# Artificial Neural Networks for predicting cooling load in buildings in tropical countries

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## Abstract

Artificial neural networks have been used for prediction of cooling loads in buildings. Only cooling load simulations were run to evaluate the performance of the network for tropical countries like India where cooling is a critical issue. The input parameters taken for the simulation were thickness of the wall, presence of insulation on the western and the southern elevation, month of the year and day of the month as these parameter can provide quick comparison for different wall thicknesses and provision of insulation to the designer at the planning stage. The output taken is the cooling load in kWh. The building is simulated for four months from June to September when the ambient temperatures are high and cooling loads are demanding. The simulation produced satisfactory results in very less time as compared to commercially available softwares where the number of input parameter are quite large and comparative study of various options is not possible.

## Introduction

To model a building for thermal evaluation a large number of techniques are available where the exact thermal behavior of the building can be studied. Since, the calculations are computationally very heavy especially if the modeling is done using transient numerical methods, computers have been used effectively to tackle the problem. Lot of softwares are available commercially that can simulate a space and output the resulting temperature profiles or loads for the interiors. However, the results may not be accurate as a large number of assumptions need to be made in the process and it is quite impossible to quantitatively measure factors like infiltration/ exfiltration in a space. Information on thermal properties of building materials may also not be applicable for practical purposes. Moreover, in cases of retrofitting an existing building, exhaustive information of all building parameters is difficult to obtain. Quick comparison of alternatives needs to be made at the planning stages for best possible design solutions. ANNs can provide quick solutions in such situations as they are faster, are fault tolerant, can handle incomplete and noisy data and do not need exhaustive information on buildings.

ANNs can be trained with experimental data or past history and can learn the behavior and performance of the building. They can be effectively used to predict future performance based on the past history.

Neural networks have been applied in various fields in engineering like control systems, classification, and in modeling complex process transformations [2-8]. They have also been used in HVAC process identification and control [9], in hourly thermal load prediction [10] and in passive solar design of windows [11].

## Assumptions for Simulation

The building that is simulated is assumed to be in India. The building consists of a room built of masonry with no windows or infiltration. Four wall thicknesses were taken as input, 150mm, 300mm, 450mm and 600mm. The roof is assumed to be flat. Since the solar load is high on southern and western elevations, presence of insulation on these two walls is considered. The simulation is run only for summers from the month of June till September, as cooling is a critical issue in tropical countries. The output is the cooling load in kWh on a daily basis. ANN is used to predict the cooling load with minimum input. It should be noted that no actual U-values are fed into the network except for the presence or absence of insulation on two walls, which is taken as a binary input.

## Data for the neural network

In the absence of experimental data, Energy Plus software is used to generate data for the neural network. Data generated for training the network is easily measurable like thickness of the walls, presence of insulation, month of the year and day of the month and the output generated is the cooling load in kWh. Energy Plus was run for a number of cases and 976 data was generated for training and validation. The characteristic data is given in the following table.

| Thickness of the wall in cm | Insulation (binary input) | Month | Day |
|---|---|---|---|
| 15 | 0 | 6 | 1 |
| 30 | 1 | 7 | 1 |
| 45 | 1 | 8 | 1 |
| 60 | 0 | 9 | 1 |

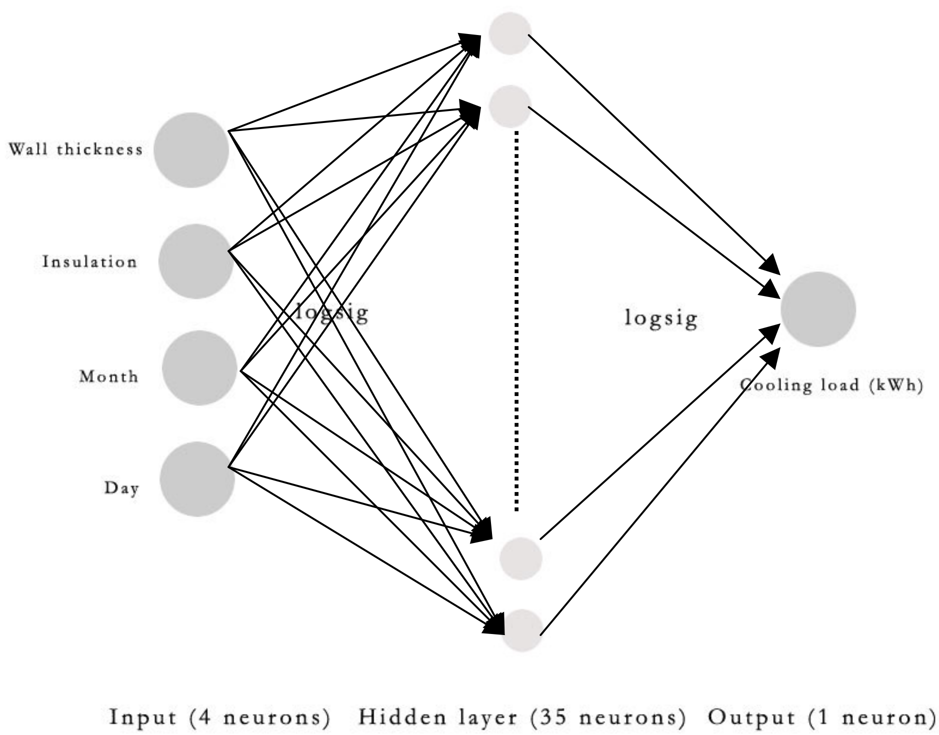
## Artificial neural network

A number of runs of the software were done to generate 976 data for training and validation of the network. Also a number of different network sizes and learning parameters were tried aiming at finding the one that could result in the best overall performance. The architecture of the network used is quite simple. The network is a feed forward backpropagation neural network with four neurons in the input layer, 25 in the hidden layer and one in the output. The activation function used in the input layer is pure linear while for the other two layers logarithmic sigmoidal function was used. As the training function for updating weights and bias values Levenberg-Marquardt backpropagation algorithm was used. As per this algorithm backpropagation is used to calculate the Jacobian jX of training performance of network with respect to the weight and bias variables X. Each variable is adjusted according to Levenberg-Marquardt,

$$jj = jX * jX$$

je = jX * E
dX = -(jj+I*mu) \ je

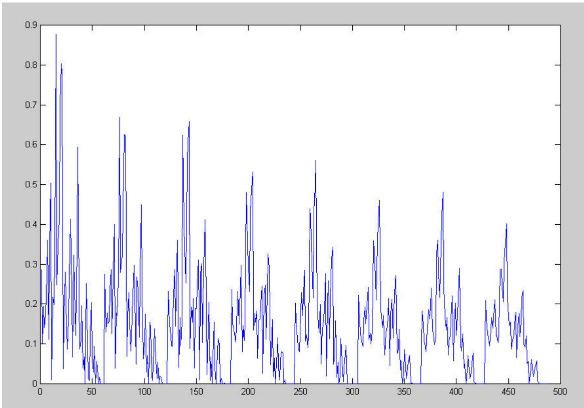
Where E is all errors and I is the identity matrix. The learning rate parameter was set to 0.05 and the momentum to 0.07. The initial weights were randomly initialized and a number of networks were simulated, each for a maximum of 100 epochs, out of which the network with the best performance was selected. In back-propagation networks, the number of hidden neurons determines how well a problem can be learned. If too many are used, the network will tend to try to memorize the problem, and thus not generalize well later. If too few are used, the network will generalize well but may not have enough "power" to learn the patterns well. Getting the right number of hidden neurons is a matter of trial and error, since there is no science to it. [14]



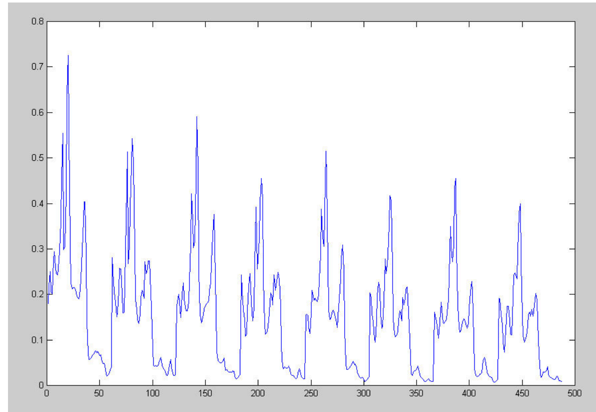

*Neural Network Architecture (Feed forward fully connected)*

## Results and Validation

Once a satisfactory degree of input – output mapping was reached, the network training was stopped and a set of new data was given to the network that it had not seen before. Simulations indicated an accuracy of 0.9119 in predicting the input samples correctly. The error that the best network had was 0.0033 with this set of new data. The simulation run for 5 networks to chose from with a maximum of 100 epochs each took around 5.24 minutes.



*Target Output*



*Simulated Output*

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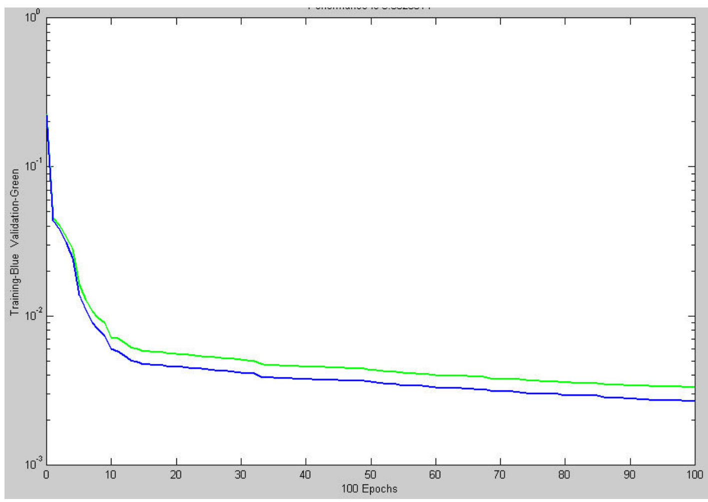


*The graph shows the simulation results for the summer months for predicting cooling loads.*

The performance of the network can further be increased by using more sophisticated network architectures. For the purpose of this paper, this simple architecture has shown promising performance for further research to be taken up in this area.

## Conclusion

Artificial neural network was used to predict cooling load in building for summer months and the network was found to perform with an accuracy of 0.9857 in predicting the input samples correctly for the data it had not seen before. The results are very promising for future and more elaborate work to be taken up in this area. The results show that ANNs can be used to predict cooling loads in buildings with reasonable accuracy.

## Future work

In future, we intend to train ANN for a room with windows and infiltration for more realistic approach to the problem. At this stage, the work was confined to primarily investigating the suitability of artificial neural networks for predicting the cooling load of a building. Due to lack of experimental data, the training data was generated using software simulation, however, for practical applications, we emphasize on experimental data for better performance of the network.

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