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RESEARCH ARTICLE

PREDICTING TOTAL VENTILATION LOSSES OF THE BUILDING USING ARTIFICIAL NEURAL NETWORK

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ABSTRACT

This paper explores total ventilation 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 ventilation losses were 1594080 kW per year. ANN application showed that data was best fit for the regression coefficient of 0.053186 with best validation performance of 570.1408 during winter.

Key Words: Artificial neural network, energy requirement, ventilation loss, absorptivity, transmissivity, validation performance, regression coefficient

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 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, GENST AT 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.

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Table 1. Dimensions of ground floor

S N	Room				Window			Door		
	No	Type	Dimensions lbh* (In Foot)	Orientation	Quantity	Dimensions lbh* (In Foot)	Orientation	Quantity	Dimensions lb** (In Foot)	Orientation
1	1	VC Office	18x8x10	-	1	4x9	S	1	3x9	N
					1	18x6	N			
2	2	VC Room	25x18x10	-	2	4x9	S	1	3x9	N
					1	10x4	N	1	3x9	W
3	-	Balcony	36x20x10	-	-	-	-	-	-	-
4	-	Pantry	20x8x10	-	1	15x7	S	1	3x9	S
5	-	Toilet VC	8x6x10	-	-	-	-	1	2x6	-
6	-	Registrar Office	30x22x10	N	1	6x5	-	1	3x9	S
					1	5x16	S			
7	4	Office Associate Dean	14x10x10	S	1	4x9	S	1	3x9	N
8	5	Office President Foundation	14x10x10	S	1	4x9	S	1	3x9	N
9	6	Seminar Hall	22x18x10	N	1	4x9	-	1	3x9	S
10	7	Accounts Office	25x12x10	-	1	4x9	E	1	3x9	S
11	8	COF Office	20x12x10	-	1	4x9	E	1	3x9	S
12	-	Registrar Room	25x12x10	-	1	4x9	E	1	3x9	S
								1	3x9	N
13	-	Director Room	20x12x10	-	1	4x9	W	1	3x9	S
14	-	Balcony	16x20x10	-	-	-	-	-	-	-
15	-	Toilet Faculty	4x6x10	-	-	-	-	-	-	-

Table 2. Dimensions of first floor

S N	Room				Window			Door		
	No	Type	Dimensions lbh* (In Foot)	Orientation	Quantity	Dimensions lbh* (In Foot)	Orientation	Quantity	Dimensions lb** (In Foot)	Orientation
1	-	Photo Stat Room	12x10x10	N	-	-	-	-	-	-
2	-	Balcony	20x16x10	S	-	-	-	-	-	-
3	101	LAB (IT)	50x25x10	N	5	5x6	N	1	4x9	S
4	102	Faculty Room	28x18x10	S	2	6x5	S	1	4x9	S
5	103	Faculty Room	22x12x10	S	1	6x5	S	1	3x9	S
					1	8x6	N			
6	104	Dean Room	22x12x10	S	1	8x6	S	1	3x9	N
					2	5x6	W			
7	-	Faculty Cabin	30x35x10	S	4	4x6	S	2	4X9	-
8	-	Seminar Hall	50x30x10	N	2	4x6	S	1	3X9	-
					4	4x6	N			
9	-	Canteen	10x8x10	S	1	10x4	S	1	3x6	N
10	-	Balcony	25x15x10	S	1	4x6	E	-	-	-

Table 3. Dimensions of second floor

S N	Room				Window			Door		
	No	Type	Dimensions lbh* (In Foot)	Orientation	Quantity	Dimensions lbh* (In Foot)	Orientation	Quantity	Dimensions lb** (In Foot)	Orientation
1	201	Microbio Lab	40x20x10	N	2	5x6	N	2	4x9	S
2	202	Tissue Culture Lab	25x20x10	S	-	-	-	1	4x6	N
3	203	Animal Lab	40x20x10	S	2	5x6	N	1	4x9	E
					3	5x6	E	1	3x6	N
4	204	Store	15x8x10	S	-	-	-	1	4x9	E
5	205	Lab	50x20x10	S	2	5x6	S	1	4x9	N
					2	4x6	S			
6	206	Lab	20x20x10	S	2	5x6	S	1	4x9	N
					1	5x6	N	1	4x9	S
7	-	Toilet She	6x8x10	N	2	4x2	N	1	3x6	S
8	-	Store	6x8x10	N	1	4X5	N	1	3x9	S
9	201	Lecture Theatre MBA	50x20x10	N	3	5x6	N	1	4x9	S
10	202	Lecture Theatre MBA	50x20x10	N	2	5x6	N	1	4x9	W
11	203	Lecture Theatre MBA	50x20x10	S	2	5x6	S	1	4x9	W
12	-	Faculty Room	18x8x10	S	2	5x6	S	1	3x6	N
								1	3x6	S
13	-	Balcony	20x15x10	S	2	5x6	S	-	-	-
					1	5x6	W			

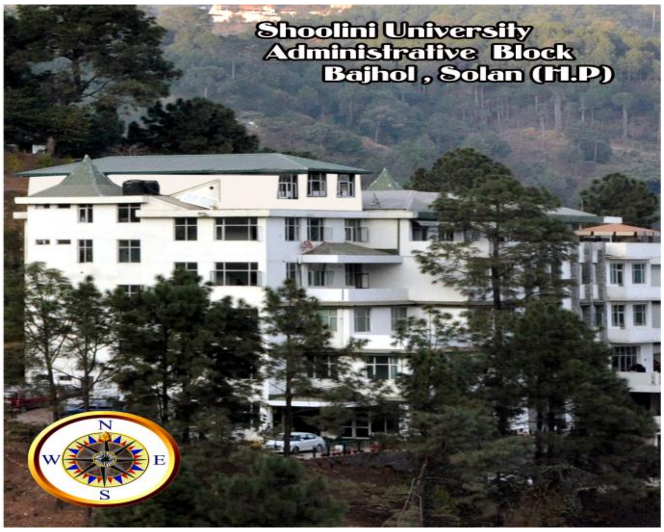

Fig 1. Shoolini University administrative block at Bajhol-Solan (HP)

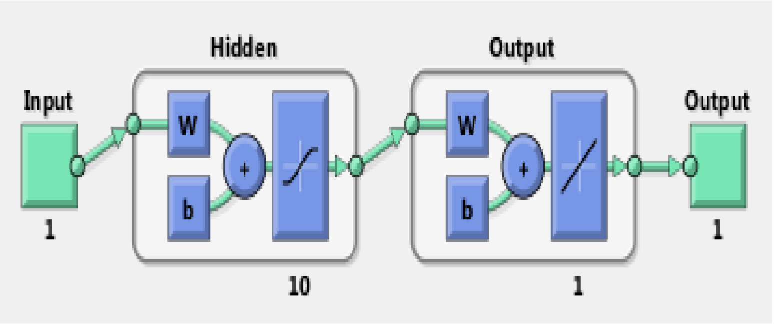

Fig 2. Architecture of neural network

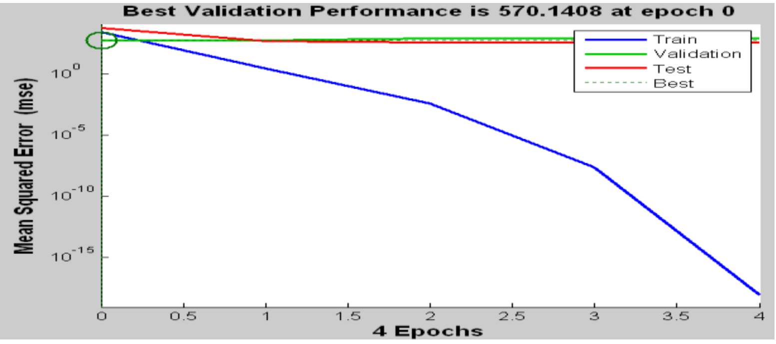

Fig 3. Validation performance of ventilation losses during winter

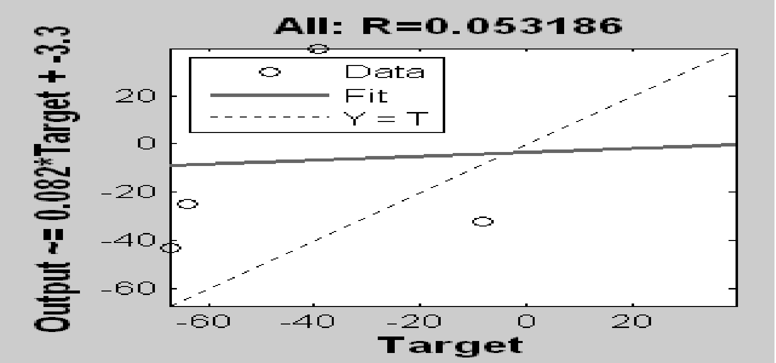

Fig 4. Regression analysis of ventilation losses during winter

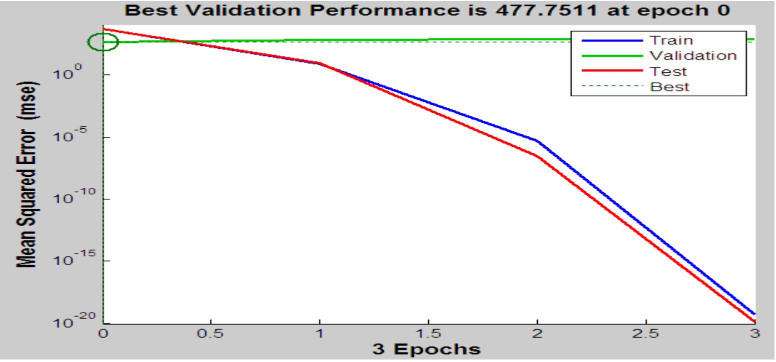

Fig 5. Validation performance of ventilation losses during summer

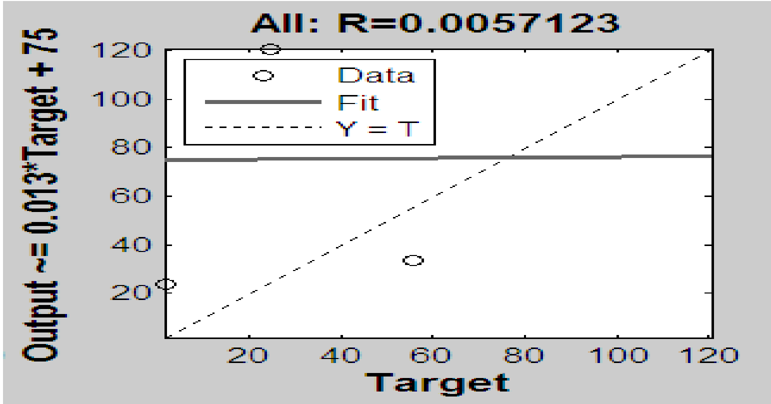

Fig 6. Regression analysis of ventilation losses during summer

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. Kalogirou 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 [3]. Ekici 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 [4]. 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 [5]. Yokoyama 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 [6]. 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 [7]. Based on the same recurrent neural network, Ben-Nakhi predicted the cooling load of three office buildings [8]. 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 [9]. Considering the influence of weather on the energy consumption in different regions, Yan 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 [10]. Wong used a neural network to predict energy consumption for office buildings with day-lighting controls in subtropical climates [11]. 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 [12]. Sheikh did Short Term Load Forecasting using ANN Technique [13]. Karatasou studied how statistical procedures can improve neural network models in the prediction of hourly energy loads [14].

MATERIALS AND METHOD:

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 floor wise building data had been measured with measuring tape as has been depicted in Table 1, Table 2, Table 3, Table 4, Table 5 and Table 6. The other required data had been taken from NASA website.

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:

$$Q_v = \rho V_r C \Delta T \qquad \text{Eq. (1)}$$

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)

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 for various places in India are available in the handbook by Mani et al (1982). 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.

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Table 4. Dimensions of third floor

S N	Room				Window			Door		
	No	Type	Dimensions lbh* (In Foot)	Orientation	Quantity	Dimensions lbh* (In Foot)	Orientation	Quantity	Dimensions lb** (In Foot)	Orientation
1	301	BT Lab	40x15x10	N	2	5x6	N	1	4x9	S
					3	5x6	W			
2	302	HOD BT	15x8x10	N	2	4x6	S	1	3x9	S
3	303	Chem LAB	40x20x10	N	2	5x6	N	1	4x6	E
					3	5x6	E	1	3x6	S
4	304	Store	6x8x10	N	1	4x5	N	1	3x9	S
5	305	Chem LAB	50x18x10	-	4	5x6	S	1	4x6	N
								1	3x6	N
6	306	Faculty Room	20x20x10	S	2	5x6	S	1	4x9	N
					1	5x6	N	1	4x9	S
7	301	Confrence Room (MBA)	50x20x10	-	2	5x6	N	1	4x9	W
8	302	Confrence Room (MBA)	50x20x10	-	3	5x6	N	1	4x9	W
9	303	Meditaion Room	40x25x10		3	5x6	N	1	4x9	W
10	-	Toilet He	6x8x10	N	2	4x2	N	1	3x6	S
11	-	Store	6x8x10	N	1	4x5	N	1	3x9	S

Table 5. Dimensions of fourth floor

S N	Room		Dimensions lbh* (In Foot)	Orientation	Window			Door		
	No	Type			Quantity	Dimensions lbh* (In Foot)	Orientation	Quantity	Dimensions lb** (In Foot)	Orientation
1	-	Canteen	60x40x10	S	5	5x6	S	1	5x9	E
					5	5x6	N	1	3x9	S
								1	4x6	W
2	-	Auditorium	60x40x10	S	3	4x6	S	1	4x6	S
					1	4x6	N	1	4x6	E
								1	4x6	W
								1	5x6	N
3	401	Lecture Theatre	50x20x10	S	3	5x6	N	1	4x9	S
4	-	Stationary Shop	15x12x10	N	1	5x6	N	1	3x6	S

Table 6.Dimensions of fifth floor

S N	Room				Window			Door		
	No	Type	Dimensions lbh* (In Foot)	Orientation	Quantity	Dimensions lbh* (In Foot)	Orientation	Quantity	Dimensions lb** (In Foot)	Orientation
1	601	Miscellaneous Room	60x25x10	S	2	5x6x10	S	1	4x6x10	E
					2	5x6x10	N			
					5	5x6x10	W			
					2	5x6x10	N			

lbh* = length x breadth x height, lb** = length x breadth

Table 7. Ventilation losses during winter

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				-1006128

Table 8. Ventilation losses during summer

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

RESULTS AND DISCUSSION

The total ventilation losses in a building during winter are calculated as (Table 7)

Q_v = - 232.9 kW = -1006128 kW per annum whose ANN graphs are shown in Fig 3 & Fig 4

The total ventilation losses in a building during summer are calculated as (Table 8)

Q_v = 136.1 kW = 587952 kW per annum whose ANN graphs are shown in Fig 5 & Fig 6

Total Load = 1006128 + 587952 kW,

Total Load = 1594080 kW

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.

CONCLUSION

The study revealed that the total ventilation 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 ventilation losses were 1594080 kW per year. ANN application showed that data was best fit for the regression coefficient of 0.053186 with best validation performance of 570.1408 during winter. The above 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 [15]. Energy savings potential (ESP) is a very important indicator for developing these technologies.

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