4 and 5 respectively. As can be seen in Figures 4 and 5, the lines representing the actual figures and the results predicted by the network are so close that they are indistinguishable. About two hours were required for the training of the network on a Pentium 450 MHz machine. The subsequent predictions for the validation cases required less than a second on the same machine; so a quick estimation time is obtained without sacrificing accuracy.

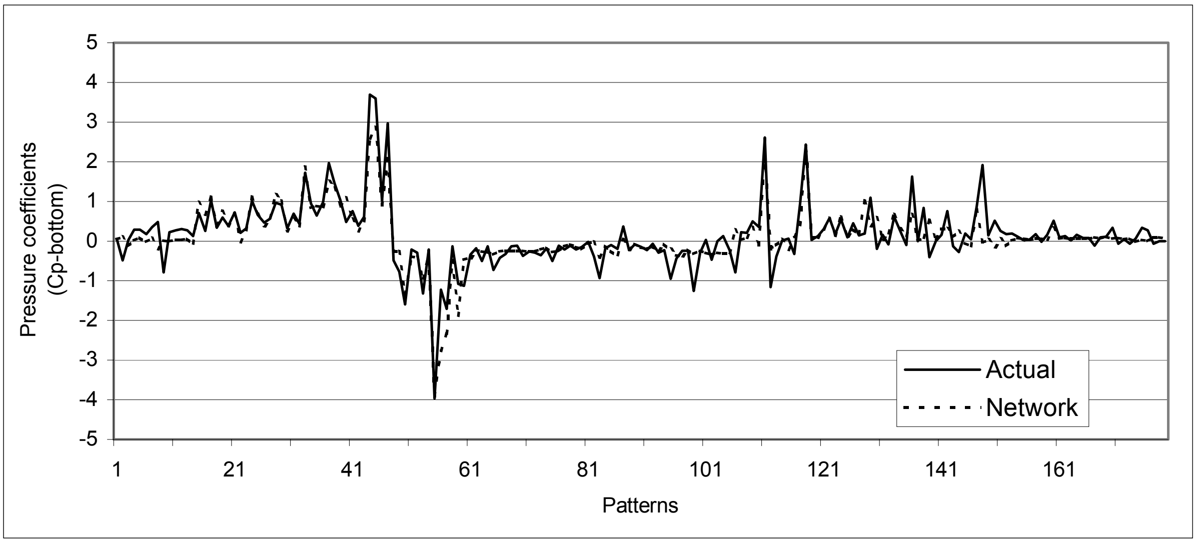

Figure 4. Comparison of the actual and ANN results for the pressure coefficient at the bottom of the opening.

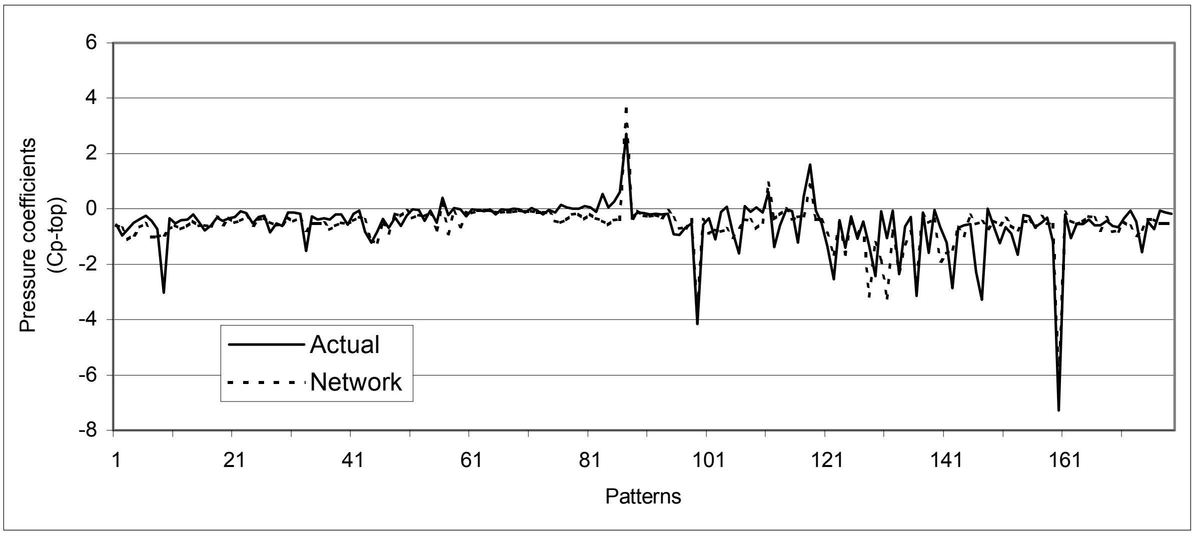

Figure 5. Comparison of the actual and ANN results for the pressure coefficient at the top of the opening.

6. CONCLUSIONS

The objective of this research was to predict the pressure coefficients at the top and bottom of the opening of a light weight test room, which is naturally ventilated using artificial neural networks. The test room is situated in a relatively sheltered location and is ventilated through adjustable louvres. Experimental values have been used for the training of the network. The outside local temperature, wind velocity and direction are monitored. The pressure coefficients at the top and bottom of the openings have been estimated from the recorded data of air pressures and velocities across the openings together with indoor air temperature and velocity. The collected data together with the air heater load and a factor indicating whether the opening is in the windward (1) or leeward (0) direction are used as input to the neural network and the estimated pressure coefficients as the output. A general regression neural network (GRNN) was employed with one hidden slab. The training was performed with satisfactory accuracy and correlation coefficients of 0.9539 and 0.9325 have been obtained for the two pressure coefficients respectively. Satisfactory results have been obtained when unknown data were used as input to the network with correlation coefficients of 0.9575 and 0.9320 respectively.

It is of interest to note that the contribution factors estimated by the network shows that the parameter with the greatest contribution is the wind speed. This finding although agrees with theory it is estimated by the network which doesn't know the importance of each input parameter.

The work presented in this paper primarily aims to show the suitability of neural networks to perform such predictions. In order to make the method more usable the training database needs to be enriched with readings from actual measurements from a number of applications. Predictions to actual buildings can be performed provided that a number of suitable sensors are installed together with a data acquisition system in order to create a database with combinations of possible weather and other operating conditions, and the required output. This can subsequently be used to train a suitable neural network of the type described in the present paper to predict the indoor air temperature of the building and/or any other required parameter. The greatest advantage of the present method is that it doesn't depend on analytic models to predict the wind velocity and direction but it uses actual measurements to predict the required parameters. This is strengthened by the fact that the source to any natural ventilation system is the wind the velocity and direction of which is continuously changing.

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NOMENCLATURE

C_p	pressure coefficients [-]
p	pressure [Pa]
z	height [m]
ϕ	wind direction [rad]
ρ	air density [kg/m^3]

Subscripts:

atm	atmospheric
dyn	dynamic
ref	reference
o	outside