NEURAL MODEL FOR AIR EXCHANGE IN HABITABLE ROOMS

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ABSTRACT

Recent years have brought the popularity of methods in which neutral networks are applied. They seem of particular importance while dealing with diagnosing, predicting and estimating. Those methods rely on collected data base, simulation and interpolation in the so-called learning process. There are attempts at neural network application in building engineering.

The paper sums up the initial phase of research on neural applications in the air exchange estimation. Due to substantial experimental database, one is able to make all the calculations whichever might be necessary, for whatever prevailing conditions, both controlled or random.

INTRODUCTION

The outline of the concept of neural network applications to air exchange problems was presented for the first time at the 6th International Conference *Roomvent '98* [1]. Numerical values of air exchange multiplication factors obtained while following this method offer solutions to some microclimate and energy issues we encounter in buildings [2], which mostly refer to technical diagnosing and forecasting. Simultaneously, we face the problem of setting up some kind of network and computer standardisation necessary if we want to formulate any solutions. It deals with the availability of software typical of neural networks [3], [4] as well as with carrying out analyses, comparative and verification studies with the use of artificial neural networks for the sake of air exchange simulation. When network logic solutions are too specific [1], there is little chance for them to become quickly or widely applied. It seems important to generate a universal network , the architecture of which would account for the relations and feedback holding in air flow. It should also be open on further extension so that new relations could be incorporated and supported by standard software.

The paper is an attempt at the selection of typical parameters, which have to be accounted for in the network architecture rendering the air exchange process in the optimum manner. What the paper focused on, was the air flow within a room. The resultant model is easily applicable and might become popular as it relies on the available software.

METHODS

Initial Data Presentation

Investigations and measurements of air exchange in a room are characterised by both random and controlled parameters [2]. On the basis of the analysis of experimental data, their impact on the final air exchange value, mutual feedback and relations, there were specified the following input data of the network structure:

n1 - K_w - wind inflow angle with regard to room wall, deg.,

n2 - T_d - internal and external temperature difference, °C,
n3 - W - wind velocity, m/s,
n4 - P - inside and outside pressure difference, Pa,
n5 - K_d - storey ordinal number,
n6 - I - quotient of the external joinery slit length sum by the room cubature, m/m^3,
n7 - V - room cubature, m ,
n8 - A_s - external joinery air permeability coefficient in accordance with the range, $m^3/m \cdot h \cdot daPa^{0.7}$: 0.5: 0.5 0.8, 1.0: 0.9 1.2, 2.0: 1.8 2.4, 3.0: 2.7 3.2.

The process state variable was assumed to be the multiplication factor of air exchange in the room N in h^{-1}. The variables n1 ÷ n4 are random parameters, whereas the variables n5 ÷ n8 are controlled parameters. Three modelling designs were considered: those of tall (8 ÷ 11 storeys) buildings, medium height (5 storeys) buildings and low (1 ÷ 2 storeys) buildings – single family houses.

Three ways of the presentation of learning data at the network inputs were analysed:
- data presented sequentially, recorded in data base in order of classes,
- data presented sequentially, recorded in data base in random order,
- data presented in random order.

Practical experience indicates that the last way is the optimum one as it allows, to the greatest extent, to avoid the blockage of the network at the disadvantageous local minimum. With this means, however, it is rather difficult to make use of the calculation termination criterion, being the drop of the summary square error below the pre-set value at the network outputs, which is obvious in case of sequential learning. It happens so because the error curve shape becomes non-monotone and it depends on that which images were fed to the network input in a given learning cycle. The second method provides monotonic learning curves but the risk of learning process unconvergence is higher. It may happen with the first method that the images recorded in the data base as the first ones dominate over the others, consequently, the network becomes unable to work out correct replies for further classes. In the extreme cases that leads to a pathological condition under which the data record order in the learning base determines the problem solvability.

In the course of the investigations into the structure of the neural model of air exchange multiplication factors, each of the three methods was tried out, yet no significant difference was found. The third method was eventually selected as being the most widely applied and the one which guaranteed the avoidance of the solutions like the local minimum.

Network Architecture

The network selection was made after the analysis of the options offered by Hopfield recurrent networks and simpler networks of perceptron type with back error propagation [5], [6]. The other type are static networks but due to the conventional extension of input and output vector of the object being modelled, by the values of previous instants, the effect of dynamic behaviour is obtained. For the sake of infiltration modelling and room air exchange multiplication factor calculations, there was eventually chosen a perceptron network with the algorithm of learning through back error propagation.

The general form of learning algorithm which allows iterative weight modification for individual layers, on the basis of error values calculated previously, is determined by the expression:

$$\delta_i^{(L)} = -\frac{\partial E}{\partial o_i^{(L)}} = (t_i - o_i^{*(L)}) \cdot (f(F(o_i^{(L)})))' \quad (1)$$

(for output layer L)

$$\delta_i^{(l)} = \sum_k \delta_k^{(l-1)} \cdot w_{ki}^{(l+1)} \cdot (f(F(o_i^{(l)})))' \quad (2)$$

(for arbitrary hidden layer l)

where:

E - value of current learning error,

t_i - learning intended value for output i,

o_i - aggregated by summation weighed input information of the so-called processing elements (PE_i),

o_i^* - output signal PE_j,

w_{ki} - weight connection,

$(f(F(\ )))'$ - derivative from transition function PE, being the compound of output function $f(\ )$ and activation $F(\ )$.

Finally, the weight change Δw_{ij} for any layer not being the output layer can be written as:

$$\Delta w_{ij}^{(l)} = \eta \cdot \delta_i^{(l)} \cdot o_j^{*(l-1)} \quad (3)$$

where η is a learning coefficient. In a single algorithm course weights are modified according to the dependence:

$$w_{ij}^{(t+1)} = w_{ij}^{(t)} + \Delta w_{ij} \quad (4)$$

where t is time.

Value η increase leads to quicker learning, yet it increases weight oscillation and can result in the process destabilisation. In order to counteract the appearance of excessive weight oscillation accompanying too high values of learning coefficient η, there was introduced a smoothing coefficient α.

$$w_{ij}^{(l+1)} = w_{ij}^{(l)} + \Delta w_{ij}^{(l)} + \alpha \cdot \Delta w_{ij}^{(l-1)} \quad (5)$$

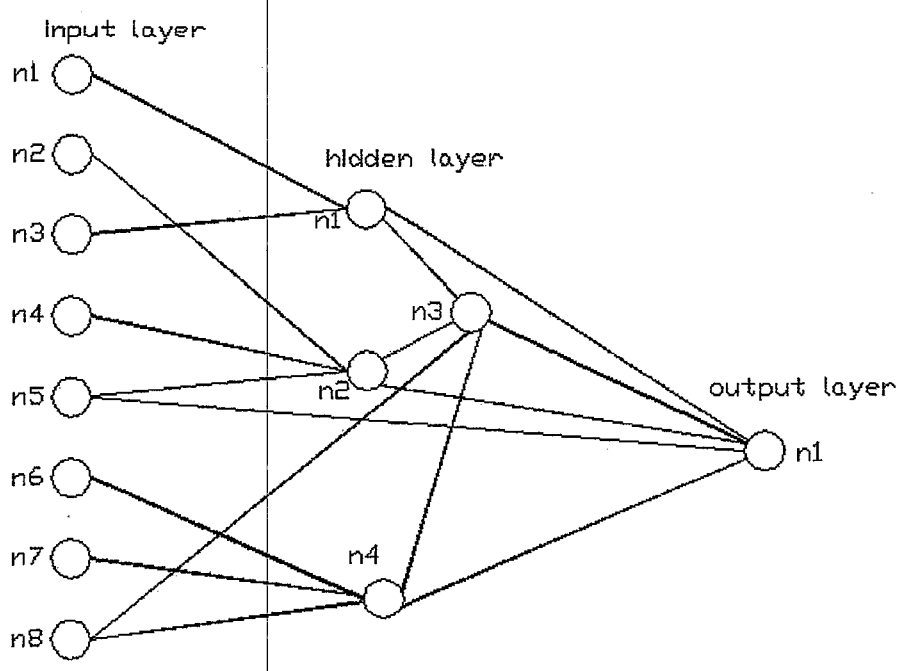

Figure 1. Network connection structure

Due to network structure analysis based on air exchange phenomenon, it was possible to select one-layered model with one hidden layer composed of 4 neutrons (Fig. 1). Increasing either the number of layers or that of neurones did not affect the accuracy of the results obtained. It significantly prolonged the time of processing and network learning instead. Moreover, there was increased demand on calculation devices.

The following neutrons were located in the hidden layer:

n1 – wind pressure,
n2 – static pressure value,
n3 - pressure value weighed sum,
n4 – neurone which accounts for slit "efficiency" in the room joinery.

Neurone n in the output layer specifies room air exchange multiplication factor.

RESULTS

Investigations revealed that the network including 100,000 learning cycles approached a moment at which there was no improvement of the values obtained. Further analysis of the cycle number impact demonstrated that in the course of learning, the network passed in cycles between two minimum's being very close to each other. While calculating the accuracy and the congruence of the results obtained, the number of 100,000 cycles seemed the optimum one and the verification investigations were performed with this number of learning cycle repetitions.

The verification relied on the calculations of model values root mean square deviation from the measurement values. The results obtained were juxtaposed in diagrams in Figs 2a,b,c for low, medium height and tall objects, respectively:

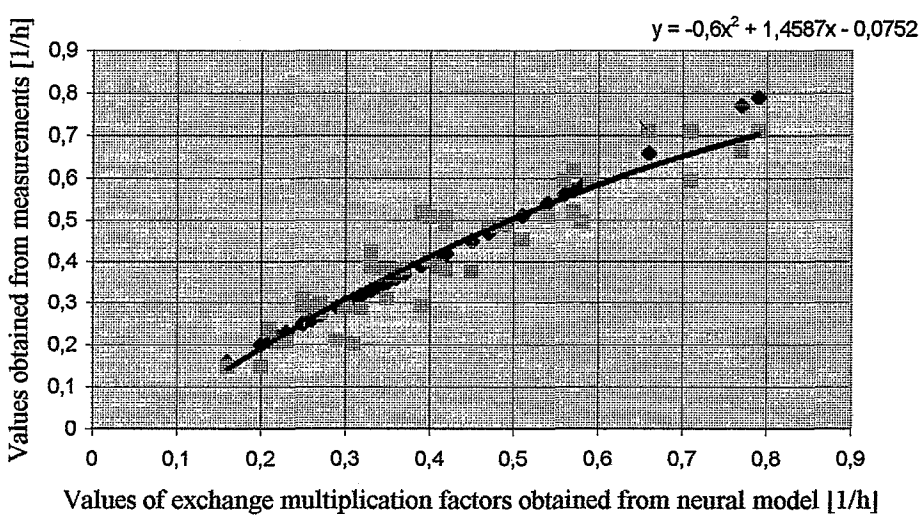

Figure 2a. Measurement values versus model values 2-storeyed buildings – room

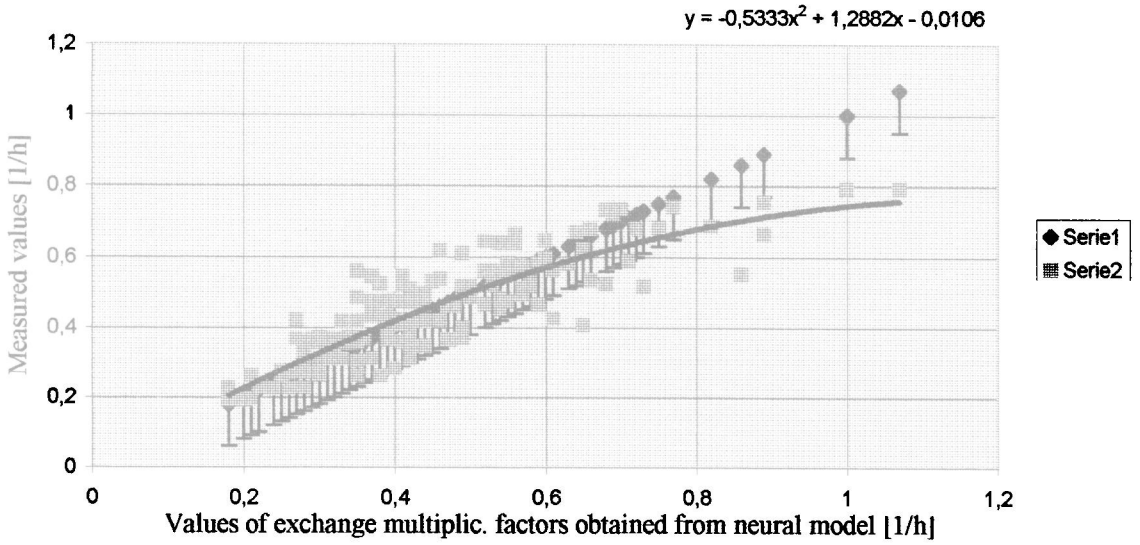

Figure 2b. Measurement values versus model values 5-storeyed buildings – rooms

The diagram diagonal illustrates 100% congruity between neural model values and measurement values. The congruity of results is high. At greater values of exchange multiplication factors there occurs a constant error between the model and measurement values. Examining trend line values shown in diagrams, one can see that the trend might be easily eliminated due to the correction coefficient determined from the difference between the trend line and the value $y=x$.

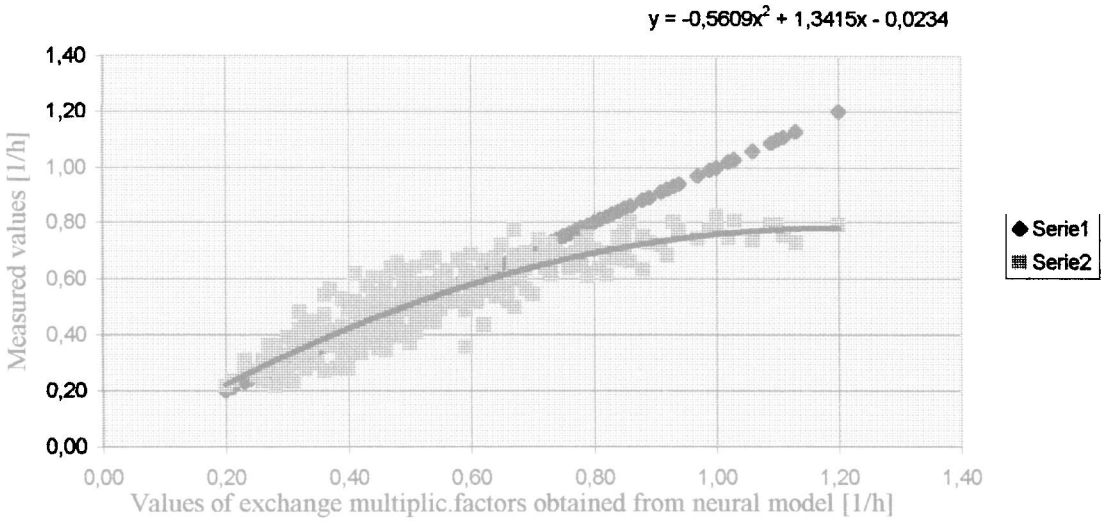

Figure 2c. Measurement values versus model values 11-storeyed buildings – rooms

Values of mean square deviations obtained for individual buildings are presented in Table 1. Mean square errors below 15% as found in the models provide good results, satisfying the requirements of a decision model which is to provide generalised description of the phenomenon.

Table 1. Mean square deviation values

No.	Building type	Storey average number	Mean square deviation
1	Low	2	11.9 %
2	Medium height	5	13.3 %
3	Tall	11	14.1 %

DISCUSSION

The network structure presented in the paper is structurally simple and can be operated with standard neurone calculation software.

Mean square deflection of the order of 15% guarantees positive verification of the neural model for the sake of air exchange research.

An extended network version would be capable of incorporating air flow issues within the whole building.

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