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.

Research Highlights:
- Use of Artificial Neural Network to find energy requirement of a building during summers
- Carbon emission calculation
- Recommendations for renewable energy use
- Regression coefficient calculation
- Graphical representation of validation performance

Key Words: Artificial neural network, energy requirement, heat gain, ventilation losses, carbon emission.

I. 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. 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 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. 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 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 occupants 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 total building. 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.

II. 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]:

\[
Q_{\text{total}} = Q_c + Q_s + Q_i + Q_v
\]

(1)

where

- \(Q_{\text{total}}\) 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

1.2 Conduction

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

\[
Q_c = AU\Delta T
\]

where

- \(A\) = surface area (\(m^2\))
- \(U\) = thermal transmittance (\(W/m^2K\))
- \(\Delta T\) = 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:

\[
T_{so} = T_0 + \alpha ST/ho - \epsilon\Delta R/ho
\]

where

- \(T_0\) = daily average value of hourly ambient temperature (\(K\))
- \(\alpha\) = absorptance of the surface for solar radiation
- \(ST\) = daily average value of hourly solar radiation incident on the surface (\(W/m^2\))
- \(ho\) = outside heat transfer coefficient (\(W/m^2K\))
- \(\epsilon\) = emissivity of the surface
- \(\Delta R\) = 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.

1.2 Solar Heat Gain

The solar gain through transparent elements can be written as:

\[
Q_s = \alpha_s \Sigma AiSgiri
\]

(3)

where

- \(\alpha_s\) = mean absorptivity of the space
- \(Ai\) = area of the \(i\)th transparent element (\(m^2\))
- \(Sgiri\) = daily average value of solar radiation (including the effect of shading) on the \(i\)th transparent element (\(W/m^2\))
- \(\tau_i\) = transmissivity of the \(i\)th transparent element
- \(M\) = number of transparent elements

1.3 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:

\[
Q_v = \rho Vr CD\Delta T
\]

(4)

where,

- \(\rho\) = density of air (\(kg/m^3\))
- \(Vr\) = ventilation rate (\(m^3/s\))
- \(C\) = specific heat of air (\(J/kgK\))
- \(\Delta T\) = temperature difference (\(T_o - T_i\)) (\(K\))

1.4 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].
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]:
Uglazing = 5.7 W/m²K
Uwall = 3 W/m²K
Uroof = 2.3 W/m²K

Daily average outside temperature throughout year = 24.9 °C
Outside heat transfer coefficient is 22.7 W/m²K
Inside design temperature was 19 °C
Mean absorptivity of the space is 0.6
Transmissivity of window is 0.8
Density of air is 1.2 kg/m³
Specific heat of air is 1005 J/kg K

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 1)
Qc = 22.6 kW = 97632 kW per annum whose ANN graphs are shown in Fig 1 & Fig 2
The total solar gain in a building is calculated as (Table 2)
Qs = 67.4 kW = 84924 kW per annum whose ANN graphs are shown in Fig 3 & Fig 4
The total ventilation losses in a building are calculated as (Table 3)
Qv = 136.1 kW = 587952 kW per annum whose ANN graphs are shown in Fig 5 & Fig 6
The total internal gain in a building is calculated as (Table 4, 5 and 6)
Qi = 108.5 kW = 104160 kW per annum whose ANN graphs are shown in Fig 7 & Fig 8
The total energy requirement during winter is calculated as (Table 7)
Qm = 97632 + 84924 + 587952 + 104160 = 874668 kW per annum whose ANN graphs are shown in Fig 9 & Fig 10

**Discussion:**
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 [19]. 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.

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

| Wall Exposed to Sun | Material | U (W/m²K) | A (m²) | Tso | Qc (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        |

Table 1. Conduction Losses

| Wall Exposed to Sun | A (In m) | Sg (W/m²) | Qs (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       |

Table 2. Heat Gain

| Wall Exposed to Sun | A (In m) | Sg (W/m²) | Qs (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       |

Table 3. Ventilation Losses
### Table 4. Heat production rate in a human body [17]

| Activity                                      | Rate of heat production (W) | Rate of heat production (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                 |

### Table 5. Wattage of common household appliances [17]

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

### Table 6. Internal Heat Gain

| Floors       | Occupants | Tube Lights | Bulbs | Fan | AC (1.5 ton each) | Others       | Qc (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 Instrument=2 | 24.0       |
| Second       | 110       | 62          | 3     | 12  | 2                | Television=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

### Table 7. Total heat load in kW

|                     | Qc | Qs | Qv | Qm |
|---------------------|----|----|----|----|

### Table 8. Carbon emission and cost [20] & [21]

| 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      | 57,250.91           |
| Solar Energy| 0                              | 0                            | 0             | -                   |

### Fig. 1 Validation Performance of Conduction Losses (Qc)

![Fig. 1 Validation Performance of Conduction Losses (Qc)](image)

### Fig. 2 Regression Analysis of Conduction Losses (Qc)

![Fig. 2 Regression Analysis of Conduction Losses (Qc)](image)

### Fig. 3 Validation Performance of Heat Gain (Qs)

![Fig. 3 Validation Performance of Heat Gain (Qs)](image)
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