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Predicting Total Solar Heat Gain of the Building Using Artificial Neural Network

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Abstract: *This paper explores total solar heat gain of a six storey building by using neural fitting tool (nftool) of neural network of MATLAB Version 7.11.0.584 (R2010b) with 32-bit (win 32). The calculated total solar heat gain was 199080 kW per year. ANN application showed that data was best fit for the regression coefficient of 0.99794 with best validation performance of 48.9906 during winter.*

Key Words: *Artificial neural network, energy requirement, solar heat gain, regression coefficient*

I. Introduction

Himachal Pradesh is located in north India with Latitude 30^o 22' 40" N to 33^o 12' 40" N, Longitude 75^o 45' 55" E to 79^o 04' 20" E, height (from mean sea level) 350 m to 6975 m and average rainfall 1469 mm. For our study we have taken a building in Solan district which is located between the longitudes 76.42 and 77.20 degree east and latitudes 30.05 and 31.15 degree north the elevation of the district ranges from 300 to 3,000 m above sea level. The winter during six months (October to March) are severe and people use electricity (provided on subsidized rates) and conventional fuels (wood, LPG and coal). The summer during six months (April to September) people use electricity (provided on subsidized rates) to lower down the temperature. These results are burden on already depleting conventional fuels and same time causing emission of CO_2 and global warming. The other option to meet out energy requirement is solar passive technologies. This requires measured data of solar radiation which is not available in the state. This can be estimated by using various models on the basis of sunshine hour or temperature data. The mean hourly values of such data for various places in India are available in the handbook by [1]. As in statistical methods we have to deal with higher level of mathematics. Due to tough calculations, the probability of error is more. Evaluation, estimation and prediction are often done using statistical packages such as SAS, SPSS, GENSTAT etc. Most of these packages are based on conventional algorithms such as the least square method, moving average, time series, curve fitting etc. The performances of these algorithms are not robust enough when the data set becomes very large. This approach is very much time as well as mind consuming. Therefore ANN is much better than these methods. Neural networks have the potential for making better, quicker and more practical predictions than any of the traditional methods. They can be used to predict energy consumption more reliably than traditional simulation models and regression techniques. Artificial Neural Networks are nowadays accepted as an alternative technology offering a way to tackle complex and ill-defined problems. They are not programmed in the traditional way but they are trained using past history data representing the behavior of a system.

ANNs are the most widely used artificial intelligence models in the application of building energy prediction. In the past twenty years, researchers have applied ANNs to analyze various types of building energy consumption in a variety of conditions, such as heating/cooling load, electricity consumption, sub-level components operation and optimization, estimation of usage parameters. In 2006, [2] did a brief review of the ANNs in energy applications in buildings, including solar water heating systems, solar radiation, wind speed, air flow distribution inside a room, pre-diction of energy consumption, indoor air temperature, and HVAC system analysis. Olofsson developed a neural network which makes long-term energy demand (the annual heating demand) predictions based on short-term (typically 2–5 weeks) measured data with a high prediction rate for single family buildings [3]. Kreider reported results of a recurrent neural network on hourly energy consumption data to predict building heating and cooling energy needs in the future, knowing only the weather and time stamp [4]. Kalogirou used neural networks for the prediction of the energy consumption of a passive solar building where mechanical and electrical heating devices are not used [5]. Wong used a neural network to predict energy consumption for office buildings with day-lighting controls in subtropical climates [6]. Aydinalp showed that the neural network can be used to estimate appliance, lighting and space cooling energy consumption and it is also a good model to estimate the effects of the socio-economic factors on this consumption in the Canadian residential sector [7]. Sheikh did Short Term Load Forecasting using ANN Technique [8]. Karatasou studied how statistical procedures can improve neural network models in the prediction of hourly energy loads [9].

II. Methods And Material

The six storey administrative block of Shoolini University building at Bajhol-Solan (HP) “Fig 1” has been taken for the study, which worked for seven hours during a day time. The dimensions were length 45 m, 15 m wide and 18 m in height. The neural fitting tool (nftool) of neural network of MATLAB Version 7.11.0.584 (R2010b) with 32-bit (win 32) had been used. The temperature and humidity of the building had been measured by using ‘Thermo Hygrometer’. The other required data had been taken from NASA website.

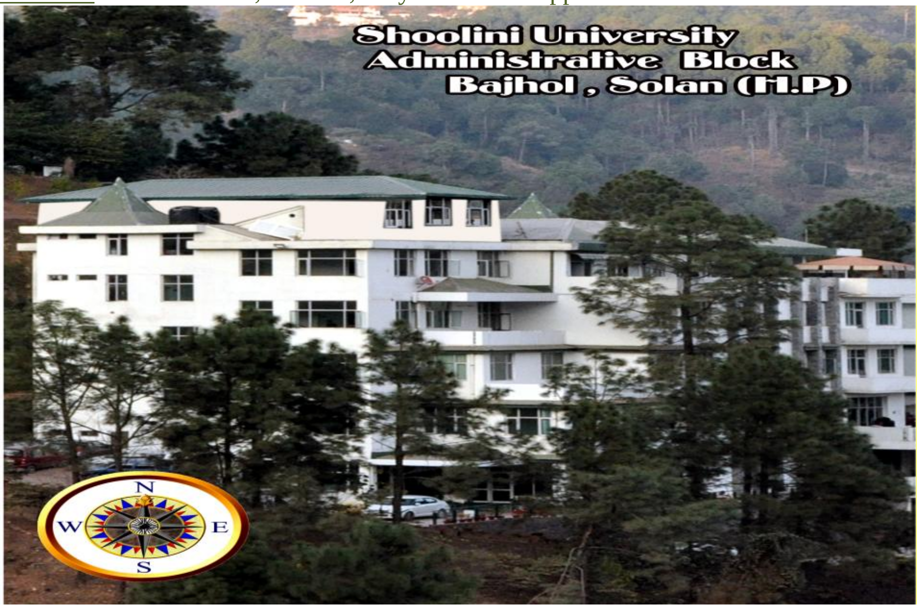

Fig 1. Shoolini University administrative block at Bajhol-Solan (HP)

The solar gain through transparent elements can be written as:

$$Q_s = \alpha_s \Sigma A_i S_{gi} \tau_i \quad (1)$$

where

α_s = mean absorptivity of the space, A_i = area of the ith transparent element (m^2), S_{gi} = daily average value of solar radiation (including the effect of shading) on the ith transparent element (W/m^2), τ_i = transmissivity of the ith transparent element.

Irrespective of developing a new model the neural fitting tool (nftool) of neural network of MATLAB Version 7.11.0.584 (R2010b) with 32-bit (win 32) had been used. Out of six samples four had been used for training, one sample each had been used for validation and testing. The architecture of the artificial neural network used in the study is shown in “Fig 2”.

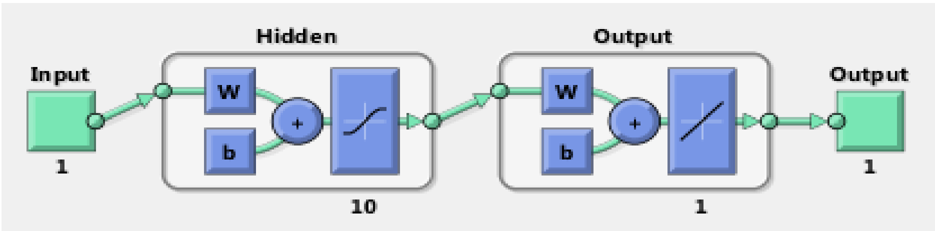

Fig.2 Architecture of neural network

III. RESULTS

The total solar gain in a building during winter is calculated as “Table 1”.

Table 1. Solar Heat Gain During Winter

Wall Exposed to Sun	A (In m)	S_g (W/m^2)	Q_s (In kW)
South wall	206.0	202.4	20
North wall	89.7	0	0
West wall	54.4	109.7	2.9
East wall	36.4	107.2	1.9
Roof	518	264.8	65.8
		Total heat gain per annum	114156

Q_s = 90.6 kW = 114156 kW per annum whose ANN graphs are shown in “Fig 3” & “Fig 4”

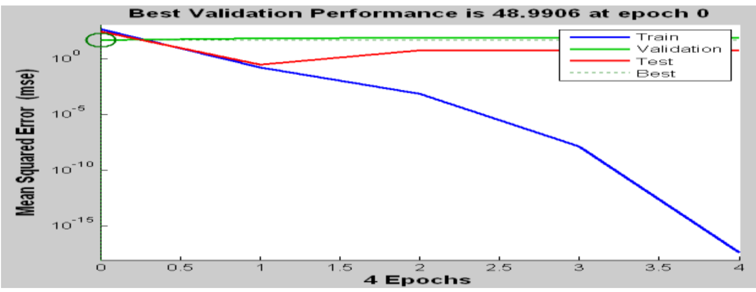

Fig 3. Validation performance of solar heat gain during winter

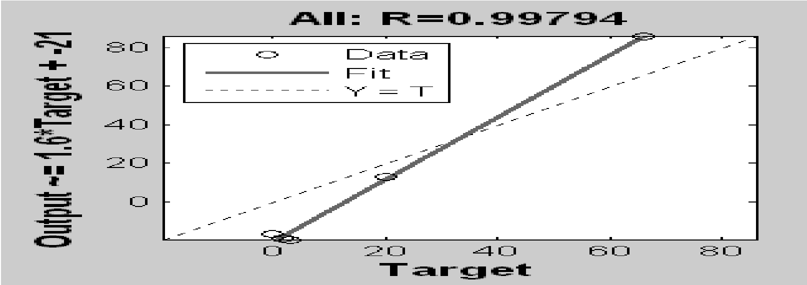

Fig 4. Regression analysis of solar heat gain during winter

The total solar gain in a building during summer is calculated as “Table 2”.

Table 2. Solar Heat Gain During Summer

Wall Exposed to Sun	A (In m)	S_g (W/m^2)	Q_s (In kW)
South wall	206.0	202.4	12.5
North wall	89.7	0	0
West wall	54.4	109.7	3.1
East wall	36.4	107.2	1.8
Roof	518	264.8	50.0
		Total heat gain per annum	84924

Q_s = 67.4 kW = 84924 kW per annum whose ANN graphs are shown in “Fig 5” & “Fig 6”

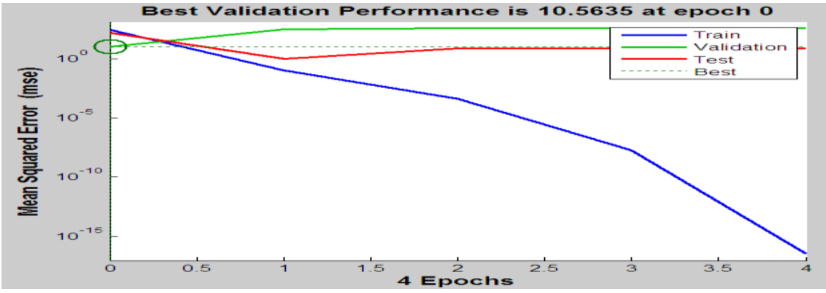

Fig.5. Validation performance of solar heat gain during summer

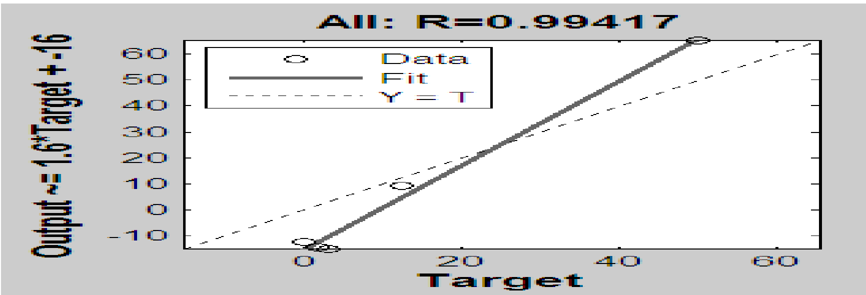

Fig.6. Regression analysis of solar heat gain during summer

Total Load = 1211228 +874668 kW,
Total Load = 2085896 kW

IV. DISCUSSION

In most residential buildings, optimization of thermal comfort and energy consumption is not achieved. From the above system descriptions one can see that ANNs have been applied in a wide range of fields for modelling, prediction and control of building energy systems. What is required for setting up such systems is data that represents the past history and performance of the real system and a suitable selection of ANN models. The accuracy of the selected models is tested with the data of the past history and performance of the real system. The neural network model was used with 10 hidden neurons which didn’t indicate any major problem with the training. The validation and test curves were very similar. The next step in validating the network was to create a regression plot, which showed the relationship between the outputs of the network and the targets. If the training were perfect, the network outputs and the targets would be exactly equal, but the relationship was rarely perfect in practice. The three axes represented the training, validation and testing data. The R value was an indication of the relationship between the outputs and targets. If R = 1, this indicated that there was an exact linear relationship between outputs and targets. If R was close to zero, then there was no linear relationship between outputs and targets.

V. CONCLUSION

The study revealed that the total solar heat gain of a six storey building by using neural fitting tool (nftool) of neural network of MATLAB Version 7.11.0.584 (R2010b) with 32-bit (win 32) was 199080 kW per year. ANN application showed that data was best fit for the regression coefficient of 0.99794 with best validation performance of 48.9906 during winter. These results necessitate the use of solar passive technologies to meet out this energy requirement during winters and summers. Increasing awareness of environmental issues has led to development of a large number of energy conservation technologies for buildings, especially in more developed countries [10]. Energy savings potential (ESP) is a very important indicator for developing these technologies.

VI. Limitations

ANN models like all other approximation techniques have relative advantages and disadvantages. There are no rules as to when this particular technique is more or less suitable for an application. Result of ANN depends upon number of hidden layer neurons. In order to get optimize result we should select optimize number of hidden layer neurons. One way of selecting hidden layer neuron using optimize algorithm technique and other way is hit and trial method. In existing proposed model hit and trial method has been used but it is never easy to comment that the used number of hidden neurons is perfect.

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