Predicting Energy Requirement for Cooling the Building Using Artificial Neural Network

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Abstract: This paper explores total cooling load during summers 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 cooling load was 0.87 million 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 in case of conduction losses. To meet out this energy demand various fuel options are presented along with their cost and carbon emission.

Keywords: Energy requirement, heat gain, ventilation losses, conduction losses, carbon emission, regression coefficient.

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 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. During six month's summers (April to September) people use electricity (provided on subsidized rates) and other conventional fuels (diesel/petrol) to lower down the temperature. These result in 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. The mean hourly values of such data for various places in India are available in the handbook by Mani [1]. The major problem is to calculate the energy demand of a building during summers. 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 [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, prediction of energy consumption, indoor air temperature, and HVAC system analysis. In [3], Yokoyama *et al*. 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*. [4] 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 [5] predicted the cooling load of three office buildings. Considering the influence of weather on the energy consumption in different regions, Yan and Yao [6] 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 [7] has successfully used

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neural networks for predicting hourly electricity consumption as well as chilled and hot water for an engineering center building. Nizami and Al-Garni [8] tried a simple feed-forward neural network to relate the electric energy consumption to the number of occupancy and weather data. Wong *et al*. [9] 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*. [10] predicted air-conditioning load in a building, which is a key to the optimal control of the HVAC system. Lee *et al*. [11] used a general regression neural network to detect and diagnose faults in a building's air-handling unit. Aydinalp *et al*. [12] 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. Gouda *et al*. [13] 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*. [4] reported results of recurrent neural networks on hourly energy consumption data. Karatasou *et al*. [14] studied how statistical procedures can improve neural network models in the prediction of hourly energy loads. Azadeh *et al*. [15] 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). We have taken a university building having six storey which works for seven hours during a day time. The dimensions are length 45 m, 15 m wide and 18 m in height.

METHOD AND MATERIAL

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 [16]:

$$Q_{total} = Q_c + Q_s + Q_i + Q_v \tag{1}$$

where

Q_{total} is total energy requirement if it is –ve then heating is required and if it is +ve then cooling is required.

Q_c is conduction losses in a building

Q_s is solar gain in a building

Q_i is internal gain in a building

Q_v is ventilation losses in a building

Conduction

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

$$Q_c = AU\Delta T \tag{2}$$

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

Solar Heat Gain

The solar gain through transparent elements can be written as:

Table 1: Heat Production Rate in a Human Body

Activity	Rate of heat production	
	(W)	(W/m²)
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

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

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

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:

$Q_v = \rho V_r C \Delta T$ (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 [17].

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 [17].

Table 2: Wattage of Common Household Appliances

Equipment	Load (in W)
Television	400
Refrigerator	120
Coffee Machine	400
Computer	150
Ceiling Fan	200
Air Conditioner	2500

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

Following data was used in the present study.

The overall heat transfer coefficients for window, door and walls are [18]:

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

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

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

Daily average outside temperature throughout year = 24.9 ^0C

Outside heat transfer coefficient is 22.7 W/m^2K

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/kg K

Table 3: Conduction Losses

Wall Exposed to Sun	Material	U (W/m^2K)	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

Mean hourly values of data shown in Table **3** for various places in India are available in the handbook by Mani [1].

RESULTS

The total conduction losses in a building are calculated as Table **3**.

Q_c = 22.6 kW = 97632 kW per annum whose ANN graphs are shown in Figures **1** and **2**.

The total solar gain in a building is calculated as Table **4**.

Q_s = 67.4 kW = 84924 kW per annum whose ANN graphs are shown in Figures **3** and **4**.

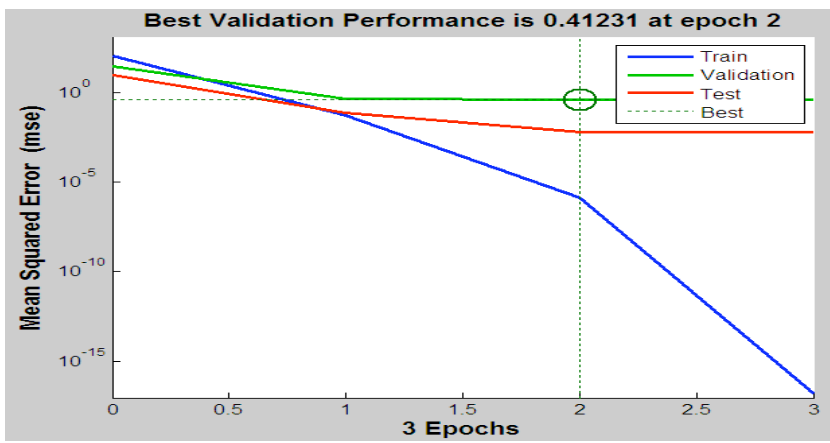

Figure 1: Validation Performance of Conduction Losses (Q_c).

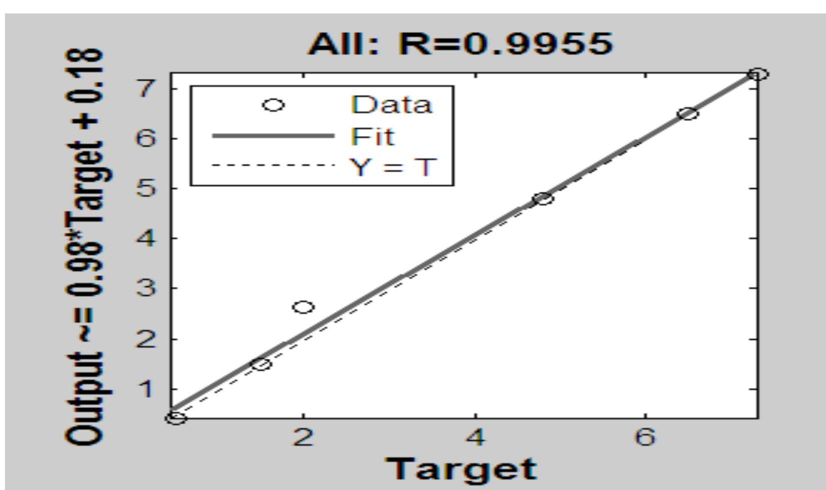

Figure 2: Regression Analysis of Conduction Losses (Q_c).

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	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

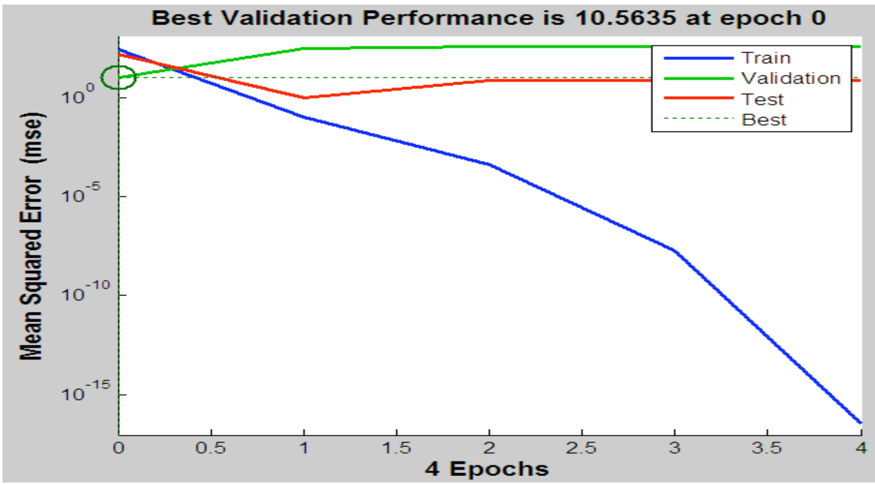

Figure 3: Validation Performance of Heat Gain (Q_s).

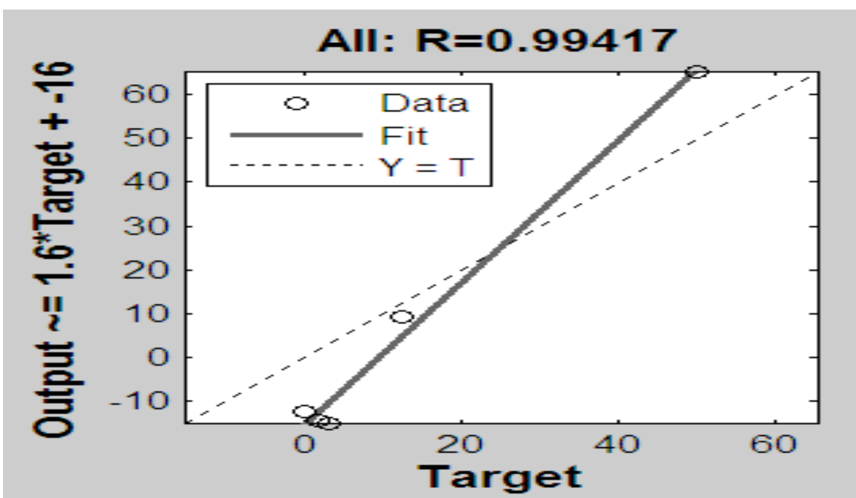

Figure 4: Regression Analysis of Heat Gain (Q_s).

The total ventilation losses in a building are calculated as Table **5**.

Q_v = 136.1 kW = 587952 kW per annum whose ANN graphs are shown in Figures **5** and **6**.

The total internal gain in a building is calculated as Table **6**.

Q_i = 108.5 kW = 104160kW per annum whose ANN graphs are shown in Figures **7** and **8**.

The total energy requirement during winter is calculated as Table **7**.

Q_m = 97632 + 84924 + 587952+ 104160 = 874668 kW per annum whose ANN graphs are shown in Figures **9** and **10**.

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	3.3	27.1
North	1.2	1005	0.2	1.6
West	1.2	1005	3.3	27.1
East	1.2	1005	3	24.6
Roof	1.2	1005	6.8	55.7
Total ventilation losses per annum				587952

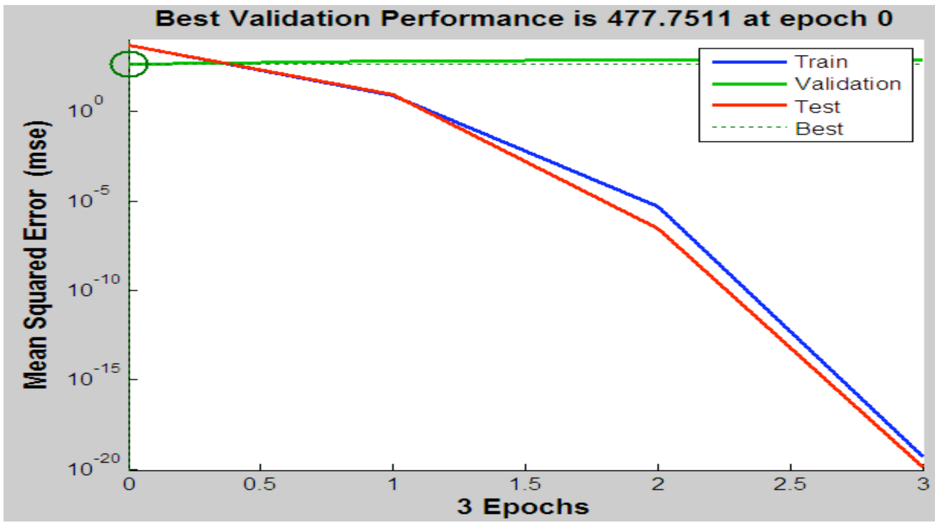

Figure 5: Validation Performance of Ventilation Losses (Q_v).

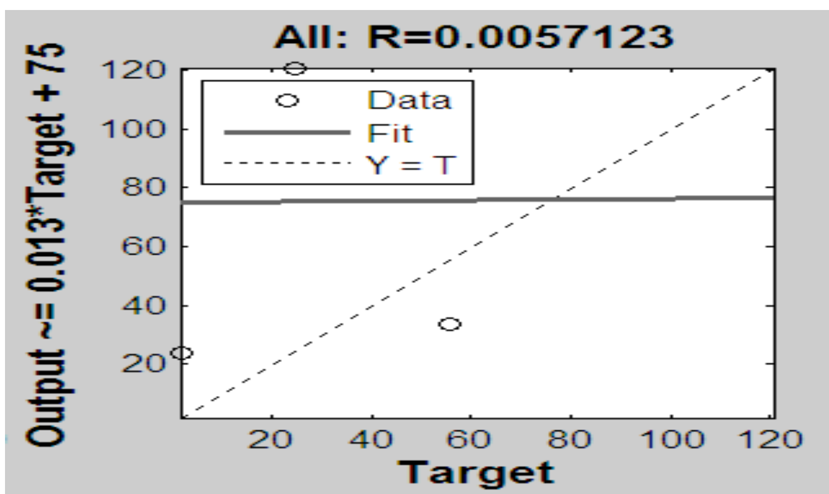

Figure 6: Regression Analysis of Ventilation Losses (Q_v).

DISCUSSION

The neural network model was used with 10 hidden neurons. Figures **1**, **3**, **5**, **7** and **9** 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 [19]. Here we had used mean

Table 6: Internal Heat Gain

Floors	Occupants	Tube Lights	Bulbs	Fan	AC (1.5 ton each)	Others	Q_i (in kW)
Ground	18	43	2	15	2	Television=1 Computer=15 Refrigerator=1	17.9
First	35	57	3	16	4	Computer=66 Refrigerator=1 Instument=2	24.0
Second	110	62	3	12	2	Television=1 Computer=2 Refrigerator=1 Instrument=4	27.7
Third	96	58	2	14	-	Computer=2 Instrument=8	19.7
Fourth	60	67	2	12	-	Television=1 Computer=1 Refrigerator=2	15.5
Fifth	6	8	-	14	-	-	3.7
Total internal heat gain per annum							104160

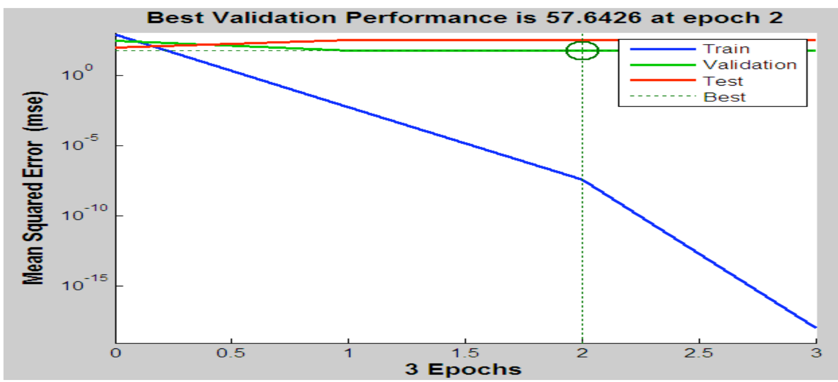

Figure 7: Validation Performance of Internal Heat Gain (Q_i).

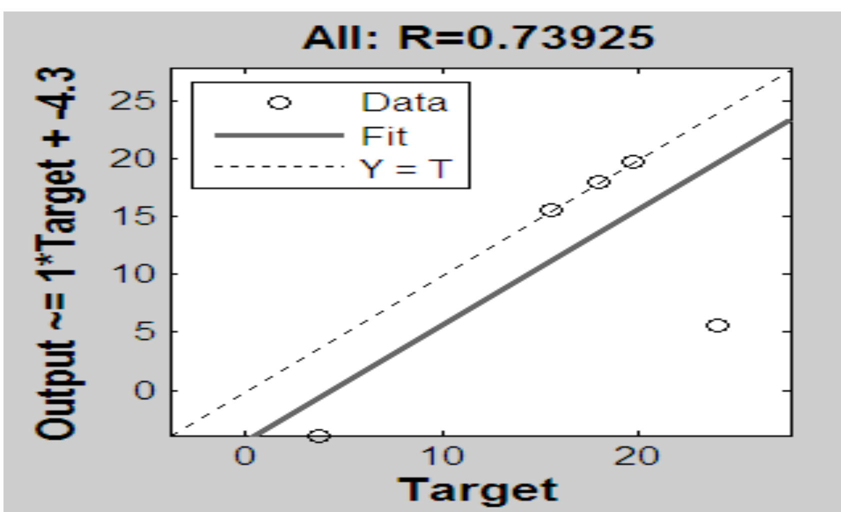

Figure 8: Regression Analysis of Internal Heat Gain (Q_i).

Table 7: Total Heat Load in kW

	Q_c	Q_s	Q_v	Q_i	Q_m
	22.6	67.4	136.1	108.5	334.6
Annual value	97632	84924	587952	104160	874668

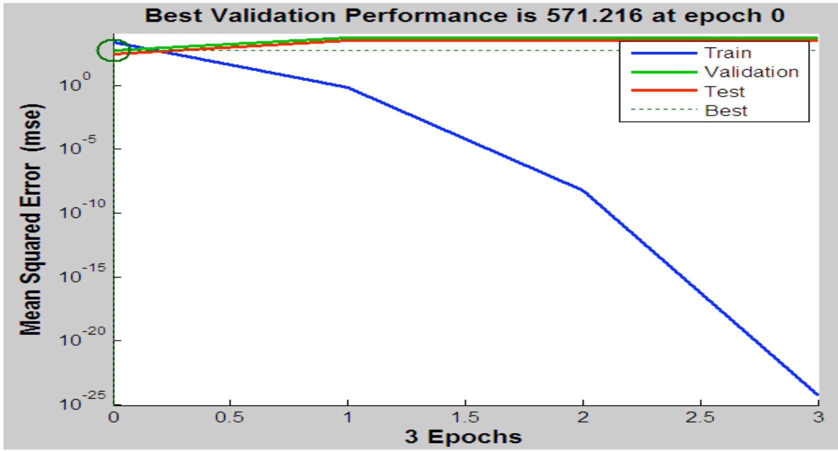

Figure 9: Validation Performance of Heat Load (Q_m).

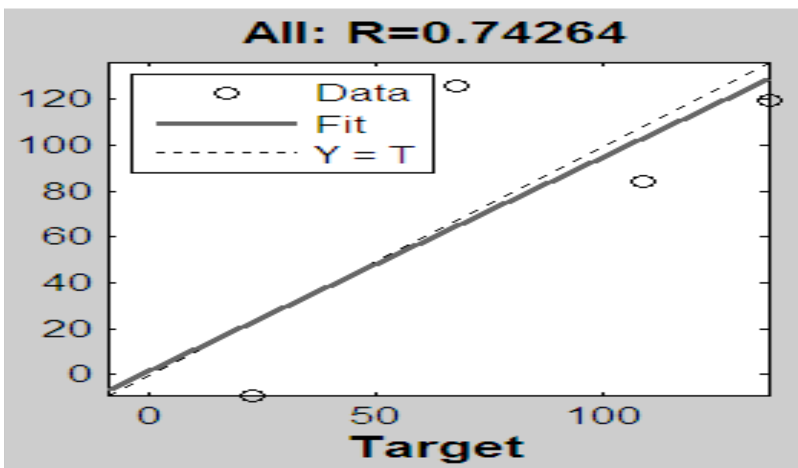

Figure 10: Regression Analysis of Heat load (Q_m).

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 Figures **2**, **4**, **6**, **8** and **10**. 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.

CONCLUSIONS

The study reveals that the total cooling load of a six storey building is 0.87 million kW thus, cooling is required to meet out this energy demand. If we use electricity it will produce 3.5 ton carbon per annum and the cost of electricity used will be $ 47,709.16 as depicted in Table **8**.

If we use diesel to meet out this energy requirement then 236.2 ton of carbon will be emitted and it will cost

Table 8: Carbon Emission and Cost

Fuel	Carbon Emission per kWh (in g)	Total Carbon Emission (in kg)	Fuel Required	Total cost (in USD)
Electricity	4	3,498.7	-	47,709.16
Diesel	270	2,36,160.4	69,973.4	57,250.96
Solar Energy	0	0	0	-

$57,250.9. The above results necessitate the use of solar passive technologies to meet out this energy requirement during summers.

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