Predicting Total Conduction Losses of the Building Using Artificial Neural Network

Rajesh Kumar^{1,*}, RK Aggarwal², Dhirender Gupta³, Jyoti Dhar Sharma¹

¹Deptt. of Physics, Shoolini University, Bajhol, Distt. Solan (HP)- 173 212 India

²Deptt. of Environmental Science, University of Horticulture & Forestry, Solan (HP) -173230 India

³Deptt. of Physics, Govt P G College, Bilaspur (HP) – 174001 India

*Corresponding Author: rajesh.shoolini@gmail.com

Copyright © 2013 Horizon Research Publishing All rights reserved.

Abstract This paper explores total conduction losses 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 conduction loss was 329184 kW per year. ANN application showed that data was best fit for the regression coefficient of 0.9955 with best validation performance of 0.41231 during summer.

Keywords Artificial Neural Network, Energy Requirement, Conduction Loss, Regression Coefficient

1. Introduction

Himachal Pradesh is located in north India with Latitude 30° 22' 40" N to 33° 12' 40" N, Longitude 75° 45' 55" E to 79° 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 CO₂ 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 [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. Kalogirou 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, prediction of energy consumption, indoor air temperature, and HVAC system analysis [2]. 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]. Neural networks were used for the prediction of the energy consumption of a passive solar building where mechanical and electrical heating devices are not used [4]. Neural network was used to predict energy consumption for office buildings with day-lighting controls in subtropical climates [5]. 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 [6]. Sheikh did Short Term Load Forecasting using ANN Technique [7]. Kreider reported results of recurrent neural networks on hourly energy consumption data [8]. Ekici predicted building heating loads without considering climatic variables [9]. Karatasou studied how statistical procedures can improve neural network models in the prediction of hourly energy loads [10].

2. Materials and Methods

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.

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

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. The rate of heat conduction (Q_c) through any element such as roof, wall or floor under steady state can be written as

$$Q_c = AU\Delta T \quad (1)$$

where

A = surface area (m^2), U = thermal transmittance (W/m^2K), ΔT = temperature difference between inside and outside air (K)

If the surface is also exposed to solar radiation then

$$\Delta T = T_{so} - T_i$$

where T_i is the indoor temperature; T_{so} is the solar air temperature, calculated using the expression:

$$T_{so} = T_o + \alpha S_T / h_o - \epsilon \Delta R / h_o$$

where

T_o = daily average value of hourly ambient temperature (K), α = absorptance of the surface for solar radiation, S_T = daily average value of hourly solar radiation incident on the surface (W/m^2)

h_o = outside heat transfer coefficient (W/m^2K), ϵ = emissivity of the surface

ΔR = difference between the long wavelength radiation incident on the surface from the sky and the surroundings, and the radiation emitted by a black body at ambient temperature

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.

Figure 2. Architecture of neural network

The overall heat transfer coefficients for window, door and walls in this study were taken as

$$U_{\text{glazing}} = 5.7 \text{ W/m}^2\text{K}$$

$$U_{\text{wall}} = 3 \text{ W/m}^2\text{K}$$

$$U_{\text{roof}} = 2.3 \text{ W/m}^2\text{K}$$

Daily average outside temperature throughout the year = 13.9°C

Outside heat transfer coefficient is $22.7 \text{ W/m}^2\text{K}$

Inside design temperature is 19°C

Mean absorptivity of the space is 0.6

Transmissivity of window is 0.8

Density of air is 1.2 kg/m^3

Specific heat of air is 1005 J/kgK

Table 1. Conduction losses during winter

Wall Exposed to Sun	Material	U (W/m^2K)	A (m^2)	TSO	Q_c (In kW)
South wall	Brick Masonry	3	630.1	13.9	-6.5
North wall	Brick Masonry	3	746.0	8.6	-20.5
West wall	Brick Masonry	3	224.0	13.4	-2.8
East wall	Brick Masonry	3	196.0	11.4	-3.6
Roof	Tin	3.2	518.0	15.6	-4.1
Glazing	Glass	5.7	386.5	11.7	-16.1
Total conduction losses per annum					-231552

3. Results

The conduction losses of the building in winter are calculated as (Table 1)

$Q_c = -53.6 \text{ kW} = -231552 \text{ kW}$ per annum whose ANN graphs are shown in Fig 3 & Fig 4

Figure 3. Validation performance of conduction losses (Q_c) during winter

Figure 4. Regression analysis of conduction losses (Q_c) during winter

Figure 5. Validation performance of conduction losses (Q_c) during summer

Figure 6. Regression analysis of conduction losses (Q_c) during summer

$$\begin{aligned} \text{Total Conduction Losses} &= Q_c (\text{In winter}) + Q_c (\text{In summer}) \\ &= (231552 + 97632) \text{ kW} \\ &= 329184 \text{ kW} \end{aligned}$$

The conduction losses of the building in summer are calculated as (Table 2)

Table 2. Conduction losses during summer

Wall Exposed to Sun	Material	U (W/m ² K)	A (m ²)	T _{so}	Q _c (In kW)
South wall	Brick Masonry	3	630.1	22.3	4.8
North wall	Brick Masonry	3	746.0	19.2	2.0
West wall	Brick Masonry	3	224.0	22.3	0.5
East wall	Brick Masonry	3	196.0	22	1.5
Roof	Tin	3.2	518.0	25.8	6.5
Glazing	Glass	5.7	386.5	22.3	7.3
Total conduction losses per annum					97632

$Q_c = 22.6 \text{ kW} = 97632 \text{ kW}$ per annum whose ANN graphs are shown in Fig 5 & Fig 6

4. 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.

5. Conclusions

The study revealed that total conduction losses 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 329184 kW per year. ANN application showed that data was best fit for the regression coefficient of 0.9955 with best validation performance of 0.41231 during summer. The above results necessitate the use of solar passive technologies during winter and summer. Increasing awareness of environmental issues has led to development of a large number of energy conservation technologies for buildings, especially in more developed countries [11]. Energy savings potential (ESP) is a very important indicator for developing these technologies.

- [8] J. K. Kreider, D. E. Claridge, P. Curtiss, R. Dodier, J. S. Haberl and M. Krarti, Building energy use prediction and system identification using recurrent neural networks, *Journal of Solar Energy Engineering*, Vol. 117, No.3, 161–6.
- [9] B. B. Ekici and U. T. Aksoy, Prediction of building energy consumption by using artificial neural networks, *Advances in Engineering Software*, Vol. 40, No. 5, 356–62.
- [10] S. Karatasou, M. Santamouris and V. Geros, Modeling and predicting building's energy use with artificial neural networks: methods and results, *Energy and Buildings*, Vol. 38, No. 8, 949–58.
- [11] M. Chikada, T. Inoue et al., Evaluation of Energy Saving Methods in a Research Institute Building, CCRH. PLEA2001-The 18th Conference on Passive and Low Energy Architecture, Florianopolis-BRAZIL, 883–888, 2001

REFERENCES

- [1] A. Mani and S. Rangarajan, *Solar radiation over India*, Allied Publishers, New Delhi, 1982.
- [2] S. A. Kalogirou, Artificial neural networks in energy applications in buildings, *International Journal of Low-Carbon Technologies*, Vol. 1, No. 3, 201–16.
- [3] T. Olofsson and S. Andersson, Long-term energy demand predictions based on short-term measured data, *Energy and Buildings*, Vol. 33, No. 2, 85–91.
- [4] S. A. Kalogirou and M. Bojic, Artificial neural networks for the prediction of the energy consumption of a passive solar building, *Energy*, Vol. 25, No. 5, 479–91.
- [5] S. L. Wong, K. K. W. Wan and T. N. T. Lam, Artificial neural networks for energy analysis of office buildings with day lighting, *Applied Energy*, Vol. 87, No. 2, 551–7.
- [6] M. Aydinalp, V. I. Ugursal and A. S. Fung, Modeling of the appliance, lighting, and space cooling energy consumptions in the residential sector using neural networks, *Applied Energy*, Vol. 71, No. 2, 87–110.
- [7] S. K. Sheikh and M. G. Unde Short Term Load Forecasting using ANN Technique, *International Journal of Engineering Sciences & Emerging Technologies*, Vol. 1, No. 2, 27-107.