BUILDING HEATING LOAD ESTIMATION USING ARTIFICIAL NEURAL NETWORKS

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ABSTRACT

The objective of this work is to train an artificial neural network (ANN) to learn to predict the required heating load of buildings with the minimum of input data. An ANN has been trained based on 250 known cases of heating load, varying from very small rooms (1-2 m^2) to large spaces of 100 m^2 floor area. The type of rooms varied from small toilets to large classroom halls, while the room temperatures varied from 18°C to 23°C. In addition to the above, an attempt was made to use a large variety of room characteristics. In this way the network was trained to accept and handle a number of unusual cases. The data presented as input were, the areas of windows, walls, partitions and floors, the type of windows and walls, the classification on whether the space has roof or ceiling, and the design room temperature. The network output is the heating load. Preliminary results on the training of the network showed that the accuracy of the prediction could be improved by grouping the input data into two categories, one with spaces of floor areas up to 7 m^2 and another with floor areas from 7 to 100 m^2. The statistical R^2-value for the training data set was equal to 0.988 for the first case and 0.999 for the second. Unknown data were subsequently used to investigate the accuracy of prediction. Predictions within 10% for the first group and 9% for the second were obtained. These results indicate that the proposed method can successfully be used for the estimation of the heating load of a building. The advantages of this approach compared to the conventional algorithmic methods are (i) the speed of calculation, (ii) the simplicity, and (iii) the capacity of the network to learn from examples and thus gradually improve its performance. This is done by embedding experiential knowledge in the network and thus the appropriate U-values are considered. Such an approach is very useful for countries where accurate thermal properties of building materials are not readily available.

1. INTRODUCTION

The cornerstone of a successful design of a heating system is the accurate estimation of the building heating load. A number of commercial software programs are currently available for the estimation of the heating load of buildings (e.g. ASHRAE Code, Carrier E20-II). These programs basically perform multiplications between the areas of the various building envelope components with the corresponding U-values and the effective temperature difference (fabric losses). The results of these multiplications are added to obtain the space heating load. To this a 10% safety factor is usually added. The building envelope components usually considered are the external walls, windows, partitions, floors, ceilings or roofs, and the infiltration losses.

Commercial load estimation programs are generally time consuming, especially when it comes to identifying the proper U-values of the various building components. Furthermore the cost of these programs could be prohibitively high for small consulting offices. There is therefore, a need for alternative approaches to this task. The recently developed technology of artificial neural networks (ANN) could offer such an alternative approach.

Neural networks are widely accepted as a technology offering an alternative way to tackle complex and ill specified 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 and generalization at very high speed. The power of neural networks in modeling complex mappings and in system identification has been demonstrated (Kohonen, 1984; Narendra & 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 modeling complex process transformations (Kah *et al.*, 1995; Kreider and Wang, 1995; Pattichis *et al.*, 1995; Curtiss *et al.*, 1995; Kalogirou *et al.*, 1996a and 1996b).

The aim of this study is to investigate the suitability of neural networks as tools for the estimation of the heating load of buildings using the minimum possible set of input data. This will facilitate the work of design engineers in the field. This method is more useful, for small countries, like Cyprus, where local building material thermal properties are not accurately known. Property values taken from published references are not always valid for the materials used locally. This is so because although the same material might be specified, the composition and manufacturing method of the materials could be different.

The maximum error in the prediction of the heating load, using the proposed method, is expected to be confined within 10%. This is compatible with the value of the safety factor usually used in such designs.

2. ARTIFICIAL NEURAL NETWORKS

Artificial neural networks (ANN) mimic somewhat the learning process of a human brain. Instead of complex rules and mathematical routines, ANN’s are able to learn the key information patterns within a multidimensional information domain. In addition, the inherently noisy data does not seem to present a problem, since they are neglected.

ANN models represent a new method in system prediction. ANNs operate 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 a non-linear regression might perform. Another advantage of using ANNs is their ability to handle large and complex systems with many interrelated parameters. They seem to simply ignore excess data that are of minimal significance and concentrate instead on the more important inputs.

A schematic diagram of a typical multilayer feedforward neural network architecture is shown in Fig. 1. The network usually consists of an input layer, some hidden layers and an output layer. In its simple form, each single neuron is connected to other neurons of a previous layer through adaptable synaptic weights. Knowledge is usually stored as a set of connection weights (presumably corresponding to synapses in biological neural systems). Training is the process of modifying the connection weights in some orderly fashion using a learning method. The network uses a learning mode, in which an input is presented to the network along with the desired output and the weights are adjusted so that the network attempts to produce the desired output. The weights after training, contain meaningful information whereas before training the random weights have no meaning.

The most popular learning algorithms are the backpropagation and its variants (Werbos, 1974; Rumelhart *et al.*, 1986). A training set is a group of matched input and output patterns used for training the network, usually by suitable adaptation of the synaptic weights. The outputs are the dependent variables that the network produces for the corresponding input. It is important that all the information the network needs to learn, is supplied to the network as a data set. When each pattern is read, the network uses the input data to produce an output which is then compared to the training pattern, i.e., the correct or desired output. If there is a difference the connection weights (usually but not always) are altered in such a direction so that the error is decreased. After the network has run through all the input patterns, if the error is still greater than the maximum desired tolerance, the ANN runs again through all the input patterns repeatedly until all the errors are within the required tolerance. When the training reaches a satisfactory level, the network holds the weights constant and uses the trained network to make decisions, identify patterns, or define associations in new input data sets not used to train it.

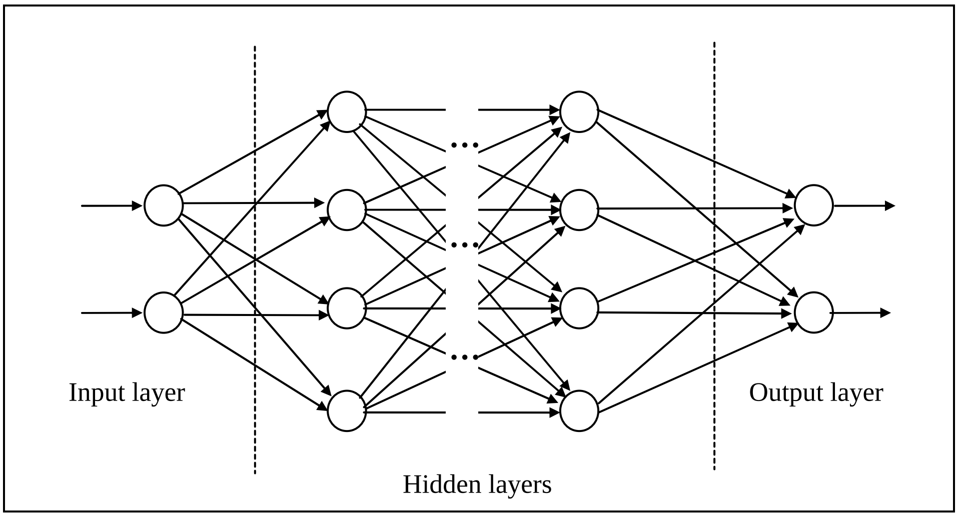


Fig. 1. Schematic diagram of a multilayer feed forward neural network.

3. HEATING LOAD ESTIMATION USING ARTIFICIAL NEURAL NETWORKS

For the training of an artificial neural network, data from 250 known cases were used. These were selected from successful past designs for which the owners expressed their satisfaction. The data varied from small rooms 1-2 m^2 in area to large spaces of 100 m^2 floor area. The type of rooms used ranged from small toilets to large classroom halls while the room design temperature varied from 18^oC to 23^oC. In addition, these rooms exhibited a large variety of structural characteristics e.g. rooms with and without windows, with and without external walls, of diverse types of construction, etc. This variety in data was thought necessary for enabling the ANN to learn a large spectrum of cases. On a test run, the applicability of the ANN's for such predictions was investigated using the whole range of possible data for training the network. This training gave excellent results with an R^2-value equal to 0.9990. This accuracy confirmed the potential of ANNs for such predictions.

In order to facilitate the work of designers it is desirable to reduce the number of data required for calculations. The data used for the training of the network, are those that mostly affect the heating load and are easily obtainable. These are shown in Table 1. It may be observed that the infiltration losses have not been explicitly taken into account. This is so because these depend on the window area, and hence are indirectly taken into account by the network.

Some parameters which are important to the estimation of the heating load, such as the type of wall and glazing have also been incorporated. In these cases no exact U-values were used but instead class numbers such as 0, 1, 2 etc. corresponding to each type of construction have been assigned.

Table 1. Input data used for the training of the network.

Window area (m^2)
External wall area (m^2)
Partition area (m^2)
Floor area (m^2)
Roof / Ceiling code (1 = ceiling, 2 = roof)
Window type code (see Table 2)
Wall type code (see Table 3)
Design room temperature (^oC)

Tables 2 and 3 list the various classes of windows and walls used in this study as well as their corresponding U-values. These are referring to the most usual types of wall constructions and glazings found in Cyprus. It is pointed out that for this study no details on the various types of roofs, ceilings and partitions have been used. This has been done because in Cyprus there is not much variation in the above constructions and also because at this stage the study aims at establishing the suitability of artificial neural networks for heating load calculations and not to produce an all encompassing engineering tool. Such a tool should be enriched with a greater variety of structural construction types and trained also for different ambient conditions.

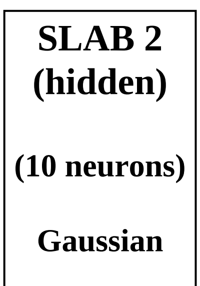
Table 2. Window types used for network training.

Class value	Description	U-value (W/m^2K)
0	No window	-
1	Single glazing	6.4
2	Double glazing	3.2

Table 3. Wall types used for network training.

Class value	Description	U-value (W/m^2K)
0	No wall	-
1	Single wall	2.0
2	Double wall without insulation	1.5
3	Double wall with 25mm polystyrene	1.2
4	Double wall with 25mm polyurethane	1.0

Various network architectures have been investigated aiming at finding the one that could result in the best overall performance. The architecture, from those tested, that gave the best results and finally adopted is shown in Fig. 2. This architecture has three hidden slabs of different activation functions. The input slab activation function was linear, while the activations used in the other slabs are indicated in Fig. 2 (Gaussian for slab 2, Tanh for slab 3, Gaussian complement for slab 4). The network consists of ten neurons in each hidden slab. Eight input neurons have been used, corresponding to the values shown in Table 1 for an eight-element input vector of the training data set. The output is a single unit corresponding to the value of the actual heating load in kcal/hr for each room. The backpropagation learning algorithm has been used. The network gain was set to 0.1 and the momentum factor to 0.5. The training data set was composed of 225 patterns while the test data set used for network verification had 25 patterns.



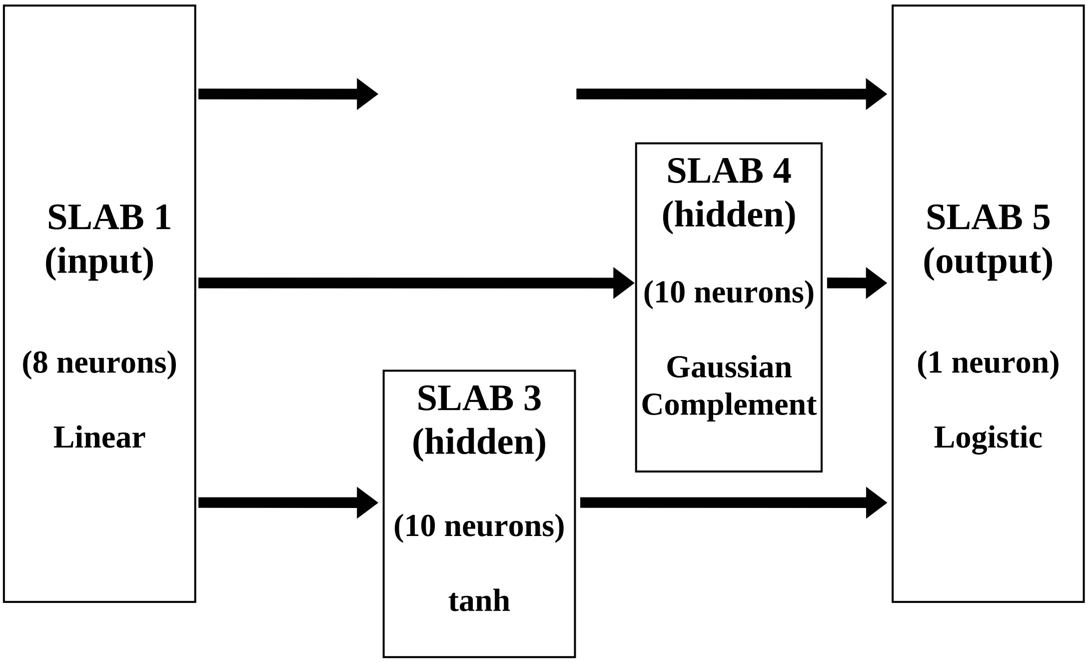


Fig. 2. Neural network architecture employed.

The training data were learned with an R^2-value of 0.9985. In the early stages of the work, the network did not produce results of adequate accuracy. The maximum difference between predicted and actual heating load was 15.2%. This error is quite high and it was decided to split the training data in two groups; one for small rooms of floor area up to $7m^2$ and another for rooms of floor area varying between 7 and $100m^2$. For each group a different network of architecture similar to the one shown in Fig. 2 was trained. The first group (small room area data file) comprised of 80 cases and the second group (large room area data file) comprised of 170 cases. The R^2-values obtained for these networks were 0.9990 and 0.9996 respectively, while the maximum difference between predicted and actual heating load was confined to 9%.

4. RESULTS / VALIDATION

Once a satisfactory degree of input - output mapping has been reached, the network training is freezed and the set of completely unknown test data is applied for verification. In more than 90% of the cases tested, the difference between predicted and actual heating load, for the testing set, was confined to less than 5%. The remaining 10% of the cases had a difference between 5% and maximum of 10%. Typical test results for some rooms of the "small spaces network" are shown in Table 4 and for the "large spaces network" in Table 5.

Table 4. Test results for the "small spaces network".

Room #	Actual load (kcal/hr)	ANN predicted load (kcal/hr)	% difference
1	470	418	-10
2	454	447	-1.3
3	917	964	+5

Table 5. Test results for the “large spaces network”.

Room #	Actual load (kcal/hr)	ANN predicted load (kcal/hr)	% difference
1	3207	3491	+9
2	3629	3724	+2.6
3	2701	2598	-3.8
4	2120	2107	-0.6

It can be seen from these Tables that the heating load estimation was performed with adequate accuracy. The cases shown in Tables 4 and 5 are specifically selected to show the range of accuracy obtained and in particular the minimum and maximum deviations. It should be noted that although a relatively high percentage difference has been obtained for some cases, this does not affect the size of the heating radiators to be selected for each room. This is so because the sizes of commercial radiators which are available, vary in steps of 0.1m and 0.2m, which correspond to a difference in heating load of about 220 kcal/hr and 450 kcal/hr respectively. The errors of the test runs presented in Tables 4 and 5 are well within the above values.

5. CONCLUSIONS

Once trained, the network estimates the heating load very fast. The accuracy of the present method is better than 90% which is well within the acceptable level used by design engineers. At this stage the work was confined at primarily investigating the suitability of artificial neural networks for heating load estimation. In order for the network to be of significant use to Building Services Engineers it needs to be enriched with more training cases and more diverse constructional and environmental parameters. Furthermore it is estimated that its performance will improve with use, since the network has the capability of learning from examples. As these become available, they may be used to retrain the network and hence to improve its accuracy. This method may also be applied for the cooling load estimation, a job which is much harder. We are currently working in this direction and we will report the results as soon as they are available.

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