Estimation of Daily Heating and Cooling Loads Using Artificial Neural Networks

SOTERIS KALOGIROU, *Department of Mechanical Engineering, Higher Technical Institute, P. O. Box 20423, Nicosia 2152, Cyprus, Tel: +357-2-306266, Fax: +357-2-494953, Email: skalogir@spidernet.com.cy*
GEORGE FLORIDES, *Department of Mechanical Engineering, Higher Technical Institute, Cyprus*
COSTAS NEOCLEOUS, *Department of Mechanical Engineering, Higher Technical Institute, Cyprus*
CHRISTOS SCHIZAS, *Department of Computer Science, University of Cyprus, Nicosia, Cyprus*

ABSTRACT

The objective of this work is to use Artificial Neural Networks for the estimation of the daily heating and cooling loads. The daily loads of nine different building structures have been estimated using the TRNSYS program and a typical meteorological year of Cyprus. This set of data has been used to train a neural network. For each day of the year the maximum and minimum loads were obtained from which heating or cooling loads can be determined. All the buildings considered, had the same areas but different structural characteristics. Single and double walls have been considered as well as a number of different roof insulations. A multi-slab feedforward architecture having 3 hidden slabs has been employed. Each hidden slab comprised of 36 neurons. For the "training data set" the R^2-values obtained were 0.9896 and 0.9918 for the maximum and minimum loads respectively. The method was validated by using actual (modeled) data for one building, for all days of the year, which the network has not seen before. The R^2-values obtained in this case are 0.9885 and 0.9905 for the two types of loads respectively. The results indicate that the proposed method can be used for the required predictions for buildings of different constructions. At present the method was used primarily to investigate its suitability for this kind of predictions.

1. INTRODUCTION

The cornerstone of a successful design of an air conditioning system is the accurate estimation of the building heating and cooling loads. A number of commercial software programs are currently available for the estimation of the building loads (e.g. ASHRAE Code, Carrier E20-II program, TRNSYS, etc.). For the case of the heating load most of 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. Infiltration or ventilation losses are also considered. For the case of the cooling load, the solar heat gain through the windows is also estimated. For more detailed analysis of the loads TRNSYS is usually employed which uses the transfer function method in order to estimate the interaction of the various building components with the environment on an hourly basis for the whole year.

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 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 modelling complex mappings and in system identification has been demonstrated (Vallejo *et al.*, 1995; Cherqaoui *et al.*, 1995; Bishop, 1995). 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 (Pattichis *et al.*, 1995, Curtiss *et al.*, 1995, Kalogirou *et al.*, 1996a and 1996b).

Artificial neural networks were also used for the estimation of the heating load of buildings (Kalogirou *et al.*, 1997), for the prediction of the energy consumption of passive solar buildings (Kalogirou and Bojic, 2000) and for the estimation of the air flow in a naturally ventilated test room (Kalogirou *et al.*, 1999).

The aim of this study is to investigate the suitability of neural networks as tools for the estimation of the heating and cooling 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 accurate thermal properties of local building materials are not known. Property values taken from published references are not always valid for the materials used locally. This is because even though the same material might be specified, the composition and manufacturing method of the materials could be different. In fact, for the present estimations with TRNSYS the thermal conductivity of locally produced materials has been measured and used for the determination of the required U-values.

2. DAILY HEATING AND COOLING LOAD ESTIMATION USING ARTIFICIAL NEURAL NETWORKS

For the training of an artificial neural network, data from nine different building structures were used. For each day of the year the maximum and minimum loads have been estimated from which the maximum heating and cooling loads as well as the total amount of energy required to keep the building conditioned throughout the year can be obtained.

All the buildings considered, had the same heat transfer areas but different structural characteristics (see Figure 1). The model house illustrated in Figure 1 has a floor area of 196 m^2 and consists of four identical external walls, 14m in length by 3m in height, with a total window opening of 5.2m^2 on each wall. The window area is approximately equal to the area that a typical house would have, but instead of considering a number of windows on each wall, only one window is considered. The model house is further divided into four identical zones and the partition walls are considered as walls separating the four zones. This was done in purpose so as the model house resembles as much as possible the real buildings. Program TRNSYS has been used for the estimation of the loads employed for the training and validation of the network. Details of the program may be found in Florides *et al.* (2000).

Single and double walls have been considered as well as a number of different roof insulations. The data used as input to the network were the day, month, wall type, roof type, and the daily values of mean direct radiation, mean global radiation, maximum and minimum temperatures, mean wind speed, and mean wind direction as obtained from a typical meteorological year for Cyprus. The outputs were the minimum and maximum loads for the day. The indoor conditions considered are 21°C for the heating season (winter) and 25°C for the cooling season (summer).

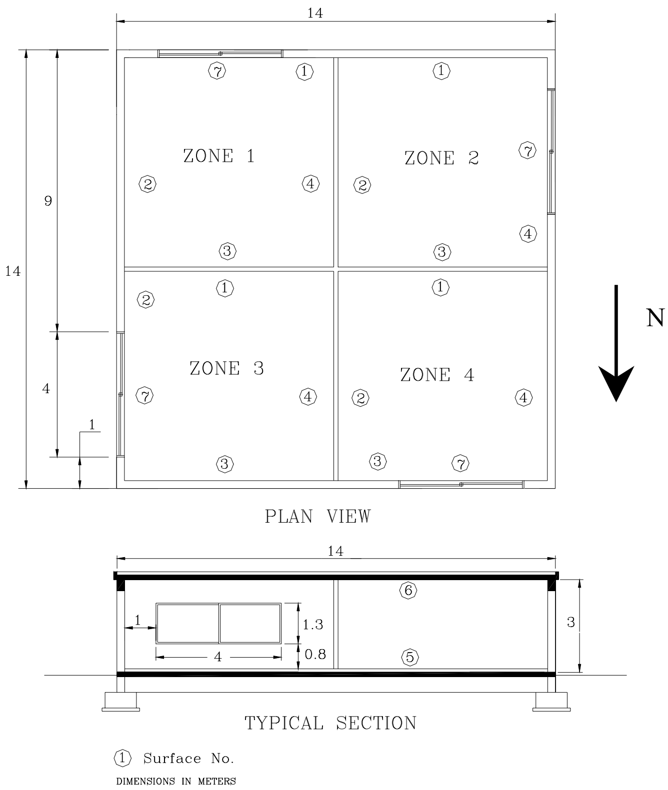

Figure 1. Drawing of the house modelled.

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 and cooling 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 loads, such as the type of wall and roof, have also been incorporated. In these cases exact U-values were not used, but instead class numbers such as 1,2,4 corresponding to each type of construction have been assigned.

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

1. Day number or Julian day (1-365)
2. Month (1-12)
3. Wall type (see Table 2)
4. Roof type (see Table 3)
5. Maximum daily direct radiation (kJ/m^2)
6. Mean daily direct radiation (kJ/m^2)
7. Maximum daily global radiation (kJ/m^2)
8. Mean daily global radiation (kJ/m^2)
9. Maximum temperature of the day (°C)
10. Mean temperature of the day (°C)
11. Mean wind speed (m/s)
12. Mean wind direction (degrees)

Tables 2 and 3 show details of the various classes of walls and roofs used in this study as well as their corresponding U-values. These refer 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 floors, 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 and cooling 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 and building orientations. All buildings considered are fitted with double glazing windows.

Table 2. Wall types used for network training.

Class value	Description	U-value (W/m^{2}K)
1	Single wall without insulation	2.0
2	Double wall with 25mm polystyrene insulation	0.83
4	Double wall with 50mm polystyrene insulation	0.53

Table 3. Roof types used for network training.

Class value	Description	U-value (W/m^{2}K)
1	Non insulated roof	2.3
2	Roof with 25mm polystyrene insulation	0.88
4	Roof with 50mm polystyrene insulation	0.55

Table 4 indicates all possible combinations of building constructions that were available for training and validation of the network. For each case, 365 patterns were available, i.e., one for each day of the year.

Various network architectures have been investigated aiming at finding the one that could result in the best overall performance. Table 5 outlines the architectures of the various neural networks, together with the coefficients of multiple determination (R^2-values) for both the training and the validation data sets.

It should be noted that for each architecture shown in Table 5 a number of different variations were tried with respect to the number of hidden neurons.

Table 4 Combination of building elements used for training and validation of the network.

Building #	Wall type (according to Table 2)	Roof type (according to Table 3)
1	1	1
2	1	2
3	1	4
4	**2**	**1**
5	2	2
6	2	4
7	4	1
8	4	2
9	4	4
Note: Data in bold randomly chosen for validation of the network.		

Table 5. Neural network architectures and performances.

Architecture	Number of neurons in each hidden slab/layer	R^2-value of training set		R^2-value of validation set	
		Maximum load	Minimum load	Maximum load	Minimum load
3 Layer Feedforward	55	0.9834	0.9762	0.9794	0.9758
4 Layer Feedforward	28	0.9827	0.9737	0.9780	0.9732
5 Layer Feedforward	18	0.9826	0.9763	0.9781	0.9712
3 Layer Feedforward	110	0.9834	0.9762	0.9794	0.9758
4 Layer Feedforward	56	0.9843	0.9784	0.9812	0.9773
5 Layer Feedforward	36	0.9847	0.9825	0.9817	0.9807
Group Method of Data Handling GMDH (polynomial net)	-	0.9708	0.9526	0.9682	0.9587
Feedforward with 3 hidden slabs	18	0.9867	0.9862	0.9833	0.9848
Feedforward with 3 hidden slabs	36	0.9896	0.9918	0.9885	0.9905

As can be seen from the data presented in Table 5 the architecture, from those tested, that gave the best results and finally adopted is the feedforward one with three hidden slabs. This architecture has three hidden slabs of different activation functions as shown in Figure 2. The input slab activation function was linear, while the activations used in the other slabs are indicated in Figure 2 (Gaussian for slab 2, Tanh for slab 3, Gaussian Complement for slab 4). The network consists of 36 neurons in each hidden slab. A relatively large number of hidden neurons have been used in order to get more “degrees of freedom” and allow the network to store more complex patterns. In fact the same architecture with smaller number of neurons in the hidden layers gave a slightly inferior performance as shown in Table 5.

Twelve input neurons have been used, corresponding to the values shown in Table 1 for a twelve-element input vector of the training data set. The two neurons of the output slab correspond to the values of the maximum and minimum loads in kJ/hr for each day of the year. The backpropagation learning algorithm has been used. The network gain was set to 0.05 and the momentum factor to 0.6.

A total of 3285 patterns were available in total (9 building cases x 365 days). From these, 2336 were used for the training of the network while 584 patterns were randomly selected and used for testing. Data for one building construction for a whole year (365 patterns) were used for validation of the network.

The training data were learned with R^2-values of 0.9896 and 0.9918 corresponding to the maximum and minimum load values respectively.

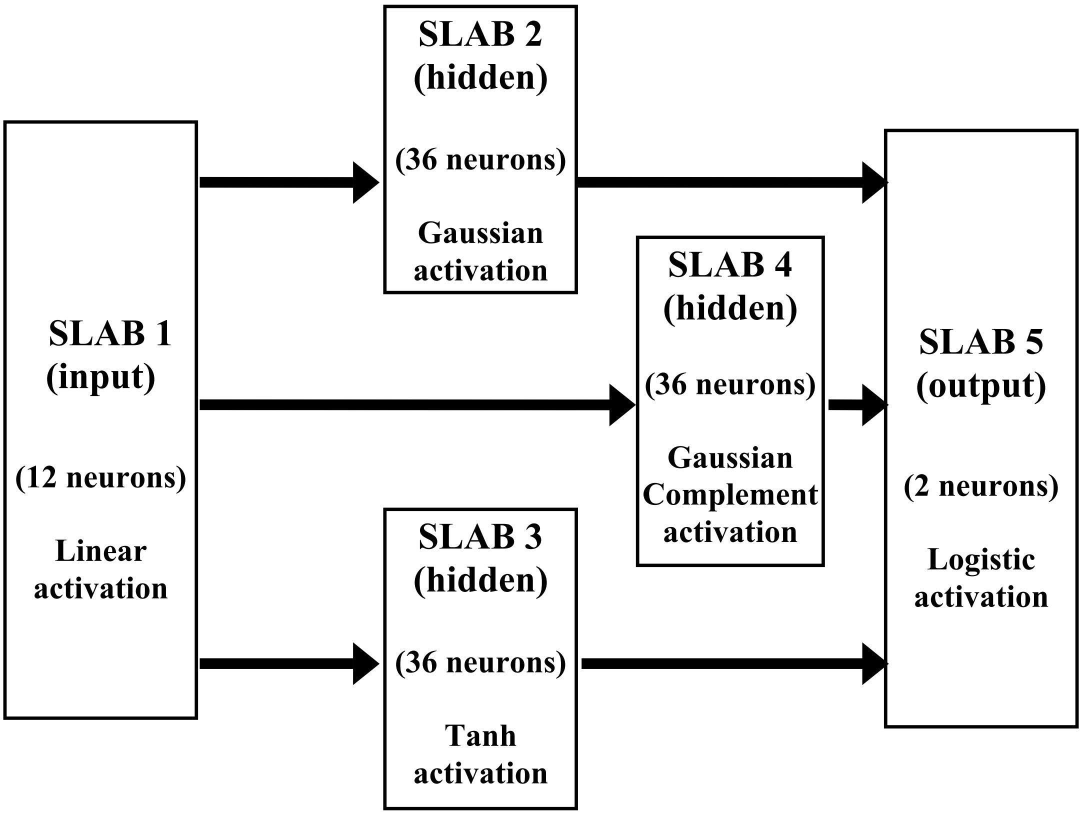

Figure 2. Neural network architecture employed.

3. RESULTS / VALIDATION

Once a satisfactory degree of input - output mapping has been reached, the network training is stopped and the set of completely unknown validation data is applied for verification. This set comprise data for a building construction for the whole year. Predictions with R^2-values of 0.9885 and 0.9905 corresponding to the daily maximum and minimum load values respectively have been obtained. Comparative graphs for all the data of the validation data set for the maximum and minimum loads are shown in Figures 3 and 4 respectively.

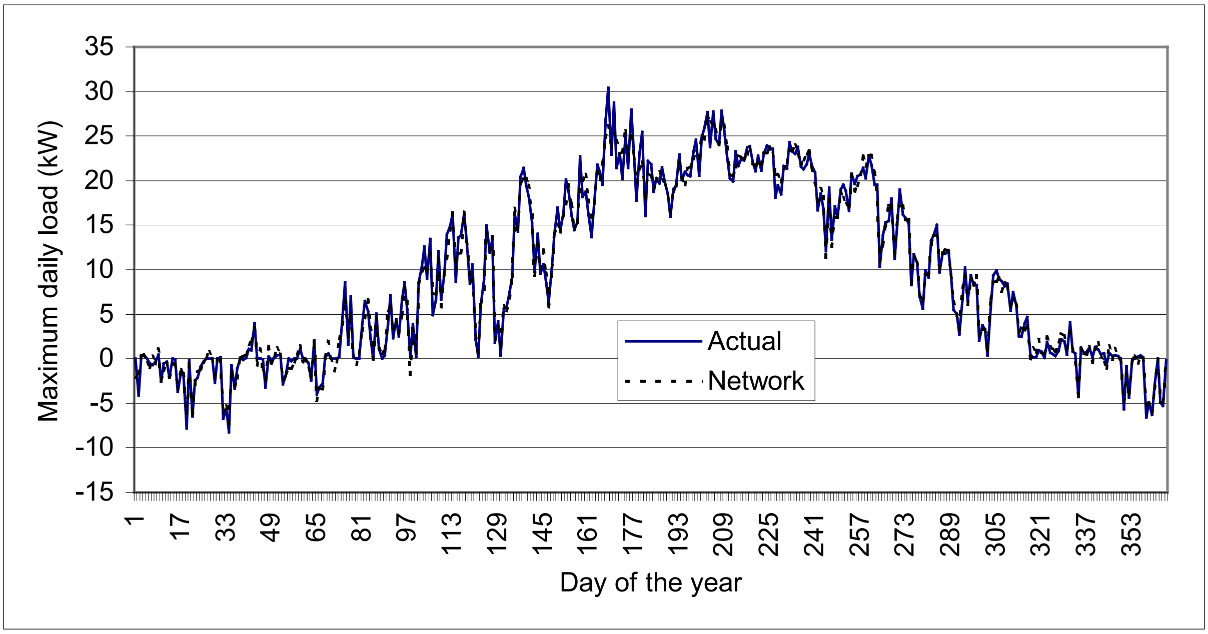

Figure 3. Comparison between the actual (modelled) and ANN predicted maximum load for the validation data set.

As can be seen from Figures 3 and 4 for most of the days, accurate prediction of the daily maximum or minimum load is obtained. More representative graphs may be obtained by plotting the actual against the predicted values of the two cases investigated here. These are shown in Figures 5 and 6 respectively. The mean relative error between the actual (TRNSYS code) and ANN predicted results and the is 2.68% and 2.52% whereas the root mean square relative error is 3.41% and 3.37% for the maximum and minimum loads respectively.

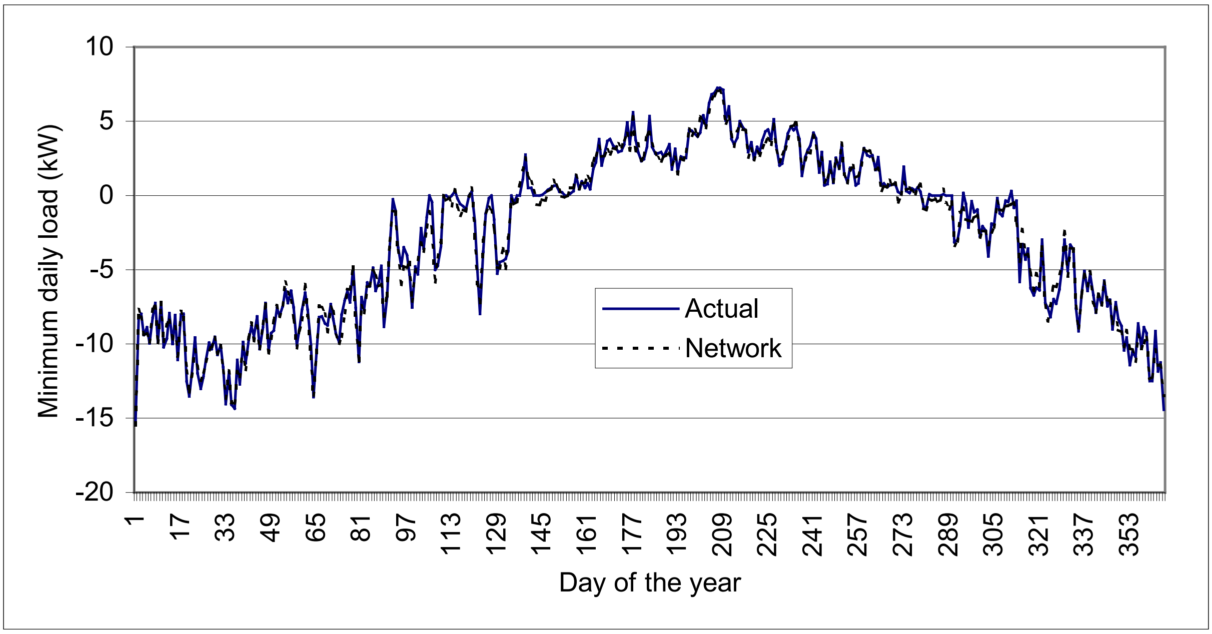

Figure 4. Comparison between the actual (modelled) and ANN predicted minimum load for the validation data set.

It should be noted that from these daily maximum and minimum loads the heating or cooling load of each day could easily be obtained. Additionally a significant advantage of the present method is that the loads for all days of the year are obtained and not just the maximum values which occurs possibly only once a year, thus the load curves can be used for other purposes as well like the estimation of the energy expenditure or energy requirement for the whole year.

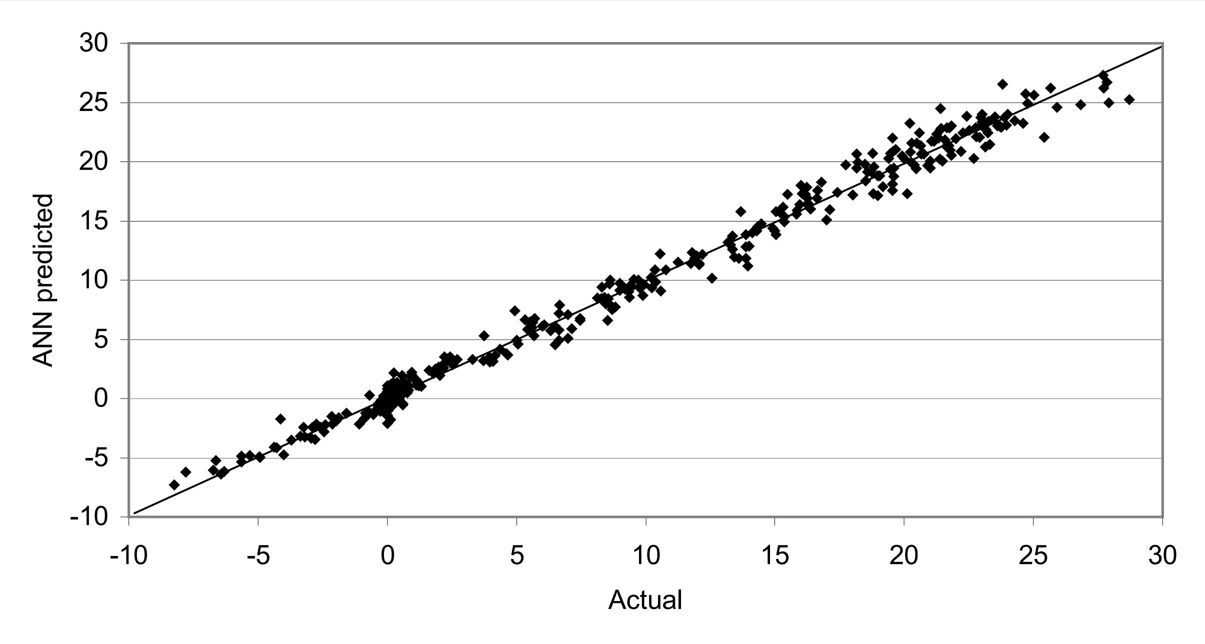

Figure 5. Comparison between the actual (modelled) and ANN predicted maximum loads for the validation data set.

It can be seen from these figures that the load estimations were performed with adequate accuracy. The cases with the greater differences shown in the figures are not important in the determination of the respective load as they occur at days where the opposite load is important, i.e. for a winter day where heating load is predominant is not important if a great difference in the maximum load (cooling load) is obtained and vice versa.

The contribution of each of the learning parameters is shown in Figure 7. This factor gives the relative importance of each learning parameter to the training of the network and is usually used to choose the input parameters in problems with many inputs. The input parameter number corresponds to the parameters shown in Table 1. As can be seen the parameter with the smallest contribution is the wall type. This agrees with the findings of the analytic method carried out with TRNSYS (Florides *et al.*, 2000). It should be noted that the ANN model reached the same conclusion without knowing the data or their importance.

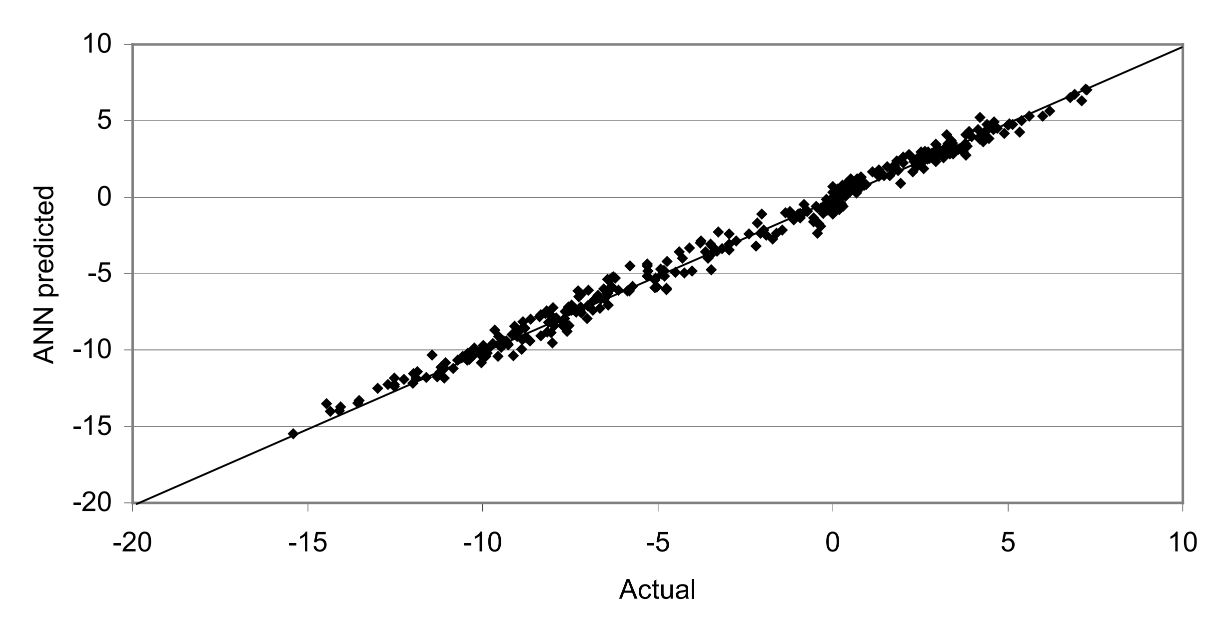

Figure 6. Comparison between the actual (modelled) and ANN predicted minimum loads for the validation data set.

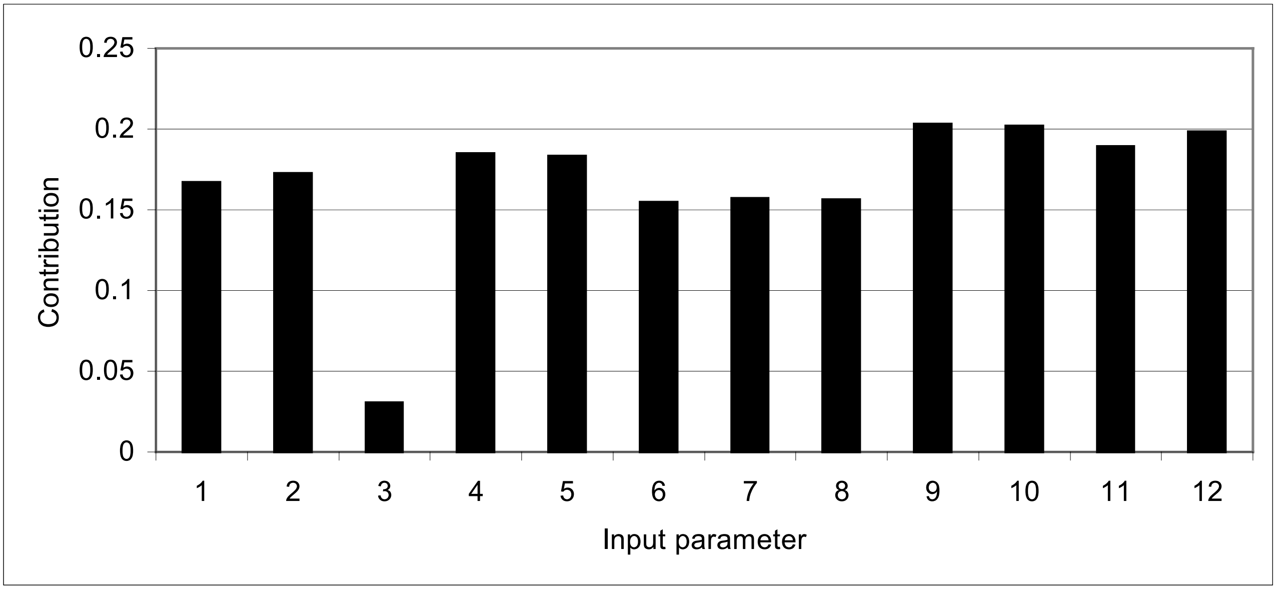

Figure 7. Contribution of each of the input parameter to learning.

4. CONCLUSIONS

The objective of this work was to use a neural network for the prediction of the heating and cooling load of buildings. For this purpose a multi-slab feedforward architecture has been employed with 3 hidden layers. Each hidden layer comprised of 36 neurons. Once trained the network estimates the heating and cooling loads very fast. The accuracy of the present method 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 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.

Also by examining the contribution factors it was found that the wall type was the least important, which agrees with the findings from conventional methods. A significant advantage of the present method, compared to the classical approach is that the loads are estimated quickly. Estimating the loads on a daily basis also requires a lot of computer power and a lot of effort to input the required data. Additionally, the results of maximum and minimum load on a daily basis can be used for the estimation of the energy consumption of a building. At present the method was used primarily to investigate its suitability for this kind of predictions. Although modeled data were used for the training of the network it has been shown that the method can be used on real data just as well. This would produce a powerful tool for such predictions.

At this stage the study aims at establishing the suitability of artificial neural networks for heating and cooling 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 and building orientations and location.

Another advantage of the present method is that the designer can investigate the effect that various construction methods can have on the building loads very easily by just changing a single number corresponding to the construction type without even required to estimate the u-value. This will be of much greater use when the database of the various construction types shown in Tables 2 and 3 is enriched.

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