Available online at http://www.journalijdr.com

International Journal of DEVELOPMENT RESEARCH

ISSN: 2230-9926

International Journal of Development Research
Vol. 3, Issue, 05, pp.014-019, May, 2013

Full Length Research Article

PREDICTING ENERGY REQUIREMENT FOR HEATING THE BUILDING USING ARTIFICIAL NEURAL NETWORK

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ARTICLE INFO

Article History:

Received 24th March, 2012
Received in revised form
22nd March, 2013
Accepted 26th April, 2013
Published online 13th May, 2013

Key words:

Artificial neural network,
Absorptance,
Transmittance,
Regression coefficient,
Heat gain,
Ventilation losses,
Carbon emission etc.

ABSTRACT

This paper explores total heat load and total carbon emissions of a six storey building by using artificial neural network (ANN). Parameters used for the calculation were conduction losses, ventilation losses, solar heat gain and internal gain. The standard back-propagation learning algorithm has been used in the network. The energy performance in buildings is influenced by many factors, such as ambient weather conditions, building structure and characteristics, the operation of sub-level components like lighting and HVAC systems, occupancy and their behavior. This complex situation makes it very difficult to accurately implement the prediction of building energy consumption. The calculated heat load was -1,211,228 kW per year. ANN application showed that data was best fit for the regression coefficient of 0.99812 with best validation performance of 1312.5203 in case of conduction losses. Comparative analysis of carbon emission by different fuels has been followed by measures for reducing carbon emission.

Research Highlights:

- Use of Artificial Neural Network to find heat load
- Carbon emission calculation
- Recommendations for renewable energy use
- Regression coefficient calculation
- Graphical representation of best validation performance

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 meter to 6975 meter 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 and latitudes 30.05 and 31.15 degree north the elevation of the district ranges from 300 to 3,000 meter above sea level. Carbon has been identified as the element that insulates our planet and is a major contributor in global warming. The average world temperature of the Earth has increased by 1 degree Fahrenheit in just the last century. Heat can be conducted through solids, liquids and gases. Some materials conduct more rapidly than others. Daily average values of hourly solar radiation can be calculated from the hourly data. As mentioned earlier, measurements of global and diffuse solar radiation are carried out on a horizontal surface. Mean hourly values of such data for various places in India are available in the handbook by Mani (1982). 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, Kalogirou (2006) 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. Kalogirou *et al*. (1997) used back propagation neural networks to predict the required heating load of buildings. The model was trained on the consumption data of 225 buildings which vary largely from small spaces to big rooms. Ekici and Aksoy (2009) used the same model to predict building heating loads in three buildings. The training and testing datasets were calculated by using the finite difference approach of transient state one-dimensional heat conduction. Olofsson and Andersson (2001) developed a neural network

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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. Yokoyama *et al*. (2009) used a back propagation neural network to predict cooling demand in a building. In their work, a global optimization method called modal trimming method was proposed for identifying model parameters.

Kreider *et al*. (1995) 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. Based on the same recurrent neural network, Ben-Nakhi and Mahmoud (2004) predicted the cooling load of three office buildings. Kalogirou *et al*. (2000) used neural networks for the prediction of the energy consumption of a passive solar building where mechanical and electrical heating devices are not used. Considering the influence of weather on the energy consumption in different regions, Yan *et al*. (2010) used a back propagation neural network to predict building's heating and cooling load in different climate zones represented by heating degree day and cooling degree day. The neural network was trained with these two energy measurements as parts of input variables. In the application of building electricity usage prediction, an early study has successfully used neural networks for predicting hourly electricity consumption as well as chilled and hot water for an engineering center building. Nizami *et al*. (1995) tried a simple feed-forward neural network to relate the electric energy consumption to the number of occupancy and weather data. Wong *et al*. (2010) used a neural network to predict energy consumption for office buildings with day-lighting controls in subtropical climates.

The outputs of the model include daily electricity usage for cooling, heating, electric lighting and total building. Hou *et al*. (2006) predicted air-conditioning load in a building, which is a key to the optimal control of the HVAC system. Lee *et al*. (2004) used a general regression neural network to detect and diagnose faults in a building's air-handling unit. Aydinalp *et al*. (2002) 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. In their follow-up work, neural net-work models were developed to successfully estimate the space and domestic hot-water heating energy consumptions in the same sector. Gouda *et al*. (2002) used a multi-layered feed-forward neural network to predict internal temperature with easily measurable inputs which include outdoor temperature, solar irradiance, heating valve position and the building indoor temperature. Kreider *et al*. (1995) reported results of recurrent neural networks on hourly energy consumption data. Ekici *et al*. (2009) predicted building heating loads without considering climatic variables. The networks were trained by only three inputs, transparency ratio, building orientation and insulation thickness. Karatasou *et al*. (2006) studied how statistical procedures can improve neural network models in the prediction of hourly energy loads. Azadeh *et al*. (2008) showed that the neural network was very applicable to the annual electricity consumption prediction in manufacturing industries where energy consumption has high fluctuation. It is superior to the conventional non-linear regression model through Analysis of Variance (ANOVA).

Experimental details

We had considered a six storey building of 45 m long, 15 m wide and 18 m in height. Under the steady state approach (which does not account the effect of heat capacity of building materials), the heat balance for room air can be written as Nayak *et al*. (2006):

$$Q_{total} = Q_c + Q_s + Q_i + Q_v \quad (1)$$

Conduction

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

$$Q_c = AU\Delta T \quad (2)$$

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:

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

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

Mean hourly values of data for various places in India are available in the handbook by Mani [1].

Solar Heat Gain

The solar gain through transparent elements can be written as:

$$Q_s = \alpha_s \Sigma A_i S_{gi} \tau_i \quad (3)$$

Where

α_s = mean absorptivity of the space
A_i = area of the with 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
M = number of transparent elements

Ventilation

The heat flow rate due to ventilation of air between the interior of a building and the outside depends on the rate of air exchange. It is given by:

$$Q_v = \rho V_r C\Delta T \quad (4)$$

where,

ρ = density of air (kg/m^3)
V_r = ventilation rate (m^3/s)
C = specific heat of air (J/kgK)
ΔT = temperature difference (To–Ti) (K)

Internal Gain

The heat generated by occupants is a heat gain for the building; its magnitude depends on the level of activity of a person. Table 1 shows the heat output rate of human bodies for various activities Bansal *et al*. (1994). The total rate of energy emission by electric lamps is also taken as internal heat gain. Table 2 shows the heat gain due to appliances (televisions, refrigerators, etc.) should also be added to the Qi Bansal *et al*. (1994).

Qi = (No of people × heat output rate) + Rated wattage of lamps + Appliance load (5)

Following data was considered throughout the year.

The overall heat transfer coefficients for window, door and walls are:

$U_{glazing}$ = 5.7 W/m^{2}K
U_{wall} = 3 W/m^{2}K
U_{roof} = 2.3 W/m^{2}K

Daily average outside temperature throughout year = 13.9 ^{0}C
Outside heat transfer coefficient is 22.7 W/m^{2}K
Inside design temperature was 19 ºC
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
Mean hourly values of data shown in Table 3 for various places in India are available in the handbook by Mani (1982).

Table 1. Heat production rate in a human body shown by Bansal (1994)

Activity	Rate of heat production	
	(W)	(W/m^2)
Sleeping	60	35
Resting	80	45
Sitting, Normal office work	100	55
Typing	150	85
Slow walking (3 km/h)	200	110
Fast walking (6 km/h)	250	140
Hard work (filing, cutting, digging etc.)	More than 300	More than 170

Table 2. Wattage of common household appliances as was given by Bansal (1994)

Equipment	Load (in W)
Television	400
Refrigerator	120
Coffee Machine	400
Gyser	3500
Computer	150

Table 3. Conduction Losses

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	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					-231,552

Q_c = - 231,552 kW per annum

Table 4. Heat Gain

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			114,156

Q_s = 114,156 kW per annum

Table 5. Ventilation Losses

Wall	Density of air (in kg/m^3)	Specific heat of air (in J/kg K)	Temperature	Q_v (In kW)
South	1.2	1005	-4.8	-39.4
North	1.2	1005	-8.2	-67.3
West	1.2	1005	-7.8	-63.9
East	1.2	1005	-6.6	-54.1
Roof	1.2	1005	1	-8.2
Total ventilation losses per annum				-1,006,128

Q_v = -1,006,128 kW per annum

Table 6. Internal Heat Gain

Floors	Occupants	Tube Lights	Bulbs	Others	Q_i (in W)
Ground	18	43	2	Television=1, Computer=15 Refrigerator=1, Geyser=1	9.8
First	35	57	3	Computer=66, Refrigerator=1 Instrument=2	17.7
Second	110	62	3	Television=1, Computer=2 Refrigerator=1, Geyser=1 Instrument=4	20.3
Third	96	58	2	Computer=2, Instrument=8	16.9
Fourth	60	67	2	Television=1, Computer=1 Refrigerator=2, Geyser=1	13.2
Fifth	6	8	-	-	0.9
Total internal heat gain per annum					151,296

Q_i = 151,296 kW per annum

Table 7. Carbon emission and cost Volker (2011)

Fuel	Carbon Emission per kWh (in g)	Total Carbon Emission (in kg)	Fuel Required	Total cost (in Rs)
Electricity	4	4,844.9	-	36,33,684
Diesel	270	3,27,031.6	97,329.4	45,06,351.2
Solar Energy	0	0	0	-

Thus Q_m = -12,11,228 kW per annum

Table 8. Total heat load in kW

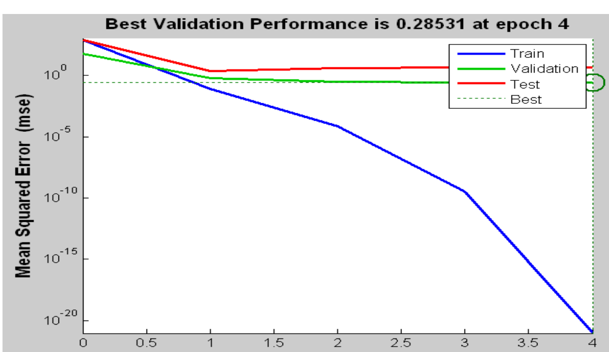
	Q_c	Q_s	Q_v	Q_i	
	-6.5	20	-39.4	9.8	
	-20.5	0	-67.3	17.7	
	-2.8	2.9	-63.9	20.3	
	-3.6	1.9	-54.1	16.9	
	-4.1	65.8	-8.2	13.2	
	-16.1	-	-	0.9	Grand Total
Q_m	-53.6	90.6	-232.9	78.8	-117.1
Q_m per annum (in kW)	-2,31,552	1,14,156	-10,06,128	1,51,296	-12,11,228

RESULTS

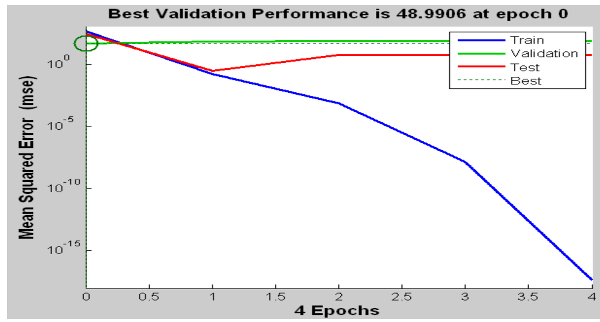
Using equations (2), (3), (4) & (5) in equation (1), we get

$Q_m = Q_c + Q_s + Q_i + Q_v$
Q_c = - 231,552 kW per annum
Q_s = 114,156 kW per annum
Q_v = -1,006,128 kW per annum
Q_i = 151,296 kW per annum
Thus Q_m = -12,11,228 kW per annum

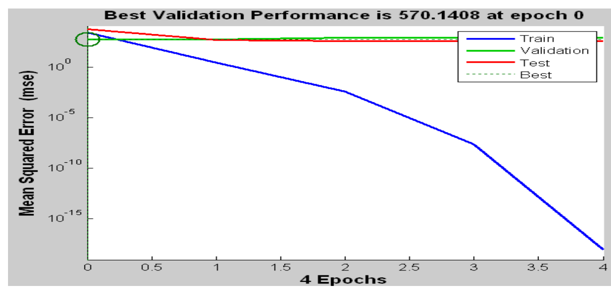
The neural network model was used with 10 hidden neurons. Fig. 1 Didn't indicate any major problem with the training. The validation and test curves were very similar. The evaluation and validation of an artificial neural network prediction model were based upon one or more selected error metrics. Generally, neural network models which perform a function approximation task will use a continuous error metric such as mean absolute error (MAE), mean squared error (MSE) or root mean squared error (RMSE). The errors will be summed over the validation set of inputs and outputs, and then normalized by the size of the validation set. Here we had used mean squared error (MSE) for the best validation performance. 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 result was shown in the Fig. 2. The three axes represented the training, validation and testing data. The dashed line in each axis represented the perfect result – outputs = targets. The solid line represented the best fit linear regression line between outputs and targets. 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.



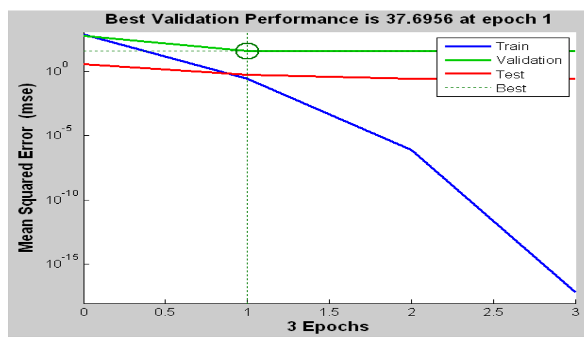
Conduction Losses (Q_c)



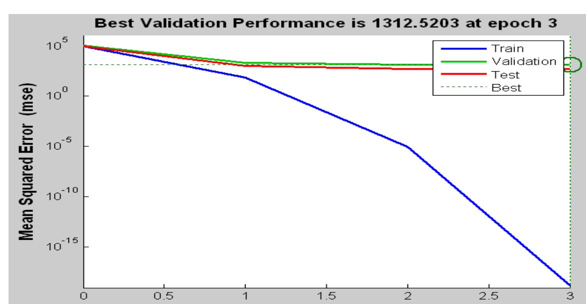
Heat Gain (Q_s)



Ventilation Losses (Q_v)

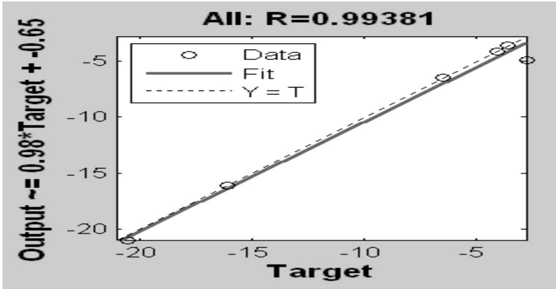


Internal Heat Gain (Q_i)

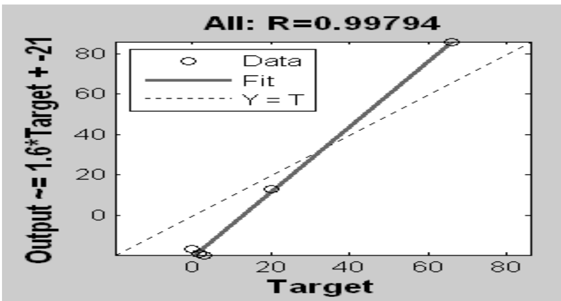


Heat load (Q_m)

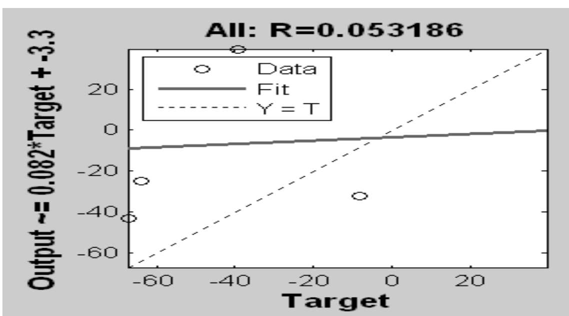
Fig. 1. Validation Performance



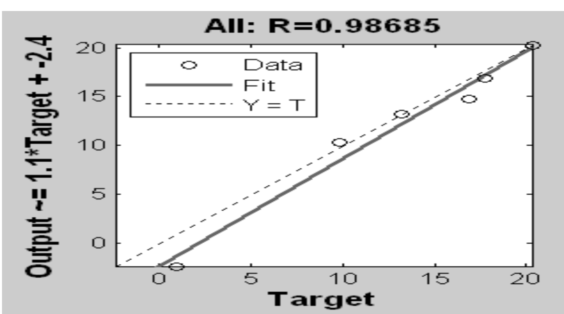
Conduction Losses (Q_c)



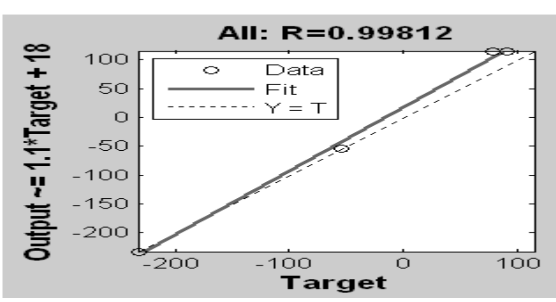
Heat Gain (Q_s)



Ventilation Losses (Q_v)



Internal Heat Gain (Q_i)



Heat load (Q_m)

Fig. 2. Regression Analysis

Conclusion

The study reveals that the total heat load of a six storey building is -1,211,228 kW which is negative and indicates that building is cool and heating is required to meet out this loss i.e. for heating purpose we will produce 4.8 ton carbon per annum if electricity has to be used which will cost Rs 36, 33, 684/- to heat the building . In case coal or wood has to be used then the carbon emission will be 411.8 ton and 472.4 ton respectively costing Rs 58,13,936/- and Rs 7,26,741.8/- respectively. Kerosene will produce 351.3 ton carbon and will cost Rs 12, 45, 850/-. If we use diesel gen set to produce power supply and heat the building then 327 ton carbon will be emitted and it will cost Rs 45,06,351.2/-. Use of LPG heaters to heat the building will emit 278.6 ton of carbon in to the atmosphere and will cost Rs 56,89,030.1/- Volker (2011) Table 7.

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