

# Can artificial neuron networks be used for control of HVAC in environmental quality management systems?

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**Abstract.** The concept of *environmental quality management* has been described in papers [1 - 4] that looked at the next generation of low energy buildings from the point of view of the occupant. Optimizing energy use is difficult for a few reasons: presence of dramatic changes in the manner we design and operate buildings, change in the role of an architect who must be a leader of interacting team, often quality management is biased towards the design more than on performance of the finished product and finally the need for integrated monitoring and modeling in the occupancy stage.

Effectively, we are integrating heating/ cooling and ventilation with the structure at the same time as we verify the appropriateness of the new methods to evaluate performance of these systems. In this process we require double controls, one by the occupant and the other by the computerized (smart) control system. The traditional approaches to modify human behavior generally failed because occupants were not given enough control over their environment. Thus, a major part of the trend to a low-carbon, climate resilient future will be focused on methodology to include path from a complex field testing of building performance to simplified testing that combined with simple monitoring and data from utilities would allow assessment of the energy and carbon emission in a district of a city.

Our experience shows that preliminary design must be optimized during the period of service for all more complex buildings such as large residential, office or commercial buildings. In this context the artificial neural network approach appears to have significant advantages. Yet, traditionally ANN requires large data set to establish functional relations during the learning stage and therefore the first question is how precise can the control of temperature be when the heat exchanger is subjected to different climatic conditions.

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## 1 Introduction to the case study

For a multi-parameter, transient case of heat and mass transfer such as in a ground air to the ground heat exchanger a traditional use of ANN would requires large data set of experimental points. We decided also to use about 1,500 experimental points and selected twenty different parameters that affects heat and mass transfer in two tested air to earth heat exchangers (AEHX) one air conditioner and one floor heating/cooling system. The two tested AEHX, one placed under the building and other next to the building, one slopped downwards, the other upwards and tested over a period of one full year were already described in the original publications [2, 4] the air conditioning and heating/ cooling system located in the floor of the tested room require no explanation. The input information included parameters of these 4 devices that were used in different configuration during 3 weeks of the hot summer period when outdoor temperature varied from 13 to 32 °C. As the output we have selected temperature and relative humidity in the tested room.

At this stage we are not analyzing individual effects of factors affecting temperature changes, (we have a good understanding of those from the previous papers) but we are asking a question typical for a control engineer, how suitable is the ANN technology to control the various factors that affects indoor environment? With other words, the current paper deals only with the establishing and validating of the ANN model to examine its convergence.

## 2 Introduction to Artificial Neural Networks

With an adequate structure, artificial neuron network permits to define an operation of the fragment of the complex system with its interaction to the not examined elements of the system. In particular, time-related property measured in a constant time interval may not have bias of time-integration of other methods [5], [6] and modelling of the random phenomena even though the results are valid only in the range of variability used in the learning data set i.e., no extrapolation is allowed. ANN can be used to multi-parameter effects where the weights of different parameters is not known; multi-layered and one-directional structure of ANN may assist in formulating the functions governing the physical properties analyzed [5, 7-12]. Nevertheless, there are many issues to be considered when using ANN, such as selecting the correct number of inputs and defining the best properties of the structure [13-19].

Generally speaking, the process is started by assuming a certain type of the relationship with coefficients that initially unknown and that are to be determined during the learning (training) period. A precision of the neuron network is defined by the regression value. The steps in using ANN are as follows: [5], [20]

1. Selection of the input information
2. Creating an ANN
3. Configuration of the ANN
4. Selecting initial weights, allowed errors and other parameters for the learning period
5. Learning period
6. Validating period
7. Testing period
8. Application period

The input data is collected in two matrixes: (a) matrix of learning arguments and (b) matrix of targets, e.g. as two columns in which the second column gives the target for the argument shown in the first column. Obviously more than one independent variable will

would make multivariant matrix with five or ten arguments corresponding to one target value [5], [20].

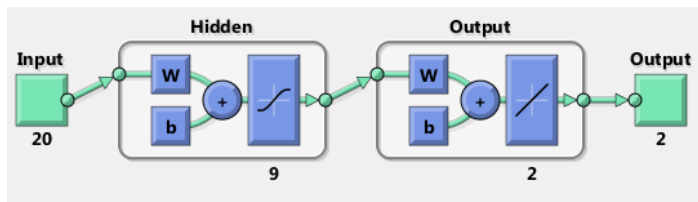
The process of establishing ANN includes selecting number and connectivity between each neuron in each chosen layer and communication between layers as well as input and output from the ANN. Next one defines the control parameters (requirements) for improving the system performance from one to the next cycle of training and validation including the initial conditions and the target at which the calculation is terminated. Typically, the criterion for termination would include a maximum difference between values calculated by ANN and the target values selected for validation of the ANN called performance function. At this stage one uses a new set of input data (arguments) and performs a test to check if the coefficients calculated during the training and validation give the expected results (targets).

### 3 Characteristics of the ANN selected for the examination

The calculations were performed using Math-lab R2011B version [5]. Measurement data processing was performed using a two-layer feedforward neural network implemented in Matlab. Figure 1 depicts the created neural network structure. This structure had one hidden layer consisting of nine neurons. There were no delays implemented on the input for this layer. The activation function for the hidden layer was tangent-sigmoidal (tansig). The output layer had a linear activation function.

The results shown below were obtained for the following ANN training settings [20]:

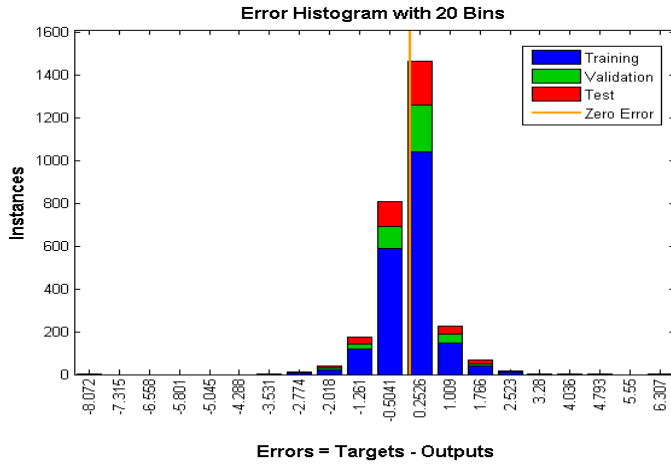
- maximum number of epochs to train: 1000;
- performance goal: 0;
- learning rate: 0,01;
- maximum validation failures: 6;
- momentum: 0,9;
- minimum performance gradient:  $10^{-10}$ ;
- maximum time to train in seconds: infinite.



**Fig. 1.** The created neural network structure

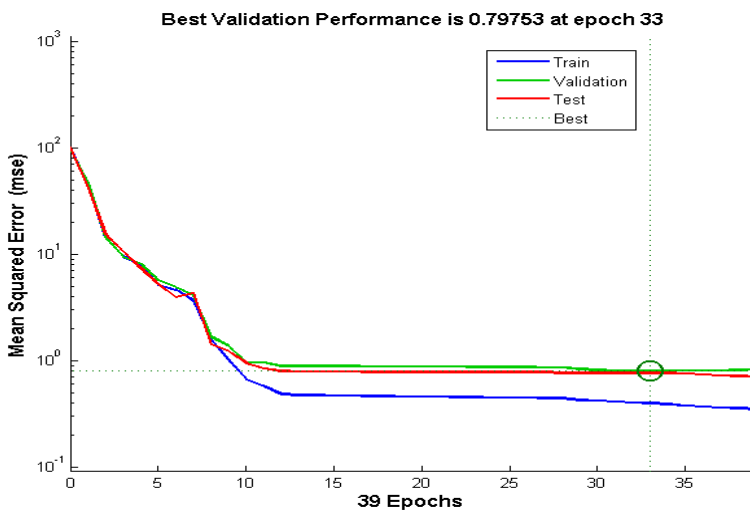
To teach the designed artificial neural network, the one-way network (up to 3 layers) training was used according to the Levenberg-Marquardt algorithm. Figure 2 depicts results obtained from the training, validation and test of the ANN in the form of an error histogram.

Figure 3 presents the artificial neural network performance graph during its learning. The ordinate axis refers to the ANN performance function values. Mean square error (MSE) was chosen as the performance function. The horizontal axis corresponds to learning epochs. The system reached the best neural network validation of the ANN performance for the 33<sup>th</sup> epoch and it was equal to 0,798. One can observe that the neural network system continued the learning algorithm for another 6 epochs to confirm the alleged local minimum for the goal set for the created network structure. From epoch 1 to 12, a downward trend in validation tests of the ANN learning can be seen.



**Fig. 2.** Error histogram

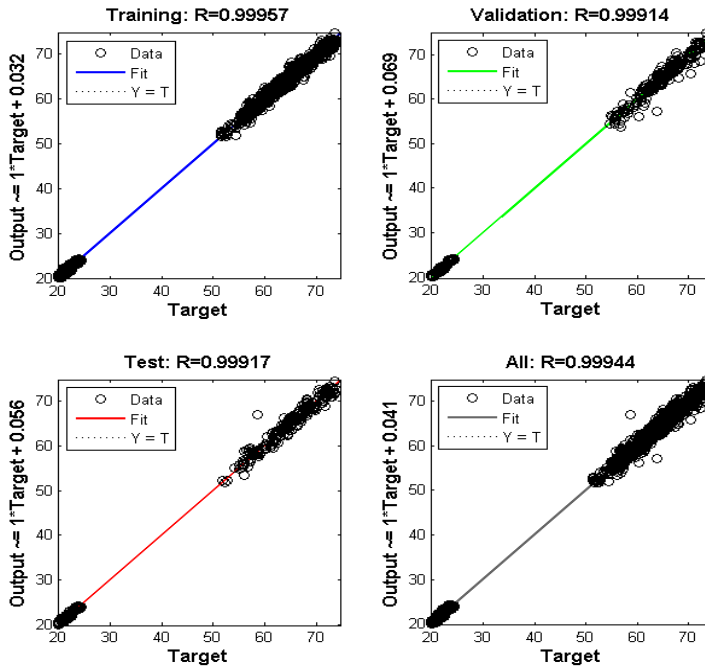
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**Fig. 3.** Performance of the ANN

Figure 4 depicts the regression results for the training, validation and test and the regression for all data assigned to the ANN learning with a supervisor. Here, the ordinate axis represents the neural network output for the given input data. The abscissa axis shows values from the actual measurements (targets), to which the values returned by the ANN should be convergent. The R = 1 regression result means that there is an unequivocal

relation between the actual value (target; from measurement or simulation) and the neural network output value.



**Fig. 4.** Regression results for the training, validation and test and the regression for all data assigned to the ANN

The regression results for the discussed case are as follows. The regression for the data assigned to the training reached  $R = 0,99967$ . The data constituted about 70% of all data assigned to the ANN learning with a supervisor. The regression for the validation was equal to  $R = 0,99914$ . The data used for this step were about 15% of all data. Lastly, the regression for the test was  $R = 0,99914$ . Consequently, the data used in this stage was about 15% of all data. One more regression value was calculated, for all data, and it was equal to  $R = 0,99944$ .

The training, validation and test are performed during the procedure of the neural network learning.

## 4 Concluding remarks

This paper is a step one in the search of better tools to introduce the environmental quality management (EQM) technology. We have identified that the quality of indoor environment in near zero energy buildings is the key to the next generation of technology. We have also acknowledged that optimizing energy use must be done in the context of extending the service life (durability) and providing indoor comfort that is not easy because of changes in the manner we design and operate buildings. We also observed that we use models of quality management biased towards the process of design far more than on performance of the finished product and therefore we need to consider an improvement of operational performance during the service life of the building.

To this end, the artificial neuron networks appear to be well suited as they integrate monitoring and modeling with a capability of self-learning process. This paper is a first step in this direction, it shows a capability of describing a multi-factorial environment while indicating that training and validating periods (see Figure 3) had a different precision of controls. Indeed, the mix of the used equipment was different in various periods of the ANN establishment, yet the overall relationships are described with a high precision.

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