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An ANN Approach for Estimation of Thermal Comfort and Sick Building Syndrome

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ABSTRACT

Thermal comfort is an important consideration in architectural design of modern building because of the implication on phgysiological impact of inhabitants. This study presents a near-nature learning strategy using Artificial Neural Networks (ANN) platform predicated on feed-forward back propagation model to predict variation in air distribution on building's component to its thermal performance with consideration for energy management. Leverberg-Marquardt (LM) Algorithm was utilized to train the required location-specific geographical data in ANN module. Correlation coefficient and mean square error were used to validate the model. The results obtained with the trained data in neural network computing on thermal performance agreed very closely with those obtained in the analytical model used in the analysis with high correlation coefficient and minimal error metric was recorded for the mean square error. We study established the suitability of ANN-based prediction of thermal comfort and energy profiling in HVAC systems for near-nature effectiveness and performance of ventilation devices which may be applicable to residential and commercial buildings. The benefit of the ANN-based strategy presented in this study could be utilized for design of ventilation machines in eco-friendly buildings.

1. INTRODUCTION

For years, buildings have been the basic shelter for man from the extremes of the outdoor environmental conditions. In order for the primary objective of building to its occupants not to be defeated, high thermal performance of the buildings should be guaranteed. With raising effects of climate change, the subject of thermal comfort and energy performance is an important consideration in building design in the recent years [1]. Pre-informed knowledge of thermal regime in building for varying categories of building under a wide range of environmental conditions is presently a critical consideration in building planning and construction. Some studies have estimated for exterior envelope, interior environmental analysis with simplifying assumptions may have showed to be ill-defined because the model is time dependent, multi-dimensional and non-linear [2]. For certain buildings, indoor thermal ambience is affected by various weather components, such as the solar irradiance, daylight, wind, and outdoor temperature. These components are critical to the energy transfer between the indoor and outdoor environments under fluctuating weather conditions [3].

Proper ventilation required adequate supply outdoor air to an enclosed space removing stale air from the space and it is significant in maintaining thermal performance in build environment [4]. Natural ventilation in building relies on wind and thermal buoyancy as driving forces while driving pressure derived from wind and thermal buoyancy are low compared to those produced by fans in mechanical ventilation system [5, 6]. Whether ventilation is natural or mechanical, it is necessary to maintain acceptable indoor air quality (IAQ). Weather buildings are heated or cooled; ventilation often constitutes a relatively large component of the heating or cooling load [7]. Poor ventilation can cause a build-up in indoor air pollutants like dust, pollen, mould, and household chemicals [8]. Numerous standards quantify the amount of ventilation that is required for acceptable IAQ. The indoor air quality procedure is an alternative to a prescribed rate of airflow in ASHRAE 62. The ventilation rate procedure of ANSI/ASHRAE Standard 62 can also be used to determine required outdoor air quantities based on occupancy information provided as evident in Ref. [9].

The selection of heating, ventilation and air-conditioning (HVAC) is a critical consideration for building owners, architects, engineers, and contractors during the design and construction phases of a building. Ghattas, et al. [10] developed a survey that outlined different type of buildings system and materials decisions that need to be made during the design and construction process. The HVAC should be selected in such a way it will not have negative impact on the total thermal performance of the building. Several factors are taken into consideration during the selection of HVAC for a building which includes preference of the building owner, available construction budget; size and shape of the building; function of the building; architectural limitations; life-cycle cost; ease of operation and maintenance; time available for construction [11].

A fundamental way to support design decisions for energy-efficient buildings is the use of building performance simulation tools (BPS) [12]. Since the inception of the building simulation discipline it has been evolving constantly as a vibrant discipline that produced a variety of Building

Performance Simulation (BPS) tools that are scientifically and internationally validated. The foundation work for building simulation was done in the 60s and 70s focusing on building thermal performance addressing load calculation and energy analysis [13]. Towards late 70s and early 80s, efforts were geared into analytically validating and experimental testing methods for codes for simulation tools. This foundation work was developed mainly within the research community of the mechanical engineering domain. Simulation tools were developed by technical researchers and building scientist aiming to address the needs of engineer.

Building simulation models can accurately quantify building energy loads but are not part of what is considered in the initial stage of building development by designer. The Building sector has a substantial shared of the primary energy supply being a major contributor to conventional fuels consumption. The main simulation tools for energy analysis are TRNSYS, DOE-2, Energyplus, BLAST, ESP-r and selection of these tool depends on type of criteria, the required accuracy, easiness, availability of required data, buildings phase [14]. Apart from simulated tools, computer based decision tool is also applicable in HVAC design process in building. Revit-MEP is a common decision making tools utilized by Architects in designing for buildings and it imports information from AUTOCAD. The building information modeling (BIM) workflow offered by Revit-MEP not only maximizes productivity but also helps to streamline design and documentation workflows. The demerit of Revit-MEP as a tool to achieve BIM is that information defined in the 3D model has to be redefined in the energy analysis feature [15]. Another strategic decision making tools utilized is a spreadsheet decision making tool. The design team have to consider many different parameters and design options from an early stage which can ultimately have a significant impact on the final performance of the building [16-18].

In view of theafore-mentioned, this study is aimed at determining the thermal performance of a residential building using four parameters namely; ambient temperature, solar radiation, relative humidity and wind speed using Artificial Neural Network (ANN). The inventor of the first neurocomputer, Dr. Robert Hecht-Nielsen, defines a neural network as a computing system made up of a number of simple, highly interconnected processing elements, which process information by their dynamic state response to external inputs. ANN is part of Artificial Intelligence (AI), while it is capable of learning to recognize non-linear input–output relationship [19]. ANN learns the relationship between input and output parameters by means of historical data. Another advantage is the ability to manage large complex systems with many parameters interrelated between themselves [20]. The artificial neural network (ANN), which is one type of the various artificial intelligence theories, can successfully operate non-linear systems or systems with unclear dynamics without the experts' intervention [21]. ANN technique has the advantages of high speed of calculation; useful in solving the non-linear problems; do not required any previous knowledge of system model; simplicity; provide good search and capability of network to learn from example. Nowadays, ANNs are widely used as an alternative technology to faced highly complex, incomplete data sets, fuzzy or incomplete information and ill-defined problems. ANN technique has disadvantaged also, because of its inability to distinguish which parameter may causing a low reading. ANNs have been implemented to problems related to the fields of optimization, pattern recognition, image processing and forecasting etc. [22].

Several works have been done in the application of artificial neural network to building modelling. Moon, et al. [23] used ANN models to examine the thermal performance of double-skin enveloped buildings under different opening conditions. In this work, they used four ANN algorithms to predict future indoor temperatures under different opening conditions of internal and external envelope. Performance test with preliminary conventional non-ANN based method in terms of thermal control and efficiency showed that ANN models can be used to predict future indoor temperature conditions. Kumar, et al. [24] used neural fitting (nftool) of neural network of Matlab to calculate total conduction losses of a six-storey building. The result showed that data was best fit for regression coefficient of 0.9955 with however a low validation performance estimated as 0.41 was obtained. To address the lean opertional performance, Suraya [25] employed ANN technique to predict model to forecast indoor environmental parameters. Performance of the developed model was evaluated using R^2 and MSE and accuracy measured using mean absolute percentage error (MAPE). Kemajou, et al. [26] applied ANN for predicting indoor air temperature in modern building, with experimental data. They used Leverberg-Marquardt inputs algorithm on MATLAB with optimal structure of multilayer perceptron (MLP) having seven input variables, thirty hidden and one neuron in the output layer. Their result testified that ANN can be valuable tool for hourly indoor air temperature prediction. In their work, Agarwa [27] predicted cooling loads in buildings in tropical countries using ANN with back propagation algorithm having four neurons in the input layer, twenty-five in the hidden layer and one in the output. Activation function used in the input is pure linear while for others, logarithmic sigmoid was used. Results showed an accuracy of 0.9857 in the predicting samples. This study lends credence to the suitability of neural algothrim in prediction of thermal conduction in building.

The present study was designed to further investigate indoor thermal performance in connection to dwellers health and comfort. Numerical observation of the variation of thermal performance determinants under steady-state approach of a residential building using neural network was undertaken. This evaluation is tested with algorithm of artificial neural network intended to inform design decision for HVAC system to be used in the building. Its envisaged that this procedure would ensure high indoor air quality of the building's occupants with minimal energy usage while preventing sick building syndrome in the built environment. This report is organized as: section 1 introduces background and literatures. The methodology and procedure for executing this study emancipated in section while results obtained and discussion on its implications is contained in section 3. The conclusions of the findings are discussed in section 4 and references are contained in section 5 of this report.

2. METHODOLOGY

In this study, a three-bedroom apartment depicted below is used as the computational study for the prediction with five family members as occupants. The building components considered in this study for each room are wall, window and door in which Table 1 is generated.

Table 1. Dimensioning of components of the building under study

		WALL		WINDOW		DOOR	
S/No	Location	Dimension	Qty	Dimension	Qty	Dimension	Qty
1	Bedroom 1	3550*4400	1	1350*1200	1	2200*900	1
2	Bedroom 2	3000*4400	2	1350*1200	2	2200*900	1
3	Bedroom 3	3850*3000	1	1350*1200	1	2200*900	1
4	Family Lounge	4975*4675	1	1350*1200	1	2200*900	1
5	Main Lounge	6110*4500	1	1350*1200	1	2200*900	1
6	Presit	2400*4750	1	1350*1200	1	2200*900	1
7	Dining	3200*3300	1	1350*1200	1	2200*900	1
8	Kitchen	3200*2850	1	1350*1200	1	2200*900	1
9	Store	975*2850	1	800*600	1	2200*900	1

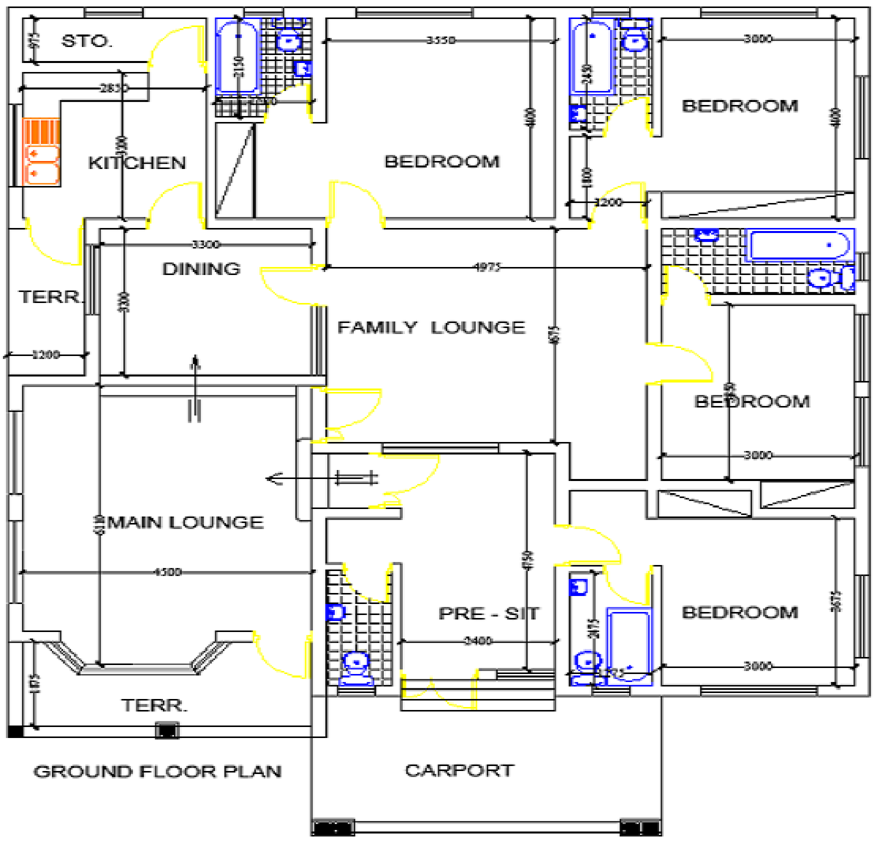

Figure 1. Computational space for the study

2.1 Thermal performance model

In estimating the thermal performance of the building, steady state approach is employed. Under steady state, the heat capacity of materials in the building is not considered. The heat balance balanced equation is given as:

$$Q_T = Q_c + Q_v + Q_s + Qi \quad (1)$$

where, Q_T is the total heat flow in the building; Q_c is the heat flow through conduction; Q_v is the heat flow through ventilation; Q_s is heat flow through solar heat gain and Qi is the internal heat gain within the building. Based on the computational space (the building) as shown in figure above, the following assumptions are made: the layout is two-dimensional; the difference between the long wavelength radiation incident on the surface from the sky and the surroundings radiation emitted by a blackbody at ambient temperature is vertical throughout i.e. ΔR is zero.

(1) Heat flow through conduction Qc

This is given as

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

where, A =Surface area (m^2); U = Thermal transmittance (W/m^{2}k); ΔT= Temperature difference between the inside and outside air (k). This equation is solved for every external constituent of elements and the results summed up. Therefore, the heat flow rate through the building envelope by conduction is the sum of the area and the U-value products of all the elements of the building multiplied by the temperature difference. It is expressed as:

$$Q_c = \sum_{i=1}^{N_c} A_i \, U_i \Delta T_i \quad (3)$$

where, i = building element; N_c= Number of occupants; With solar radiation on the surface, $\Delta T = T_{so} - T_i$; Where T_i = indoor temperature; T_{so} = sol-air temperature = $T_{so} = T_o + \frac{\alpha S_T}{h_o} - \frac{\varepsilon \Delta R}{h_o}$; Where, T_o= daily average value of hourly ambient temperature; α= absorptance of 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^{2}k); ε= emissivity of a surface; ΔR= difference between the long wavelength radiation incident on the surface from the surroundings, and the radiation emitted by a black body at ambient temperature. This is evaluated for the building components wall, window and door per day. To evaluate this, environmental data sourced from International Institute of Tropical Agriculture Moniya, Ibadan Nigeria was used to get fundamental readings like dry-bulb temperature, average humidity etc. This environmental data provided basis for the analysis of this study.

(2) Heat flow through ventilation, Qv

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:

$$Q_v = \rho v_r c \Delta t \tag{4}$$

where, ρ= densiity of air (kg/m^3); v_r= ventilation rate (m^3/s); c= specific heat of air (J/kgk); Δt= temperature difference $(T_0 - T_1)$ (k). If the number of air changes is known, then

$$v_r = {}^{NV}/_{3600} \tag{5}$$

where, N= number of air changes per hour; V= volume of the room or space (m^3)

Thus,

$$Q_v = \rho c N V \Delta t / 3600 \tag{6}$$

(3) Solar heat gain, Qs

The solar gain through transparent elements can be written as

$$Q_s = \alpha_s \sum_i^M A_i S_{gi} \tau_i \tag{7}$$

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 transparent element (W/m^2), τ_i= transmissivity of the transparent element, M= number of transparent elements.

(4) Internal heat gain, Qi

This is given as

Q_i= (No of people* heat output rate) +Rated wattage of lamps + Appliance load (8)

From the estimated value of heat flow through conduction Qc, heat flow through ventilation Qv, solar heat gain Qs, and internal heat gain Qi, the total heat flow through the building is estimated.

2.2 ANN details

ANN contains three layers with feed-forward back propagation to train the data. The learning algorithm employed in this study was leverberg-marquardt (LM) which is faster than any other algorithm [28]. LM is used because of its widely application as optimization algorithm. It outperforms simple gradient and other conjugate gradient methods in a wide variety of problems [29]. To train the network, linear transfer functions is used in inputs, sigmoid function in hidden and output layer. A computer program was developed under MATLAB software (MATLAB User's Guide, copyright, 2009). The neural network topology is represented in Figure 2.

Table 2. Heat output rate of building occupants

NO OF PEOPLE	HEATOUTPUT RATE	NH
6	100	600

Table 3. Appliance load distribution and wattage of lamps in the building

Building Component	Appliances	No of Appliance Per Component	Appliance Load (Watt)
Main Lounge	Television	1	250
	Home Theatre	1	80
	Water Dispenser	1	120
Family Lounge	Television	1	250
Bedroom 1	Television	1	250
Bedroom 2	Television	1	250
Bedroom 3	Television	1	250
Kitchen+Laundry	Dishwasher	1	3050
	Water Heater	1	3500
	Washing Machine	1	2500
	Refrigerator	1	120
			10620
Building Component	No of Lamps	Rated Wattage of Lamps	Total Rated Wattage of Lamps (In Watts)
Main Lounge	4	100	400
Family Lounge	3	100	300
Bedroom 1	3	100	300
Bedroom 2	3	100	300
Bedroom 3	3	100	300
Kitchen	2	100	200
Presit	1	100	100
Store	1	100	100
			2000

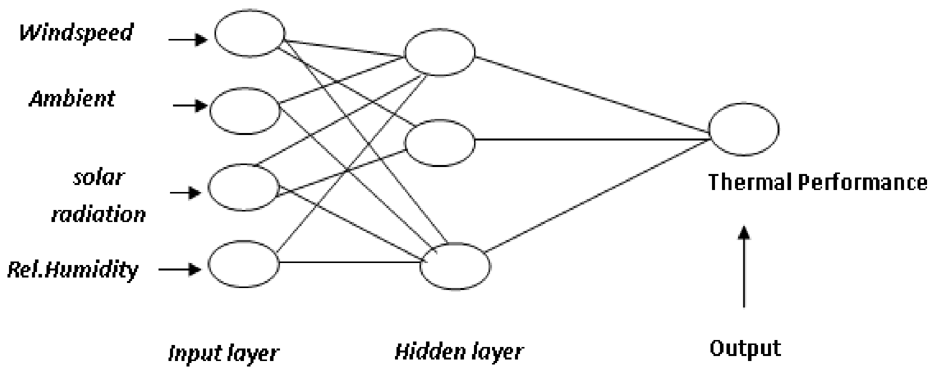

Figure 2. Neural network for the thermal performance criterion

In the training, 50 neurons were applied in the hidden layer to obtain more accurate outputs. The neurons in the hidden layer perform two tasks: They sum the weighted inputs connected to them and pass the resulting summation through non-linear activation function to the output neuron or adjacent neurons of the corresponding hidden layer.

3. RESULT AND DISCUSSION

For simplistic representation of data in estimating the thermal performance of the proposed model, the annual data were reduced to monthly estimate for the heat conduction losses (Q_C), solar heat gain (Q_S), heat flow due to ventilation (Q_V) and internal heat gain (Q_i) .The heat flow in the building was thus represented monthly as shown in Table 4 consists of heat flow due to conduction, heat flow due to ventilation, solar heat gain and internal heat gain. However, the monthly heat flow due to conduction in the building was represented separately in Table 4. This was done to separately show the distribution of the building components in the heat flow due to conduction.

Table 4. Monthly heat conduction losses in the building(In Watts)

Month	Bedroom1	Bedroom2	Bedroom 3	Family Lounge+Dinning	Mainlounge+Presit	Total Qc
Jan.	172.24	147.21	126.75	400.12	533.1	1379.42
Feb.	321.4	274.12	236.02	745.06	992.68	2569.28
Mar	327.93	279.35	240.52	759.28	1011.62	2618.7
Apr.	298.01	254.71	219.3	692.29	922.37	2386.68
May	248.75	212.61	183.05	577.86	769.91	1992.18
Jun	170.17	145.44	125.22	395.3	526.68	1362.81
Jul.	138.65	118.5	102.03	322.08	429.13	1110.39
Aug.	116.4	99.48	85.65	270.38	360.25	932.16
Sept.	123.02	105.15	90.53	285.79	380.76	985.25
Oct.	183.55	156.88	135.07	426.4	568.12	1470.02
Nov.	236.58	202.2	174.09	549.57	732.23	1894.67
Dec.	146.9	125.54	108.09	341.23	454.64	1176.4

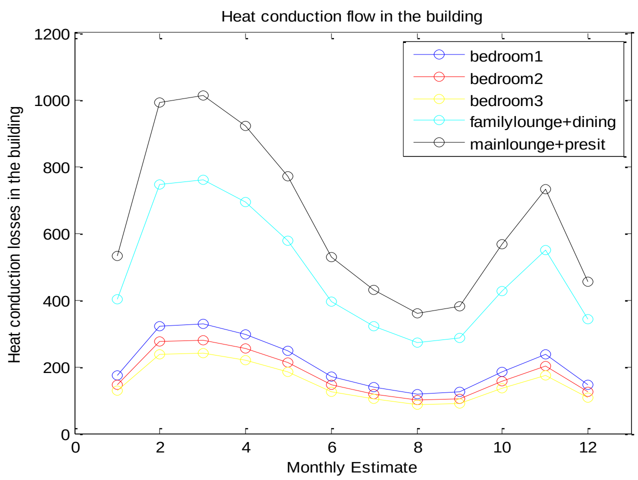

Figure 3. Graph that shows the distribution of the building components in heat flow due to conduction

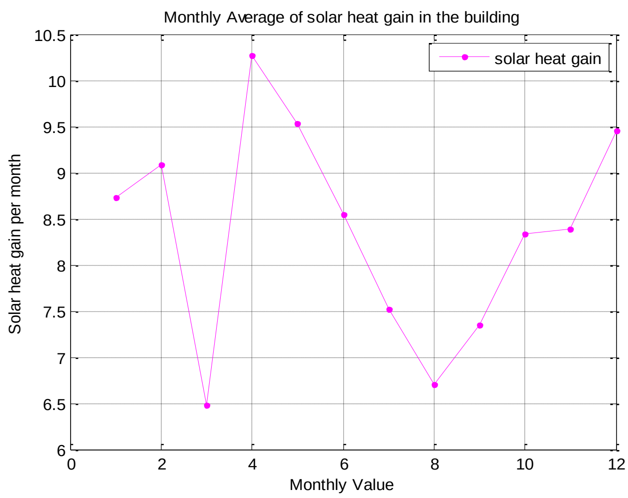

Figure 4. Graph that shows monthly solar ventilation gain in the building

From Figure 3, it can be inferred that 'the main lounge plus presit' had highest contribution of heat conduction flow in the building followed by family lounge plus dinning, bedroom1, bedroom2 and bedroom3 in that order. This variation was owed to the area of the respective component of the building and their respective envelopes like wall, window and door used in the proposed model.

Figure 4 shows the monthly distribution of heat flow due to ventilation in the building. From the graph, it could be inferred that the highest ventilation heat loss occurred in the month of March while the least occurred in the month of August. Table 5 above shows the combined heat flow in the building on monthly bases. From the table, the month that has highest degree of total heat flow March while August has lowest total heat flow in the building. This is further shown in Figure 5 below.

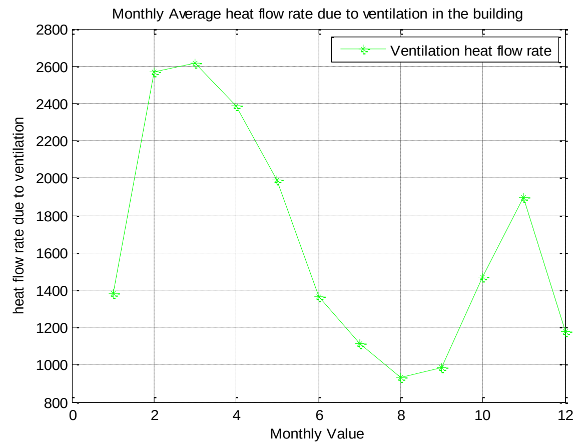

Figure 5. Graph that shows monthly heat loss in the building

Table 5. Monthly heat flow in the building (IN WATTS)

Month	Qc	Qv	Qs	Qi	Qt
January	1379.42	17342.21	8.73	13220	31950.36
February	2569.28	34313.13	9.09	13220	50111.5
March	2618.7	35769.46	6.48	13220	51614.64
April	2386.68	31501.84	10.27	13220	47118.79
May	1992.18	25764.34	9.53	13220	40986.05
June	1362.81	17018.24	8.54	13220	31609.59
July	1110.39	13721.31	7.52	13220	28059.22
August	932.16	11581.96	6.7	13220	25740.82
September	985.25	12396.82	7.35	13220	26609.42
October	1470.02	19005.12	8.34	13220	33703.48
November	1894.67	25060.45	8.39	13220	40183.51
December	1176.4	13656.76	9.46	13220	28062.62

Table 6. Data training distribution on neural network

	Percentage of data	Quantity of data
Training	70 %	256
Testing	15 %	55
Validation	15 %	55

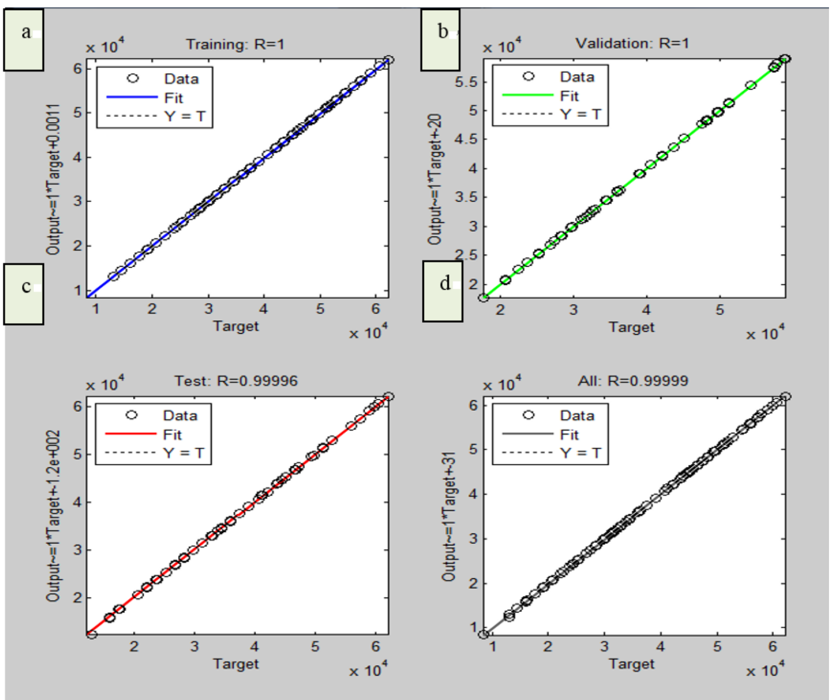

Figure 6. Results of trained data of input and output parameter under thermal performance

Table 7. Relationship between desired output and trained output under thermal performance

Relationship Between Desired Output and Trained Output		
	Correlation	MSE
Training	1.0000	0.0000
Testing	1.0000	0.0000
Validation	0.9996	0.0004
Overall	0.9999	0.00001

Estimation of thermal performance of the building

To train the ANN trained network on MATLAB, the data was divided into three for training, testing, and validation as shown below. The first three plots (i.e. Figure 6a- Figure 6c) represent the training, validation, and testing data. The dashed line in each plot represents the perfect result-output=targets. The solid line represents the best fit linear regression line between outputs and targets. The R value is an indication of the relationship between the outputs and targets. The value R ~ 0.9998 indicates that there is an exact linear relationship between outputs and targets. If R is close to zero, then there is no linear relationship between outputs and targets. For the trained network result above, the training data indicates a good fit. The validation and test results also show R values that is greater than 0.9. The validation of is presented in Figure 5 showing the relationship between the trained output and the desired output for the specified conditions in the computational model building.

4. CONCLUSION

This study was conducted as a way to estimate thermal performance in a residential building using neural network of MATLAB with Leverberg-Marquardt as its algorithm. As neural network training works on data provision, and analytical data was generated with the environmental data. To test the validity of trained data under each criterion; regression curve, correlation between desired and target output and mean square error (MSE) were used. In view of the present predictive study, the following conclusions were drawn:

(1) Thermal performance's parameter was sufficient in given a desired output of trained data with low mean square error. The low mean square error generated indicates it is a good measure of estimator quality of the values of the thermal performance (output variable) against the input values.

(2) The number of neurons in the hidden layer and epoch chosen play a major role in achieving desired result in neural network.

(3) The thermal comfort of occupants in a building is dependent on the thermal performance on the building to avoid sick building syndromes.

(4) The utilization of neural network with near-nature learning and execution capability has been demonstrated as a suitable to inform design decisions during selection of HVAC systems for residential buildings. This approach could be utilized in the design of energy-efficient HVAC systems for eco-friendly residential and public buildings.

In a further study, it is that recommended that real-time prototype design and installation of selected HVAC devices be implemented based on thermo-physical observations obtained from neural network investigation.

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