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Utilizing Artificial Neural Network for Prediction of Occupants Thermal Comfort: A Case Study of a Test Room Fitted With a Thermoelectric Air-Conditioning System

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ABSTRACT Subjective analysis of thermal comfort of occupants relates to the recording of the level of satisfaction or dissatisfaction of occupants with regard to indoor environmental conditions on a scale which ranges from −5 to +5. This requires recruitment of subjects and matching for gender, age etc. In this study, we have tried to predict the thermal comfort of occupants by observing their real behavior inside the test room fitted with a novel thermoelectric air duct (TE-AD) cooling system rather than a conventional air conditioning system. Firstly, real experimental data were collected for more than two months from the test room equipped with the TE-AD cooling system operated at an input power supply of 6 A and 5 V. After that, the ANN model was developed based on the Levenberg-Marquardt algorithm by taking experimental parameters such as air temperature, relative humidity, globe temperature, wind speed, metabolic rate, and clothing value as model input. The ANN model is optimized by developing different models with different data points as a starting input in the training and validation process. The neuron optimization has been carried out in these models to minimize the mean square error (MSE) for the ANN model. The result shows that among the three models M1, M2, and M3, the optimum predictive mean value (PMV) was obtained from M1 at 10 neurons with MSE of 0.07956, while for predicted percentage dissatisfied (PPD), M3 gives optimum accuracy at 10 neurons with MSE value of 5.1789. The ANN model is then generalized to predict thermal comfort for one week and then for one month. Finally, all the model results were validated with the experimental data.

INDEX TERMS Artificial neural network, indoor temperature, relative humidity, thermal comfort, thermoelectric air duct.

I. INTRODUCTION

Building indoor comfort conditions depend upon indoor relative humidity percentage (RH%) and temperature which must be finely adjusted to optimize building energy consumption [1], [2]. Many models and indices have been researched and developed so far for measuring accurate indoor thermal comforts such as predictive mean value (PMV) [3], index of thermal stress [4], predicted percentage dissatisfied (PPD) [5], and effective temperature [6]. The leading method among them is either decided by using a heat balance standard, which relates to heat exchange between the environment and occupants [7] or obtained from the test field data [8], [9]. For predicting indoor thermal comfort of occupants, PMV and PPD have been the most commonly used methods. However, previous researches suggest that the method of heat balance used for the prediction of indoor comfort was insufficient due to the variation of adaptation in humans in different environments [10]. So, human adaptation was introduced in the thermal comfort assessment, and the model

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was named the "adaptive thermal comfort model" [11]. This model involved the psychological, behavioral, and physiological assessment of individuals by evaluating their rating on a grade scale [12], [13]. Additionally, the greater part of the existing thermal comfort model neglects the procedures that guide occupants' thermal sensation to thermal comfort that was actually experienced [14]. Numerous models have typified a basic presumption that thermal neutrality (for example, thermal sensation with neutral level or '0') is the anticipated condition. Notwithstanding, the fulfillment of thermal neutrality doesn't prompt the most elevated thermal comfort assessment, as individuals may be inclined toward surroundings that are not neutral thermally [15]. Individuals in cold atmospheres incline toward somewhat hotter than neutral, while individuals in hot atmospheres lean toward marginally cooler than neutral [16]. There were also chances of overestimation of discomfort prediction by using thermal sensation votes [17]. Therefore, alternative models such as a data-driven or inverse model were used in prediction, as these models don't require an understanding of the physics of the system. These models also show inaccuracy in prediction for large systems such as the HVAC system implemented on the buildings. Due to the many operational parts of the HVAC system, testing of data becomes difficult.

Thus, among all the discussed techniques, the artificial neural network (ANN) is the most preferred technique because of its high accuracy in showing nonlinear frameworks contrasted with different techniques [18], [19]. ANN mirrors the human mind by utilizing a few neurons in numerous layers [20]. Loads of these neurons are commonly prepared by utilizing managed learning strategies. Properly prepared ANN can elevate any nonlinear procedure to a high level of precision [21]. Therefore, the application of ANN is now extended to the prediction of thermal comfort based on indoor climatic conditions such as air and globe temperature, RH%, and wind speed, as well as physiological factors such as metabolic rate and clothing value as input variables [22]. This technique was also used to predict subject behavior by adjusting clothing value and thermostat points that will affect comfort [23].

Chan and Chau [24] developed an ANN model for prediction of thermal comfort of urban parks located in Hong Kong for both winter and summer climatic conditions. The result shows that apart from thermal sensation, air temperature and solar radiation were dominant factors in changing the subject's comfort perception. Deng and Chen [25] investigated the effect of occupant adjustment in clothing and thermostat value on the energy consumption of buildings equipped with HVAC systems. The simulation result shows that adjustment of the above parameters by the occupants could lead to 30% energy consumption reduction by controlling thermostat and 70% by controlling occupancy. Jin *et al.* [26] and Bui *et al.* [27] used the ANN model for developing an energy-optimized model that recommends optimum power consumption, cooling, and heating loads for effective control of indoor temperature and relative humidity. Tian *et al.* [28] and Kamar *et al.* [29] developed an ANN model for prediction of refrigerant mass flow rate, cooling effect, heat rejection from the condenser, energy consumption, capacity of the refrigeration system, and COP. Muñoz *et al.* [30] developed an ANN model for prediction and control of indoor RH% and temperature. The result shows that ANN model performance in predicting the behavior of RH% and the temperature was in accordance with the experimental results.

As per our literature review, few studies have focused on the parametric issue of implementation of the thermoelectric module (TEMs); Luo *et al.* [31] developed a dynamic model of a thermoelectric radiant panel by incorporating ANN and analytical system modeling. The results of this study were centered only on parametric variables and found the optimum thickness of insulation and aluminum panels to be 40-50 mm and 1-2 mm, respectively. The ANN model considering the TEM geometrical shape factor was studied by Derebasi *et al.* [32]. Further, the ANN and thermal model of the photovoltaic thermal integrated thermoelectric cooler (PVT-TEC) collector was developed by Dimri *et al.* [33]. Dimri *et al.*'s [33] investigation also centered on parametric issues and found that the thermal model outcome was in agreement with the ANN model.

Thus, from the critical literature review, it was concluded that both numerical and analytical approaches in solving real system configuration required rigorous calculation and technical experience [34]. Therefore, for solving complex real experimental problems that involve non-linear variables, especially occupants' comfort score, and space cooling rating, the ANN model is used for forecasting the desired results of the system based on training data. In this paper, an ANN technique was applied for the following reasons: 1) it is simpler to implement and performs better at more complex temperature, relative humidity, and comfort data-sets; 2) it works well on parameters such as metabolic rates, indoor temperature, and RH% that introduce a high degree of non-linearity; and 3) it is suitable for real-time prediction applications in a test room equipped with TE-AD system where new training samples can be added or removed without extensive retraining. The significant contributions of this paper are:

a) Use of a novel thermoelectric air-cooling system instead of a conventional air conditioner system.
b) The ANN model of the test room was cooled by a novel thermoelectric air-cooling system.
c) The ANN model that can predict the thermal comfort of occupants was based on an exhaustive experimental study.

II. METHODOLOGY

A. CLIMATIC CONDITIONS

The experimental test room equipped with the TE-AD cooling system was located in Seri Iskandar, Perak, Malaysia. This city is located at coordinates 4.3836° N, 100.9714° E. The weather data was collected from weather stations (Davis Vantage Pro 2 wireless recorder) from April 2018 to June 2018. One month of data for outdoor temperature,

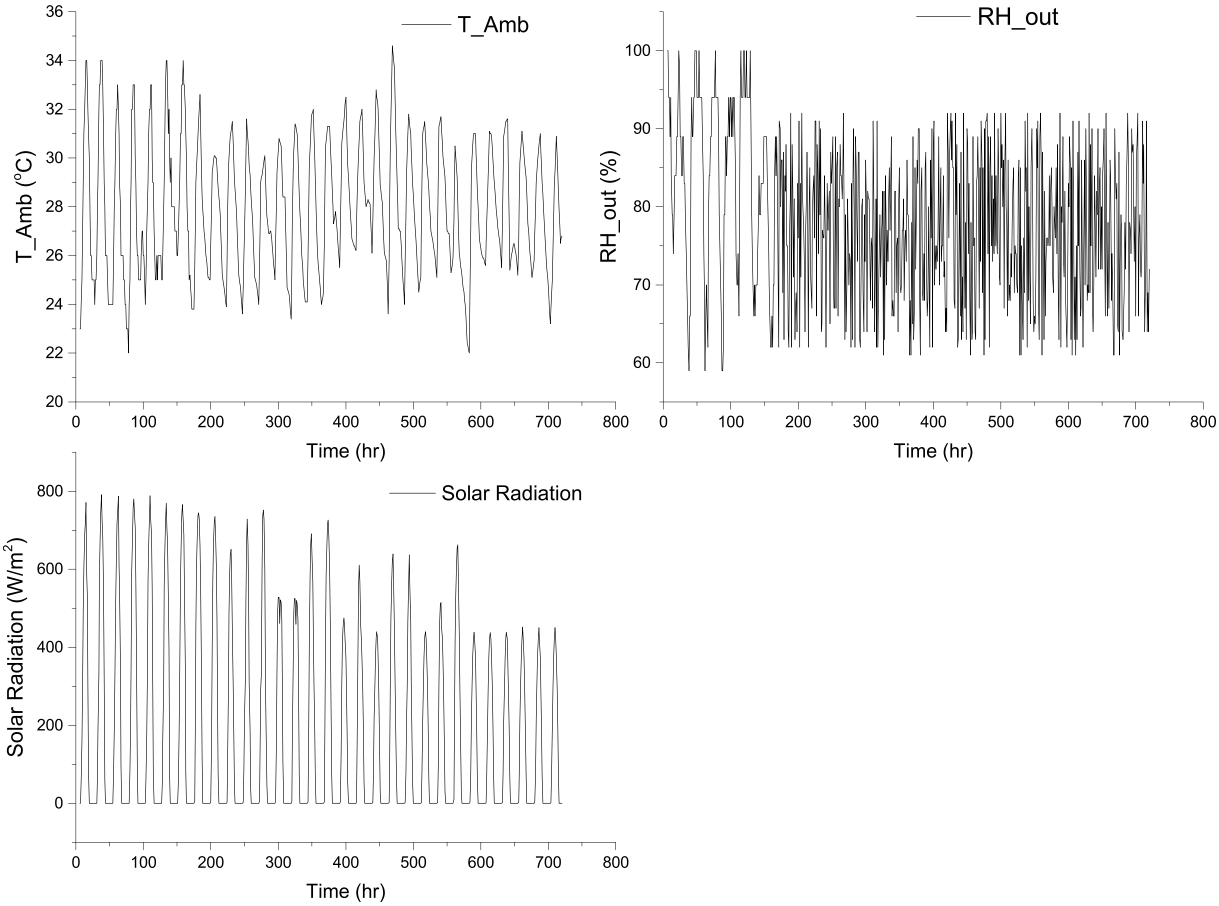

FIGURE 1. Hourly average temperature, relative humidity and solar radiation data for May 2018.

percentage of relative humidity, and solar radiation was presented in Figure 1. The average ambient temperature for May 2018 was 27.96°C; while the maximum temperature is 34.6°C and the minimum temperature is 22°C. The average relative humidity in this period was 78.25%, with a maximum value of 100% and a minimum value of 59%. The average solar radiation during this period was 185.17 W/m^2, with a maximum value of 791 W/m^2 and a minimum value of 0 W/m^2.

Similarly, the hourly averages of indoor temperature, relative humidity, occupants' metabolic rates, and clothing insulation are presented in Figure 2. The average indoor temperature during May 2018 was 24.3°C, with a maximum value of 32.2°C and a minimum value of 19.02°C. The average indoor RH% during this period was 58.48%, with a maximum value of 79% and a minimum value of 40%. Similarly, average clothing insulation and metabolic rate during this phase were 6.08 clo and 59.83 W/m^2.

B. EXPERIMENTAL PROCEDURE

1) SUBJECTS

Table 1 illustrates the anthropometric data for a set of 10 male and 10 female Malaysian nationals having an average body surface area of 1.62 m^2. The standard body surface area proportion for a person is 1.80 m^2 worldwide. During the experiment, all the participants were requested to dress up in regular summer clothes (0.5 clo).

TABLE 1. Anthropometric data of subjects.

Sex	Sample size	Age	Height(m)	Weight(kg)	BMI*
Male	*10*	*27.4±6.3***	*1.71±2.1*	*69.4±1.2*	*22.4±2.1*
Female	*10*	*26.3±2.4*	*1.64±0.6*	*54.6±0.8*	*19.6±1.4*

**STANDARD DEVIATION.

*BODY MASS INDEX= WEIGHT (KG)/ [HEIGHT (M)]^2

The mandatory condition for the experiment was discussed with the participants to familiarize them with the test procedure. The experiment permitted the subjects to bend back or forward only. They were not permitted to move from their positions or jump.

2) EXPERIMENTAL ANALYSIS OF THERMAL COMFORT

Based on previous experimental observation as reported in the article [35], the thermal comfort data was collected at optimum input power supply to the TE-AD systems

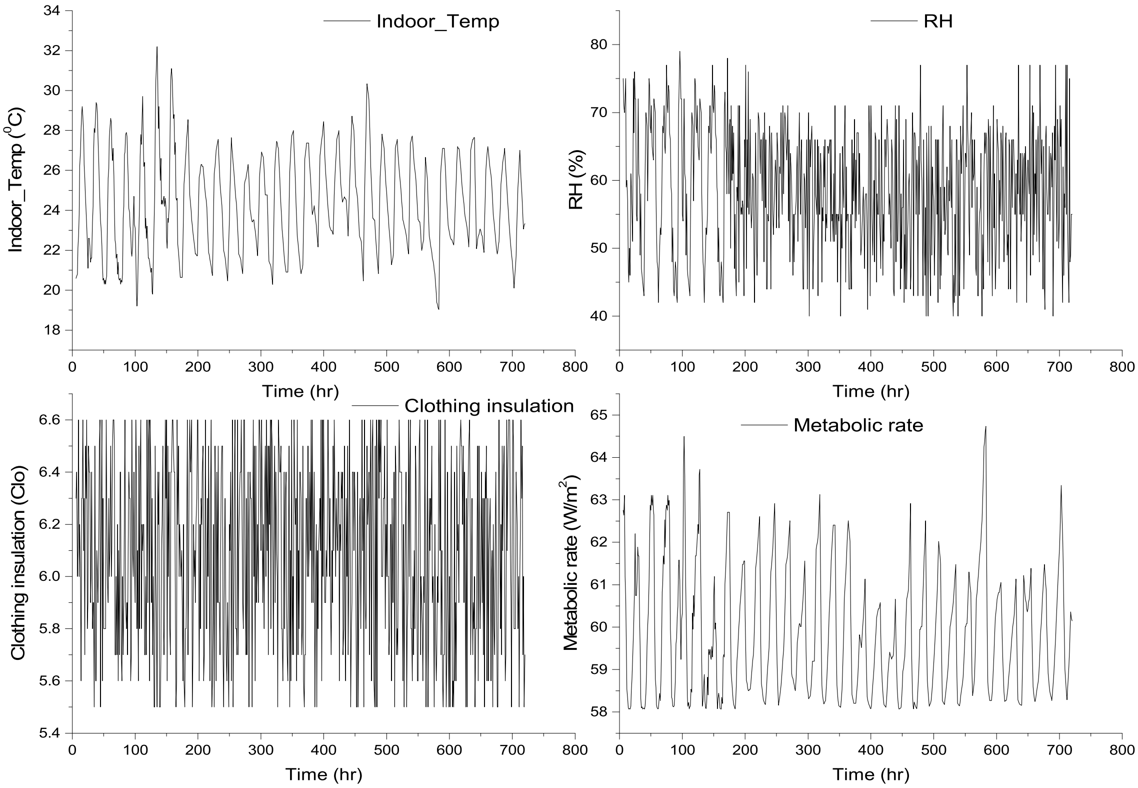

FIGURE 2. Hourly average indoor temperature, relative humidity, metabolic rate and clothing value for May 2018.

of 6A and i5V. As per ISO 7730 [36], all parameters such as radiant temperature, indoor temperature, and relative humidity, clothing value, and metabolic rate were recorded. The TE-AD system was operated for 12 hours for all possible ranges of input current. The experiment required participants to sit in the test room for 15 minutes before the start of the test to adjust them to the environment. During the 12-hour test, the participants were given a break of 15 minutes after every hour where they were required to relax, stand up, and move around the test room. The collected data consists of subjective evaluation and physical parameters' estimation. The physical assessment aimed to collect climatic parameters such as global temperature, air temperature, airspeed, humidity, and radiation. Type K thermocouples with data loggers were fitted at several positions in the test room, and TE-AD arrangement to measure the temperature was positioned as illustrated in Figure 3. Furthermore, a Globe thermometer was employed to estimate mean radiant temperature (MRT), which is a measure of the joint impact of air temperature, radiation, and air velocity on human comfort. All the instruments were placed at 7:30 am, and the data gathering started at 8 am. All sensor probes were positioned at 1.00 m above the ground alongside the respondents to meet the requirement of the research protocol of Class II. A compact solar meter was utilized to estimate the solar radiation flux density (W/m^2) during the operation of the TE-AD arrangement. The data from different instruments were gathered at every interval of 1 minute from 8 am to 8 pm. A detailed questionnaire was developed in every test session, as stated in the article [35]. Various measures of human comfort like feelings, subjective sensation, and views of occupants were analyzed through careful examination of completed surveys.

3) DATA UNCERTAINTY ANALYSIS

The uncertainty (V) in the measured value caused due to precision errors ($e_{precision}$) and biases (e_{bias}) was calculated. The precision error is linked to the repeatability of the estimation, whereas bias error relates to the accuracy and calibration of the measuring devices. The investigation was conducted in outdoor conditions for a limited duration, which restricted obtaining very precise estimations for specific weather conditions. For this reason, the investigation and estimations were carried out numerous times to calculate the precision error of different variables. Accordingly, the uncertainties in the estimations were calculated simply based on bias error. Kline and Mcclintock [37] established a technique to determine uncertainty because of bias error by asserting that for n independent normally distributed variables vi, R is a linear function described by

$$R = R\,(v_1, v_2, v_3, \ldots \ \ldots \ \ldots v_n) \tag{1}$$

The uncertainty in R relates to the uncertainties in individual variables, which can be calculated using the following

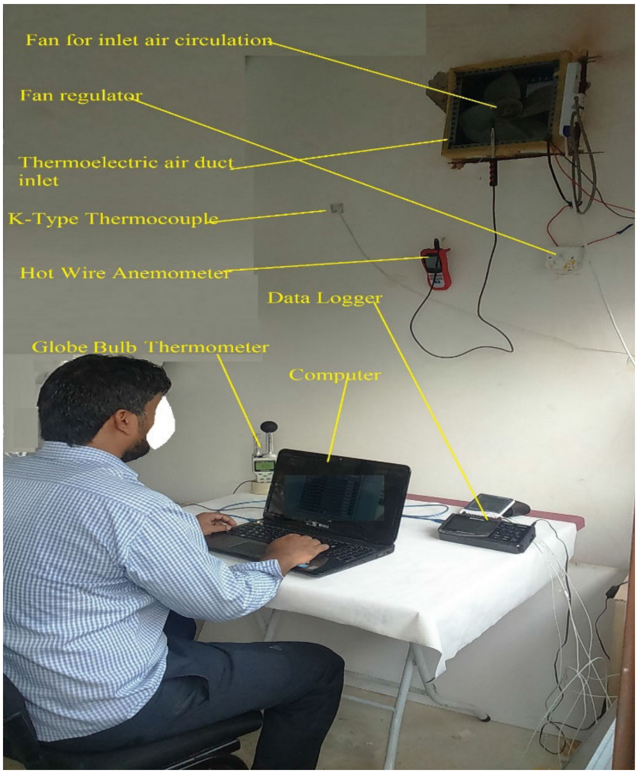

FIGURE 3. Subjective analysis of thermal comfort.

TABLE 2. Uncertainty analysis of the measured value.

`	TYPICAL VALUE(X)	UNCERTAINTY (∂x)	RELATIVE UNCERTAINTY ($\partial x/x$)
T_in(°C)	18-35	0.1	0.56
T_a(°C)	20-40	0.1	0.55
T_C(°C)	15-25	0.1	0.67
T_H(°C)	25-40	0.1	0.4
Solarimeter ($W/m^{2)}$)	100-900	2	2
Voltage *(V)*	0-30		0.3
Current *(A)*	0-10		1
Air flow *(m/s)*	1-3	0.1	5

relation known as the second-power equation.

$$\delta_R=\left[\left(\frac{\partial R}{\partial v_1}\partial v_1\right)^2+\left(\frac{\partial R}{\partial v_2}\partial v_2\right)^2+\cdots\cdots+\left(\frac{\partial R}{\partial v_n}\partial v_n\right)^2\right]^{\frac{1}{2}} \tag{2}$$

4) ARTIFICIAL NEURAL NETWORK MODEL DEVELOPMENT

The neural network structure comprises of the architecture of network and number of hidden neurons and layers. The multilayer perceptron (MLP) structure was the most commonly used prediction model in ANN architecture [38], [39]. It has been concluded that an MLP model with one hidden layer holds an adequate quantity of neurons for estimating any function with ideal exactness [40]. Utilizing more than one hidden layer seldom enhances the model, and it might present a risk of converging to a local minimum [41]. The MLP model used in this study has a hidden layer with a single output. The input vector x and output vector y consists of information of input and output layers. It can be defined as

$$\begin{aligned} y(k) &= f(y(k-1), y(k-2), \ldots\ldots\ldots\ldots, y(k-n_y), \\ &\quad \times u(k-1), u(k-2), \ldots\ldots\ldots, u(k-n_u)) \end{aligned} \tag{3}$$

Here, the subsequent output value y(k) is dependent on the past outputs as well as past input values u(k). Furthermore, n_y and n_u represent the delay-line taps of the input and output, respectively. During this investigation, the input value x was provided by the different values of the vectors x_0 to x_{nu+ny} collected on an hourly basis, as shown in Table 3, whereas the output y comprised a single output vector.

The values of outdoor and indoor RH (%) and solar radiation, input temperature, clothing value, and metabolic rate were carried by each vector. Figure 4 illustrates the single hidden layer MLP model employed in this investigation. The hidden layer of the MLP structure consisted of non-linear neurons. These neurons are depicted by non-linear functions

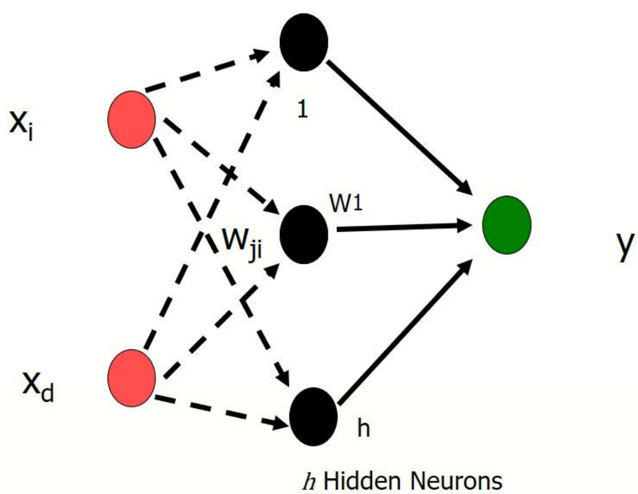

FIGURE 4. MLP schematic diagram with inputs values, weights and hidden neurons.

TABLE 3. Input and output vectors of the proposed neural network model [42].

Variables	Description	
k		Hour (A Time step between each input values)
x_0	1	Bias
x_1	$u(k\text{-}1)$	Vectors of previous values of PMV, PPD and Indoor Temp at time k-1
x_2	$u(k\text{-}2)$	Vectors of previous values of PMV, PPD and Indoor Temp at time k-2
.	.	.
.	.	.
.	.	.
x_{nu}	$u(k\text{-}n_u)$	Vectors of previous values of PMV, PPD and Indoor Temp at time k- n_u
x_{nu+1}	$y(k\text{-}1)$	Vectors of previous values of outdoor and indoor RH (%) and solar radiation, Input Temperature, Clothing value, and Metabolic rate at time k-1
x_{nu+2} .	$y(k\text{-}2)$.	Vectors of previous values of outdoor and indoor RH (%) and solar radiation, Input Temperature, Clothing value, and Metabolic rate at time k-2
.	.	.
.	.	.
		.
.	.	.
x_{nu+ny}	$Y(k\text{-}n_y)$	Vectors of previous values of outdoor and indoor RH (%) and solar radiation, Input Temperature, Clothing value, and Metabolic rate at time k- n_y
$y(k)$	$[IT(k);IH(k)]$	Vectors of previous values of outdoor and indoor RH (%) and solar radiation, Input Temperature, Clothing value, and Metabolic rate at time k

known as the activation function which is the hyperbolic tangent function f (x) = tanh(x) in this study. So, a neural network defined by a non-linear mapping of any given input x to an output y having (n_y+ n_u+ 1) input neurons (shown in Table 4), h hidden neurons and only one output neuron is presented by the relation:

$$y = y(x, w) = \sum\nolimits_{j=0}^{h} \left[w_j \times f\left(\sum\nolimits_{i=0}^{n_y+n_u+1} w_{ji} x_i \right) \right] \quad (4)$$

TABLE 4. Assessing performances of PMV model M1 for different test initialization parameters.

Hidden Neurons	Mean Squared Error for test
5	0.09965
10	0.07956
15	0.1225

The parameters of the given neural network model are characterized by weights (w) and biases (b) connecting the different layers. The weight represented by vector W describes the non-linear mapping. The values of the parameters W and b are calculated during the training stage.

5) TRAINING, TESTING, AND VALIDATION OF ANN MODEL

The learning, then testing, and finally, generalization are the three fundamental steps to acquire the optimal ANN model. The training dataset having N inputs and outputs was used in the learning phase such as $D = \{x_i, t_i\}_{i=1}^{N}$. Table 3 describes variable x as each having sample $\left(n_y + n_u + 1\right)$ as an input vector. The variable t, also called the objective variable, is the comparing estimation of the air temperature and relative humidity. This stage comprises altering w in order to limit the error function J, which is generally the addition of errors square between the test yield ti and the ANN model yield, $y_i = y\,(x_i; w)$:

$$J(w) = \frac{1}{2} \sum\nolimits_{i=1}^{N} \{y_i - t_i\}^2 = \frac{1}{2} \sum\nolimits_{i=1}^{N} e^2 \quad (5)$$

For function approximation problems, Levenberg-Marquardt is used as a learning algorithm, as it quickly converges with the least mean square error (MSE). The testing and generalization were the second and third phases, comprising of assessing the capacity of the ANN to recreate the watched phenomenon, or in other words, to give the right yields when it is defined with models that were not seen during the training stage. The dataset of testing and generalization phases were used during this phase. For checking the performance of the predictive model, various statistical techniques have been utilized by previous researchers [43], but in this study, model exhibitions are portrayed by the mean square error (MSE) and the correlation coefficient (R). MSE and R can be assessed as:

$$MSE = \sum \left(\frac{e_i^2}{N} \right), \quad (6)$$

$$R = \pm \sqrt{\frac{\sum_{i=1}^{N} (y_i - \bar{t})^2}{\sum_{i=1}^{N} (t_i - \bar{t})^2}} \quad (7)$$

III. RESULTS

A real-world scenario is employed to validate the proposed approach. As discussed earlier, research findings showed that a neural network is a valuable tool for forecasting indoor

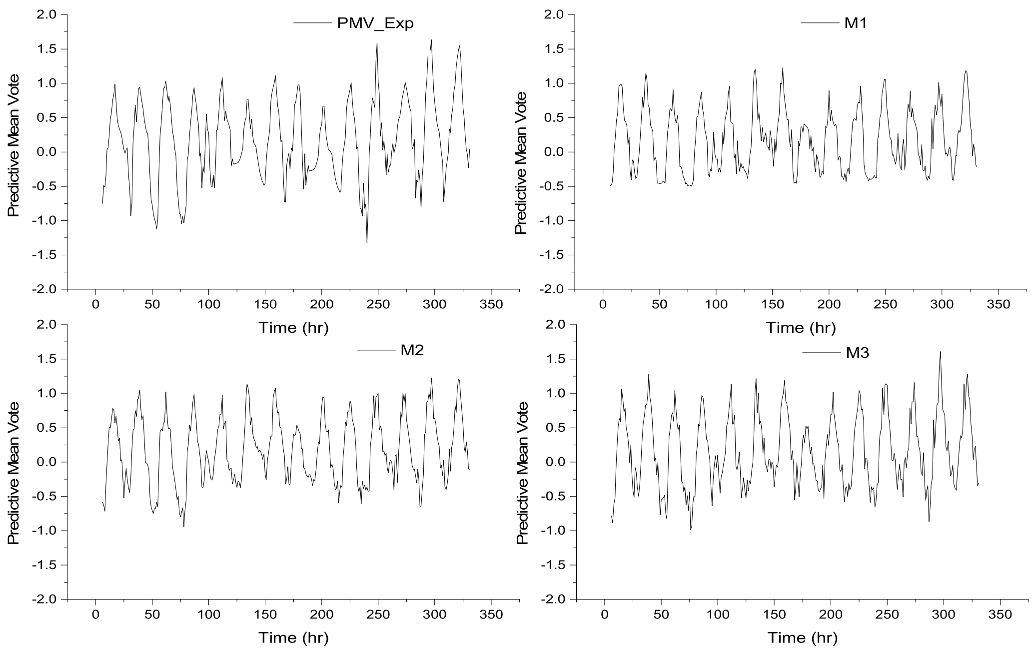

FIGURE 5. Experimental comparison of weekly PMV with ANN models.

air temperature, PMV, and PPD, utilizing the data obtained for 1 week and 1 month which makes a total data points of 1204 values for each variable. In this study, the prediction presented by the proposed neural network model is appropriate, as forecasting of hourly PMV, PPD, and indoor air temperature is needed one month in advance using the data accumulated for prior months. The investigative data comprised of hourly outdoor and indoor RH (%), solar radiation, indoor temperature, clothing value, and metabolic rate for a test chamber building located in a tropical climatic region of the town of Bandar Seri Iskandar, Perak, Malaysia. The neural network model was tested using a Levenberg-Marquardt algorithm-based software developed via MATLAB programming. The transfer function used for the development of the ANN model was *trainlm* with a learning rate of 0.01. The momentum term takes the value between 0.01 and takes the maximum value of 1.0 e ^10. The momentum term optimum value takes between 0.005 to 0.009. The proposed model after undergoing training was adopted for forecasting hourly indoor RH% and temperatures for the test data.

The basis for selecting a suitable architecture model is estimating the root mean square error or the mean square error (MSE) on the experimentally collected data. To model the investigative dataset, the number of neurons in the hidden layer for a given neural network structure is decided through trial and error. Till now, no mathematical technique is available for fixing the number of hidden elements. Haykin [44] suggested starting the training of a neural network with fewer elements that can be steadily increased throughout the training unless an optimal number is fixed after an adequate training session. In this study, MSE is calculated for different scenarios of the examined Multi-layer Perceptron (MLP) neural network for the given test dataset, as presented in Tables 4–6.

A. PMV PREDICTION USING ANN OPTIMAL STRUCTURE

The analysis of Tables 4-6 suggests that for the same number of neurons MSE is different, which means that initialization parameters have greater influence and depend upon biases and weights. The initialization parameters in the experimental dataset have been divided into three parts. In the first case, we have taken the initial 75% of data points as a training dataset and called it an M1 model, and in the second case, middle 75% data points have been used as a training dataset and called it model M2, followed by last 75% data points taken as a training dataset and called it model M3. The PMV performance based on M1 having experimental input parameters such as air temperature, globe temperature, RH%, wind speed, metabolic rate, and clothing value as shown in Table 4 has the lowest MSE as 0.07956 at 10 neurons.

Furthermore, PMV performance based on the M2 model has the lowest MSE of 0.8575 at 10 neurons, as shown in Table 5, while PMV performance based on the M3 model has the lowest MSE of 0.8126 at 5 neurons, as shown in Table 6.

The investigation reveals that the PMV performance for M1 and M2 shows the minimum error when the hidden layer comprises 10 neurons, while for M3 the minimum error was observed at 5 neurons. Among the three models, the M1 model shows the least MSE value and thus is considered the optimal model for predicting PMV based on experimental values. The PMV values for one week and one month were compared as shown in Figures 5 and 6.

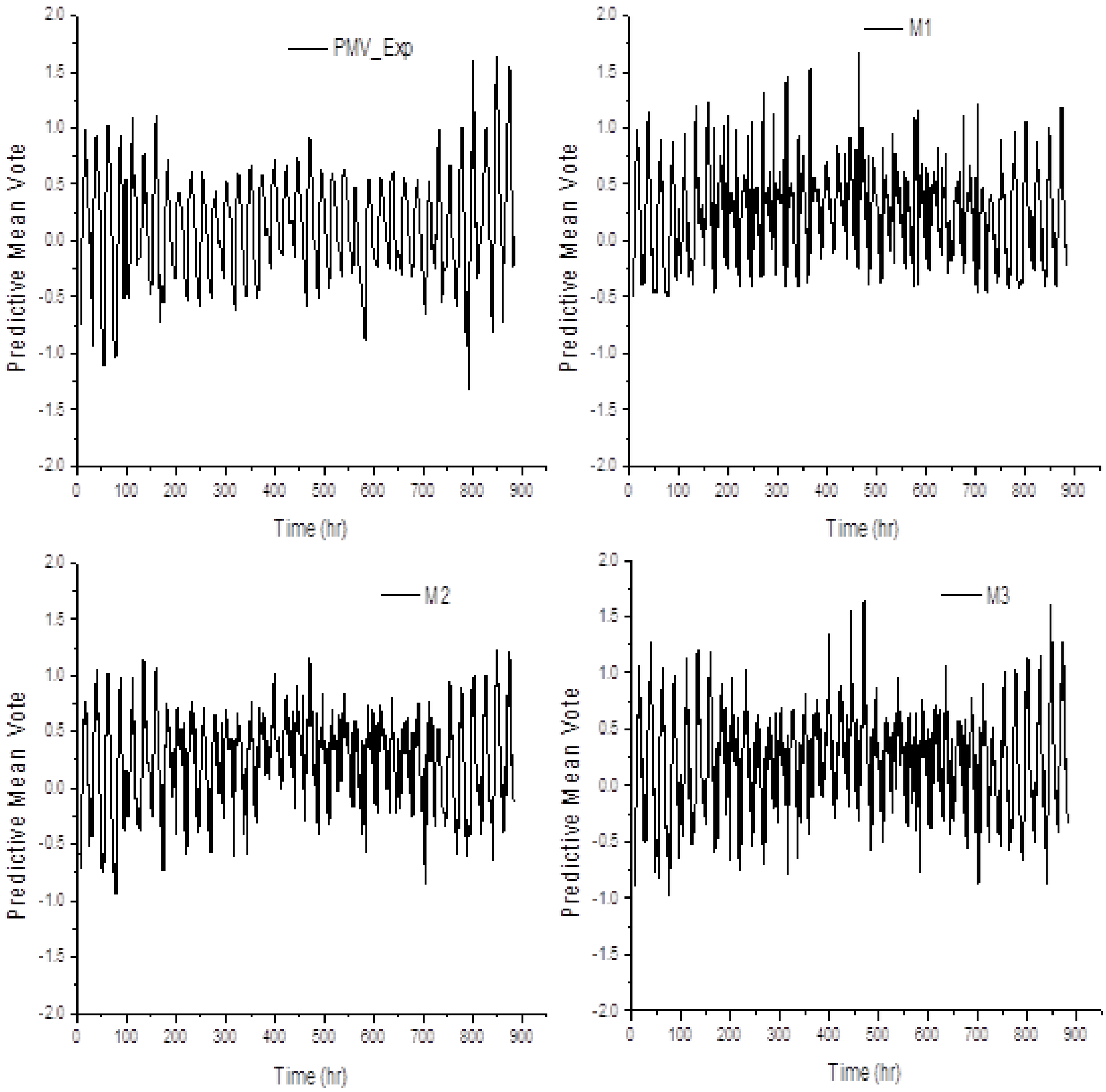

FIGURE 6. Experimental comparison of monthly PMV with ANN models.

TABLE 5. Assessing performances of PMV model M2 for different test initialization parameters.

Hidden Neurons	Mean Squared Error for test
5	0.956
10	0.8575
15	1.056

TABLE 6. Assessing performances of PMV model M3 for different test initialization parameters.

Hidden Neurons	Mean Squared Error for test
5	0.8126
10	1.1265
15	0.9896

It was observed that the experimental PMV value was close to the PMV value obtained from model M1, and thus this model is identified as the most accurate model for predicting PMV of the test room equipped with the TE-AD system and for Malaysian occupants belonging to the age range 27.4±6.3 years for male occupants and 26.3±2.4 years for female occupants.

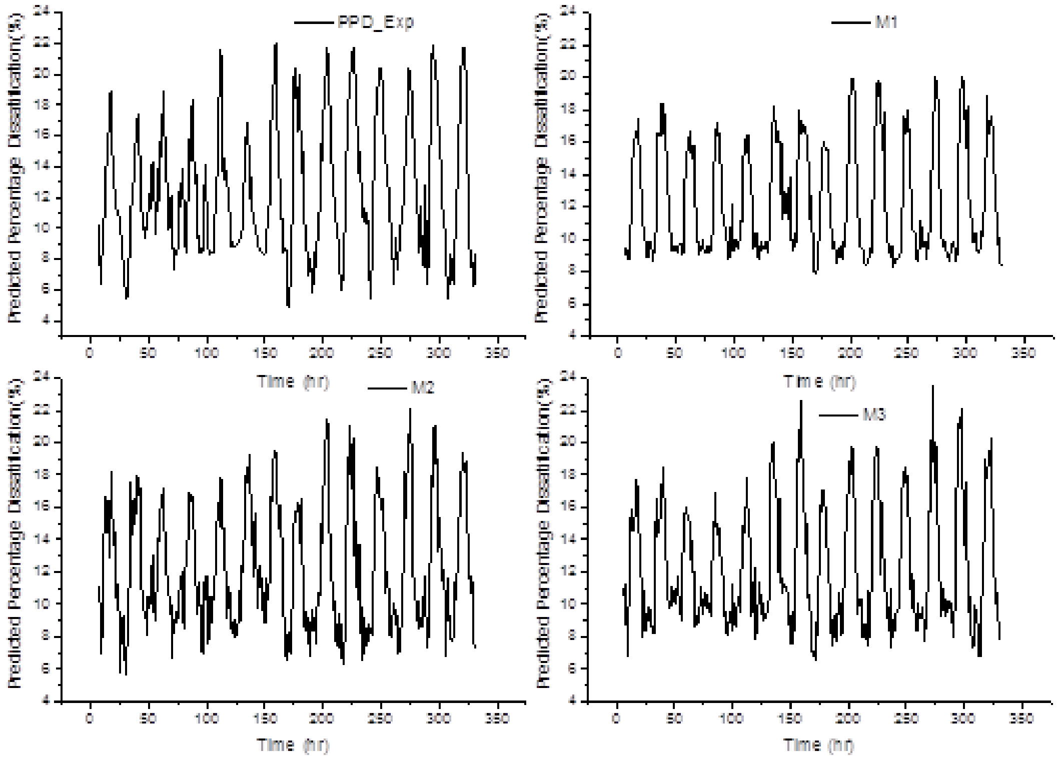

FIGURE 7. Experimental comparison of weekly PPD with ANN model.

B. PPD PREDICTION USING ANN OPTIMAL STRUCTURE

The initialization parameter in the experimental data set has been divided into three parts. In the first case, we have taken the initial 75% of data points as a training dataset and called it an M1 model, and in the second case, the middle 75% data points have been used as a training dataset and marked as model M2, followed by last 75% data points taken as a training dataset and marked as model M3. The analysis of Tables 7-9 reflects the same observation above that for the same number of neuron mean square error (MSE) is different. The PPD performance based on M1 having experimental input parameters such as air temperature, globe temperature, RH%, wind speed, metabolic rate, and clothing value as shown in Table 7 has the lowest MSE of 6.1263 at 15 neurons.

TABLE 7. Assessing performances of PPD model M1 for different test initialization parameters.

Hidden Neurons	Mean Squared Error for test
5	6.2356
10	7.9689
15	6.1263

Furthermore, PPD performance based on the M2 model has the lowest MSE of 5.8956 at 10 neurons, as shown in Table 8. PPD performance based on the M3 model has the lowest MSE of 5.1789 at 10 neurons, as shown in Table 9.

TABLE 8. Assessing performances of PMV model M2 for different test initialization parameters.

Hidden Neurons	Mean Squared Error for test
5	6.0135
10	5.8956
15	6.6590

TABLE 9. Assessing performances of PMV model M3 for different test initialization parameters.

Hidden Neurons	Mean Squared Error for test
5	7.9468
10	5.1789
15	7.4154

The analysis reveals that the PPD performance for all three models showed different minimum errors when their hidden layer comprises of different number of neurons—i.e., 15 neurons for M1, 10 neurons for M2, and 10 neurons for M3. Among the three models, M3 shows the least MSE value at 10 neurons and thus is considered the optimal model for predicting PPD based on experimental values. The PPD values for one week and for one month are compared in Figures 7 and 8.

It was observed that experimental PPD value was close to predicted PPD value obtained from model M3, and thus this model is identified as the most accurate model for predicting

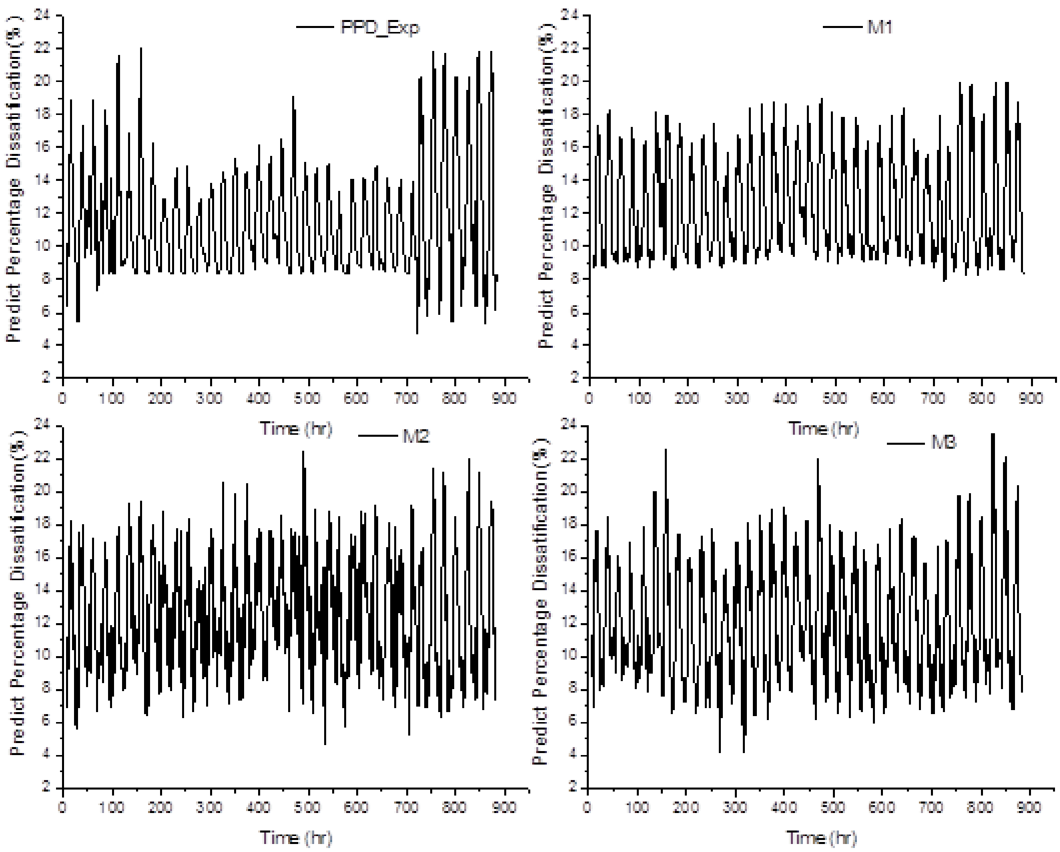

FIGURE 8. Experimental comparison of monthly PPD with ANN models.

PPD of test room equipped with the TE-AD system and for the occupants from Malaysia with age in the range of 27.4±6.3 years for male occupants and 26.3±2.4 years for female occupants.

C. INDOOR AIR TEMPERATURE PREDICTION USING ANN OPTIMAL STRUCTURE

As explained in the above sections of PMV and PPD, the different initialization parameters have been given and were defined as model M1, M2, and M3. An analysis of Tables 10-12 reflects the same observation as stated above for PPD and PMV, that for the same number of neurons, the mean square errors (MSE) are different. The indoor air temperature performance based on M1 having experimental input parameters such as air temperature, globe temperature, and solar radiation as shown in Table 10 have the lowest MSE as 0.75984 at 15 neurons.

TABLE 10. Assessing performances of indoor air temperature model M1 for different test initialization parameters.

Hidden Neurons	Mean Squared Error for test
5	0.9854
10	1.01345
15	0.75984

Furthermore, indoor temperature performance based on M2 has the lowest MSE of 0.88647 at 10 neurons, as shown in Table 11. Indoor temperature performance based on the M3 model has the lowest MSE of 0.68959 at 15 neurons, as shown in Table 12.

TABLE 11. Assessing performances of indoor air temperature M2 for different test initialization parameters.

Hidden Neurons	Mean Squared Error for test
5	1.01327
10	0.88647
15	0.98654

TABLE 12. Assessing performances of Indoor air temperature M3 for different test initialization parameters.

Hidden Neurons	Mean Squared Error for test
5	0.86489
10	0.83732
15	0.68959

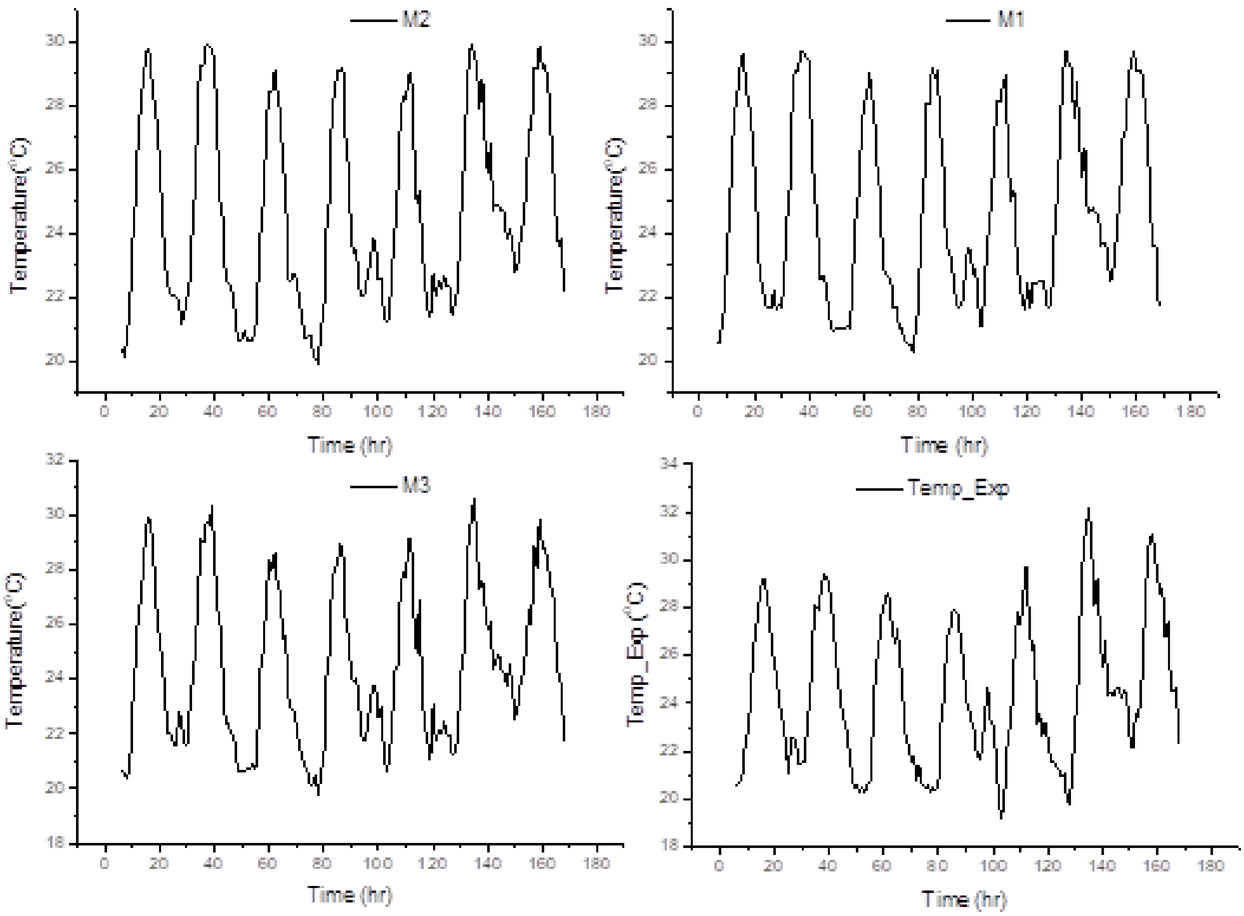

FIGURE 9. Experimental comparison of weekly indoor temperature with ANN models.

Analysis reveals that the indoor temperature performances for all the three models show the same minimum error when their hidden layer comprises the same number of neurons: 15 hidden neurons for M1, M2, and M3. M3 shows the least MSE value and thus is considered the optimal model for predicting indoor temperature based on experimental values. The indoor temperature value for one week and one month were compared in Figures 9 and 10.

It was observed that experimental indoor temperature value was close to predicted indoor temperature value obtained from model M2, and thus this model is identified to be the most accurate model for predicting the indoor temperature of the test room equipped with the TE-AD system.

D. PERFORMANCE COMPARISON OF DIFFERENT NEURONS ON THE PREDICTION MODELS

Training of a neural network model is performed for determining the parameters (weights and biases) for a given model, and also to decide the number of neurons inside the hidden layer of individual MLP structures. The testing phase helps to eliminate any model whose performance is not up to the mark. Generalization is the final step accomplished through the test validation of the models. It helps to evaluate the capability of the neural network to generate precise outputs for a different set of data that were not used during the training. A generalization dataset is applied for experimentally validating these models. So, the capability of these models to forecast the PMV, PPD, and indoor temperature for a short and long duration was examined during the generalization phase. Furthermore, the relation between the prediction period and the model performances was observed. Two prediction periods of one week and one month were selected, as shown in Figures 5 to 10. The choice of these prediction periods was made randomly, based on the test dataset and it in no way affects the outcomes. It must predict the identical results for a different week or a different month, as the parameters of the neural network model (weights and biases) once estimated during the training stage remain unchanged throughout. One of the criteria for test validation of an ANN model is qualitative analysis, which involves comparing the dynamic response of the simulated and measured values of air temperature, globe temperature, RH%, wind speed, metabolic rate, solar radiation, and clothing value graphically, to discover any dynamic differences.

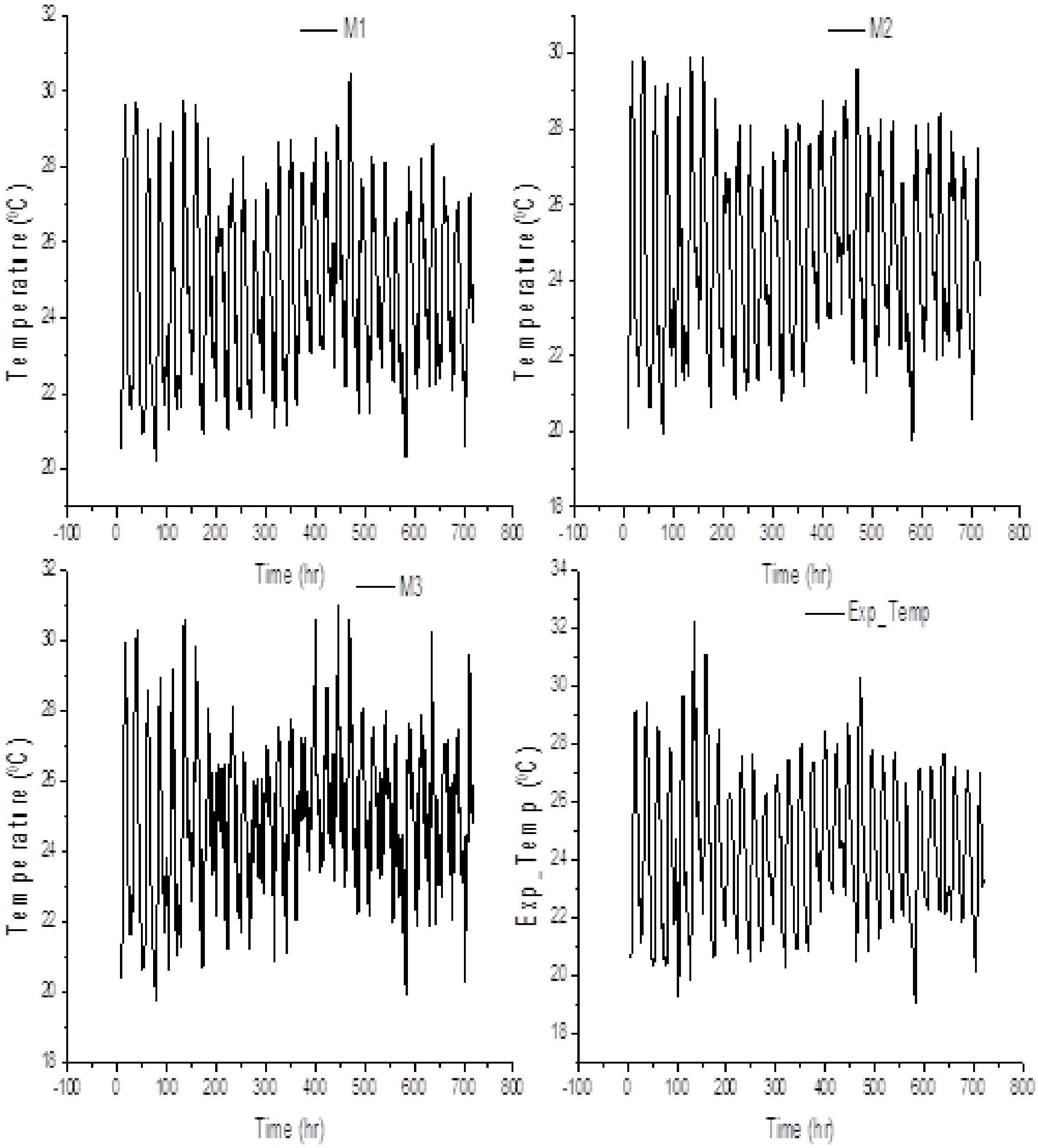

FIGURE 10. Experimental comparison of monthly indoor temperature with ANN models.

1) PMV PREDICTION FOR ANN MODEL USING DIFFERENT NEURONS

There is no mathematical correlation or fixed law to determine the exact number of neurons required to calculate the optimum neurons required for an ANN model. To optimize the performance of the ANN model, different hidden layers have been used in the ANN model development. The MSE obtained for different neurons has been given in Tables 4 through 6 for three different models and presence of different numbers of neurons. Based on Tables 4 to 6, it had been concluded that the M1 has the lowest MSE. In the following figures, the performance of model M1 has been shown at different neurons. Figure 11 shows the performance such as MSE, and regression plots for training and validation of the ANN model with 5 neurons, followed by the performance of the ANN model for 10 neurons (Figure 12), and the performance of the ANN model for 15 neurons (Figure 13). Figure 11a shows the MSE for training, testing, and validation, and the best MSE obtained is 0.0949 for validation and testing at 6 epochs. Additionally, Figure 11b displays the r-squared values for training, testing, and validation and the overall r-squared values in this model with 5 neurons were found to be 0.85213, 0.79619, 0.83573, and 0.84574 respectively.

Figure 12a shows the MSE for training, testing, and validation, and the best MSE obtained is 0.0784 for validation and testing at 4 epochs. Besides, Figure 12b displays the r-squared values for training, testing, and validation and the overall

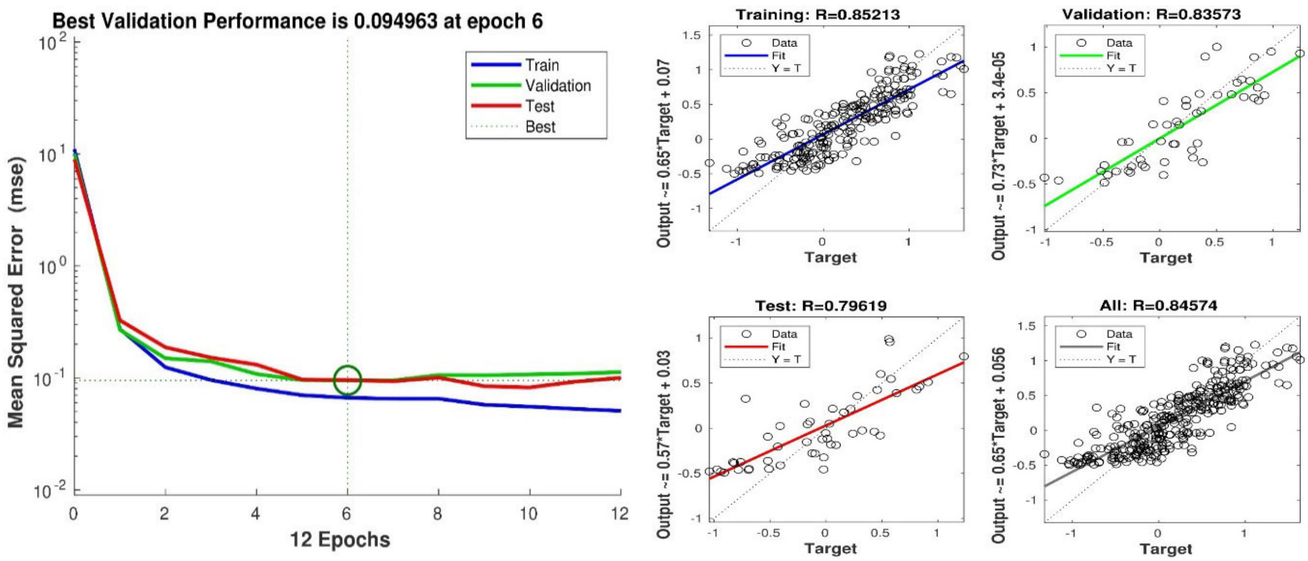

FIGURE 11. MSE and Regression for ANN model for PMV with 5 neurons.

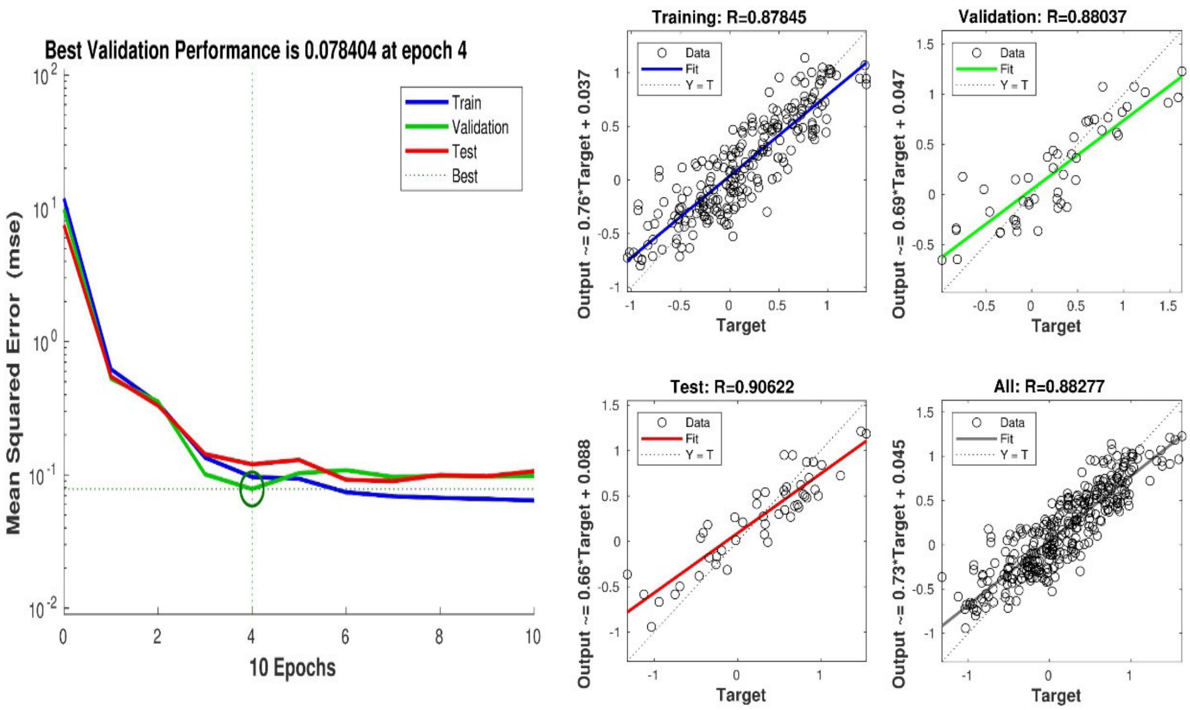

FIGURE 12. MSE and Regression for ANN model for PMV with 10 neurons.

r-squared values in this model with 10 neurons were found to be 0.87845, 0.88037, 0.90622, and 0.88277 respectively.

Figure 13a shows the MSE for training, testing, and validation, and the best MSE obtained is 0.11433 for validation and testing at 6 epochs. Further, Figure 13b presents the r-squared values for training, testing, and validation and overall r-squared values in this model with 15 neurons were found to be r-squared of 0.89447, 0.84496, 0.85488, and 0.88178 respectively.

2) PPD PREDICTION FOR ANN MODEL USING DIFFERENT NEURONS

As explained in the PMV and indoor air temperature sections above, the ANN model has been studied for different neurons for the M3 model; to optimize the performance of the ANN model different hidden layers have been used in the ANN model development. The MSE obtained for different neurons has been given in Tables 7 through 9 for the three different models and the presence of different neurons.

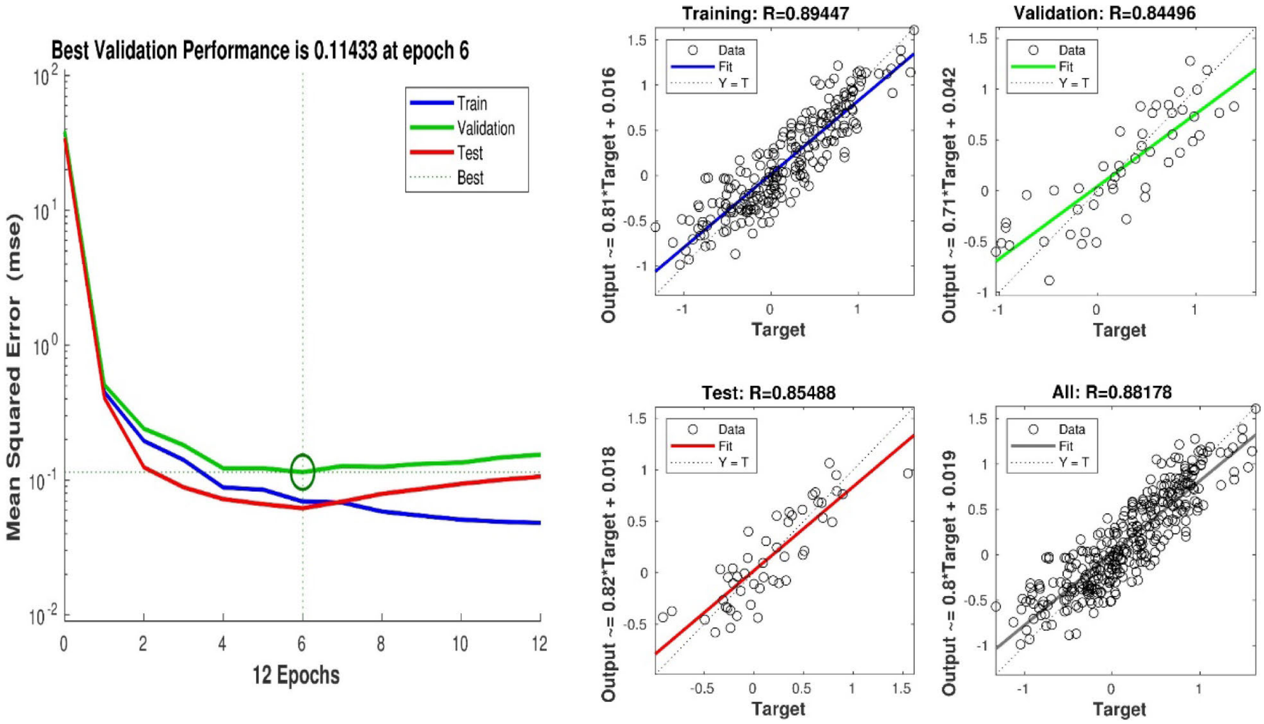

FIGURE 13. MSE and Regression for ANN model for PMV with 15 neurons.

Based on Tables 7 to 9, it had been concluded that the M3 model has the lowest MSE. In the following figures, the performance of M3 has been shown at different neurons. Figure 14 shows the performance such as MSE, and regression plots for training, testing, and validation of the ANN model for 5 neurons followed by Figure 15 which presents the performance of the ANN model for 10 neurons, and Figure 16 which displays the performance of the ANN model for 15 neurons.

Figure 14a shows the MSE for training, testing, and validation and the best MSE obtained is 5.1434 for validation and testing at 5 epochs. Likewise, Figure 14b shows the r-squared values for training, testing, and validation and overall r-squared values in this model with 5 neurons were found to be 0.84753, 0.80996, 0.78896, and 0.83192 respectively.

Figure 15a shows the MSE for training, testing, and validation, and the best MSE obtained is 7.8367 for validation and testing at 5 epochs. Moreover, Figure 15b demonstrates the r-squared values for training, testing, and validation and overall r-squared values in this model with 10 neurons were observed to be 0.88544, 0.8196, 0.75211, and 0.85164 respectively.

Figure 16a shows the MSE for training, testing, and validation, and the best MSE obtained is 7.354 for validation and testing at 7 epochs. Besides, Figure 16b demonstrates the r-squared values for training, testing, and validation and overall r-squared values in this model with 15 neurons were found to be 0.89283, 0.76799, 0.75475, and 0.85506 respectively.

E. INDOOR AIR TEMPERATURE PREDICTION FOR ANN MODEL USING DIFFERENT NEURONS

There is no mathematical correlation or fixed law to find the exact amount of neurons required to calculate the optimum neurons required for an ANN model. To optimize the performance of the ANN model, different hidden layers have been used in the ANN model development. The MSE obtained for different neurons are given in Tables 10 through Table 12 for three different models and presence of different number of neurons. Based on Tables 10 to 12, it can be concluded that the M3 model has the lowest MSE. In the following figures, the performance of M3 has been shown at different neurons. Figure 17 shows the performance such as MSE, and regression plots for training, testing, and validation of the ANN model for 5 neurons, followed by Figure 18 which shows performance of the ANN model for 10 neurons, and Figure 19 which shows the performance of the ANN model for 15 neurons.

Figure 17a shows the MSE for training, testing, and validation, and the best MSE obtained is 0.86468 for validation and testing at 9 epochs. Similarly, Figure 17b depicts the r-squared values for training, testing, and validation and overall r-squared values in this model with 5 neurons were observed to be 0.96091, 0.95609, 0.97244, and 0.96216 respectively.

Figure 18a shows the MSE for training, testing, and validation and the best MSE obtained is 0.82732 for validation and testing at 4 epochs. Likewise, Figure 18b presents the r-squared values for training, testing, and validation

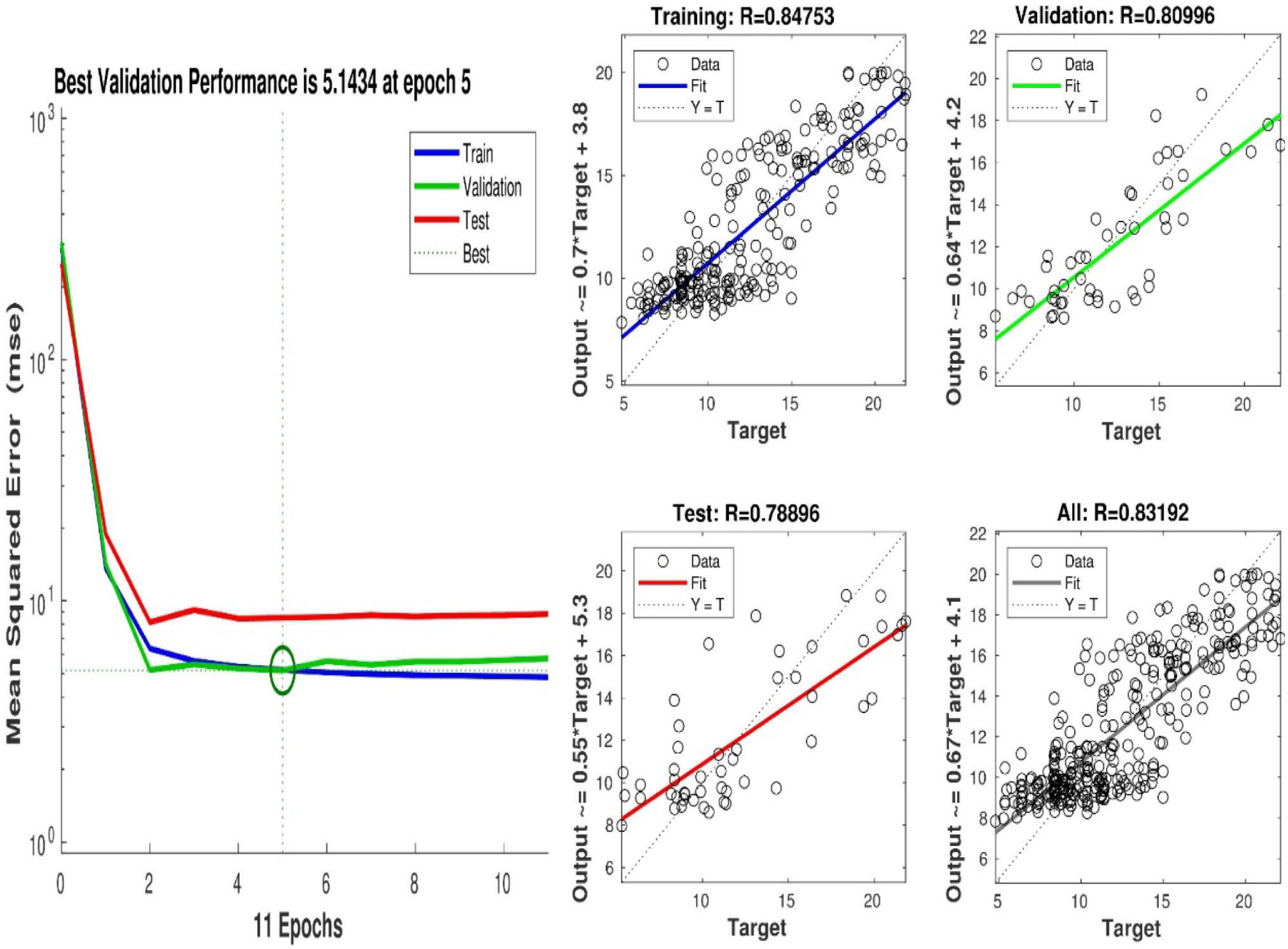

FIGURE 14. MSE and Regression for ANN model for PPD with 5 neurons.

and overall r-squared values in this model with 10 neurons were obtained to be 0.96337, 0.96507, 0.95743, and 0.962 respectively.

Figure 19a shows the MSE for training, testing, and validation and the best MSE obtained is 0.67959 for validation and testing at 5 epochs. Similarly, Figure 19b shows the r-squared values for training, testing, and validation and overall r-squared values in this model with 15 neurons were found to be 0.97347, 0.95364, 0.94899, and 0.96648 respectively.

IV. DISCUSSION

The proposed neural network model for forecasting the thermal comfort of the test room fitted with a TE-AD system has been developed to manage indoor temperature, PPD, and PMV. The training and validation of the model were performed using real experimental data that was collected for more than two months under real climatic conditions in Perak, Malaysia. The subject clothing value and metabolic rate were also considered as an input parameter for the ANN model. Numerous trials were carried out using different ANN models, and the results are summarized in Section 3. As per the outcomes, only one ANN model based on the Levenberg–Marquardt (LM) training algorithm could achieve the anticipated error rate; the remaining models failed to achieve it. Although the models based on conjugate gradient training algorithms also possess great prediction capability for the current case study, the error rates obtained were above the threshold of 0.001. For this reason, further studies were conducted on models based on the Levenberg-Marquardt (LM) algorithm. The remaining part of the study was carried out for determining the most suitable transfer function and fixing the number of process elements in the hidden layer. One of the contributions of this study is to demonstrate the application of different learning algorithms for directly predicting the PPD, PMV, and indoor temperature of the test room. The air conditioning system used for controlling indoor climatic conditions was not the traditional air conditioner system but the TE-AD system, which was running at an optimum input power supply of 6A and 5V. The second contribution of this study is the prediction of the comfort of the subjects based on their metabolic rate, clothing value, and indoor climatic conditions. The model validation and its implementation demonstrate that the identified

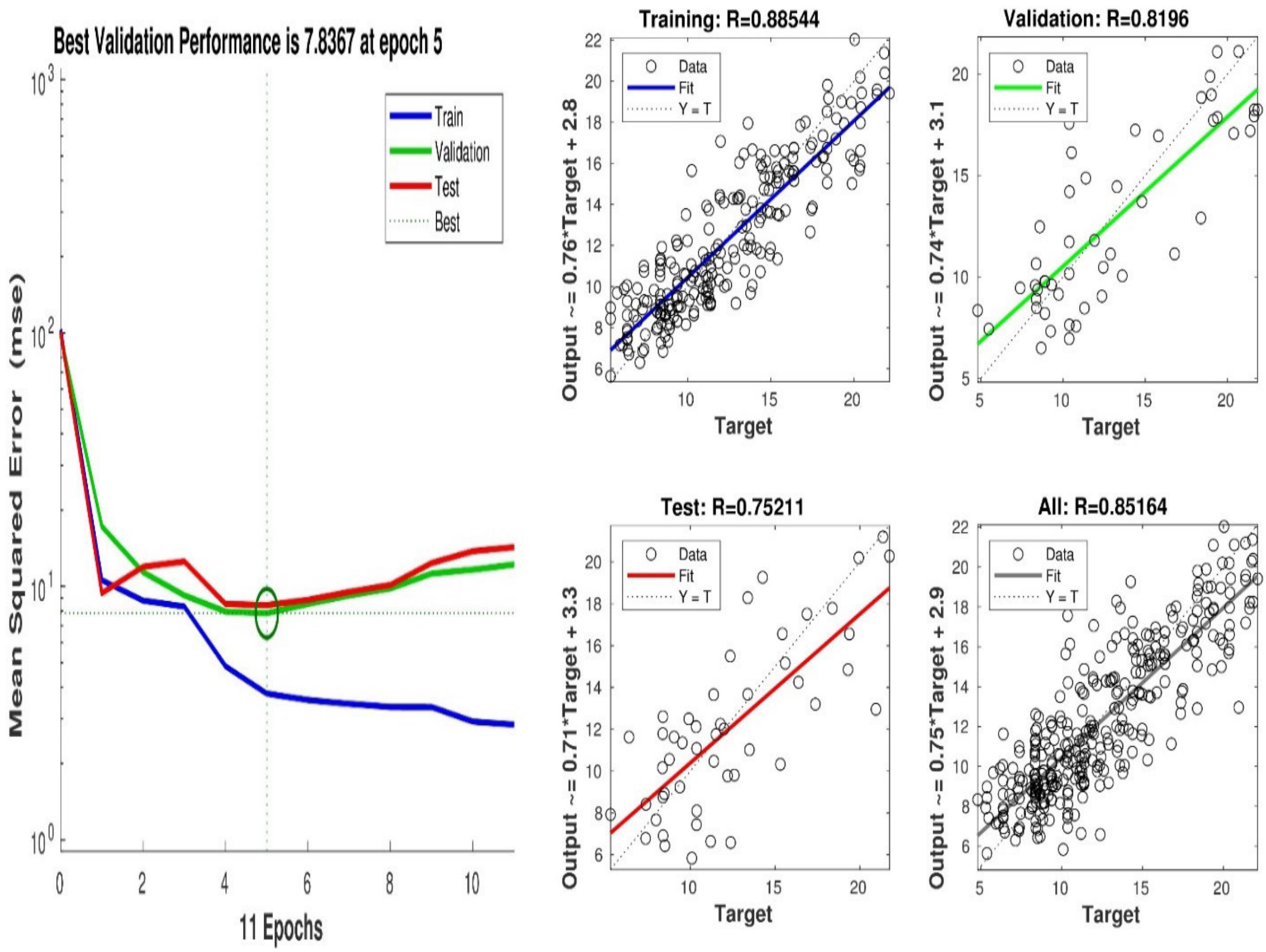

FIGURE 15. MSE and Regression for ANN model for PPD with 10 neurons.

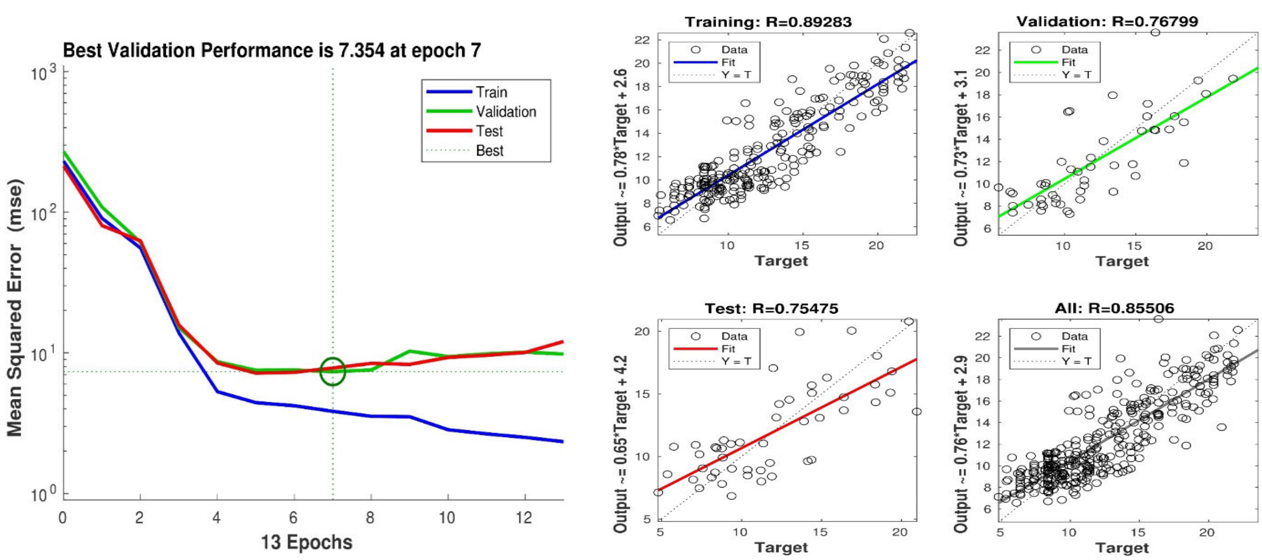

FIGURE 16. MSE and Regression for ANN model for PPD with 15 neurons.

predictive model is ideal to predict thermal comfort levels. Moreover, it is essential to highlight that the identified predictive models are accurate for environmental conditions identical to these test conditions. This study will provide a baseline model for the prediction of the comfort of occupants placed in a TE-AD system without

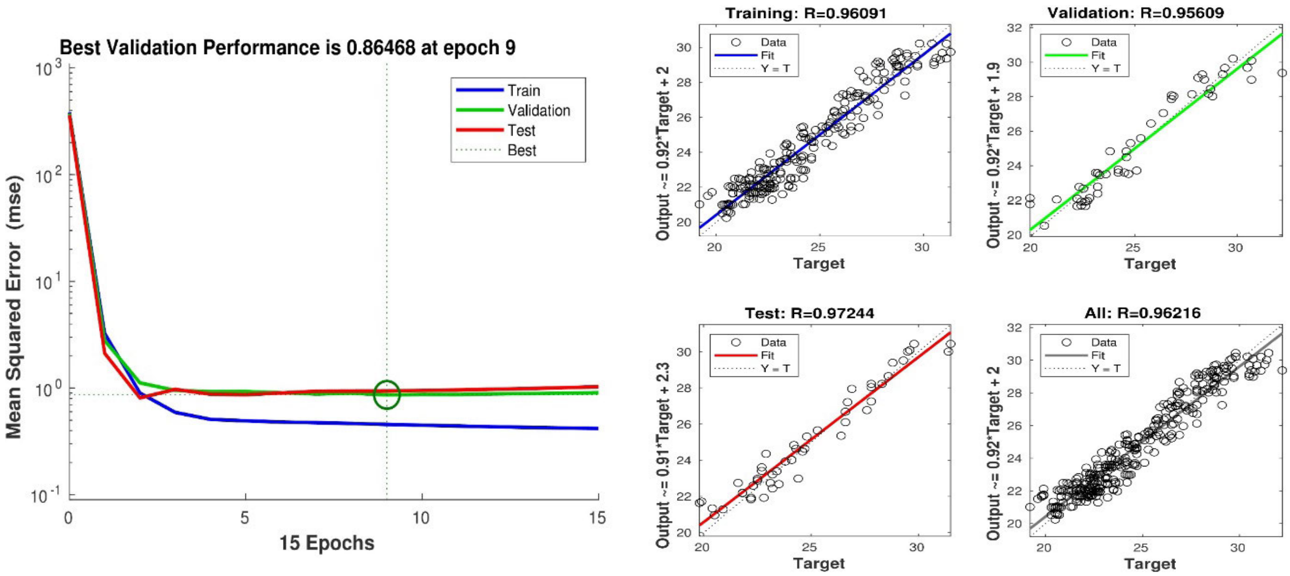

FIGURE 17. MSE and Regression for ANN model for Indoor Temperature with 5 neurons.

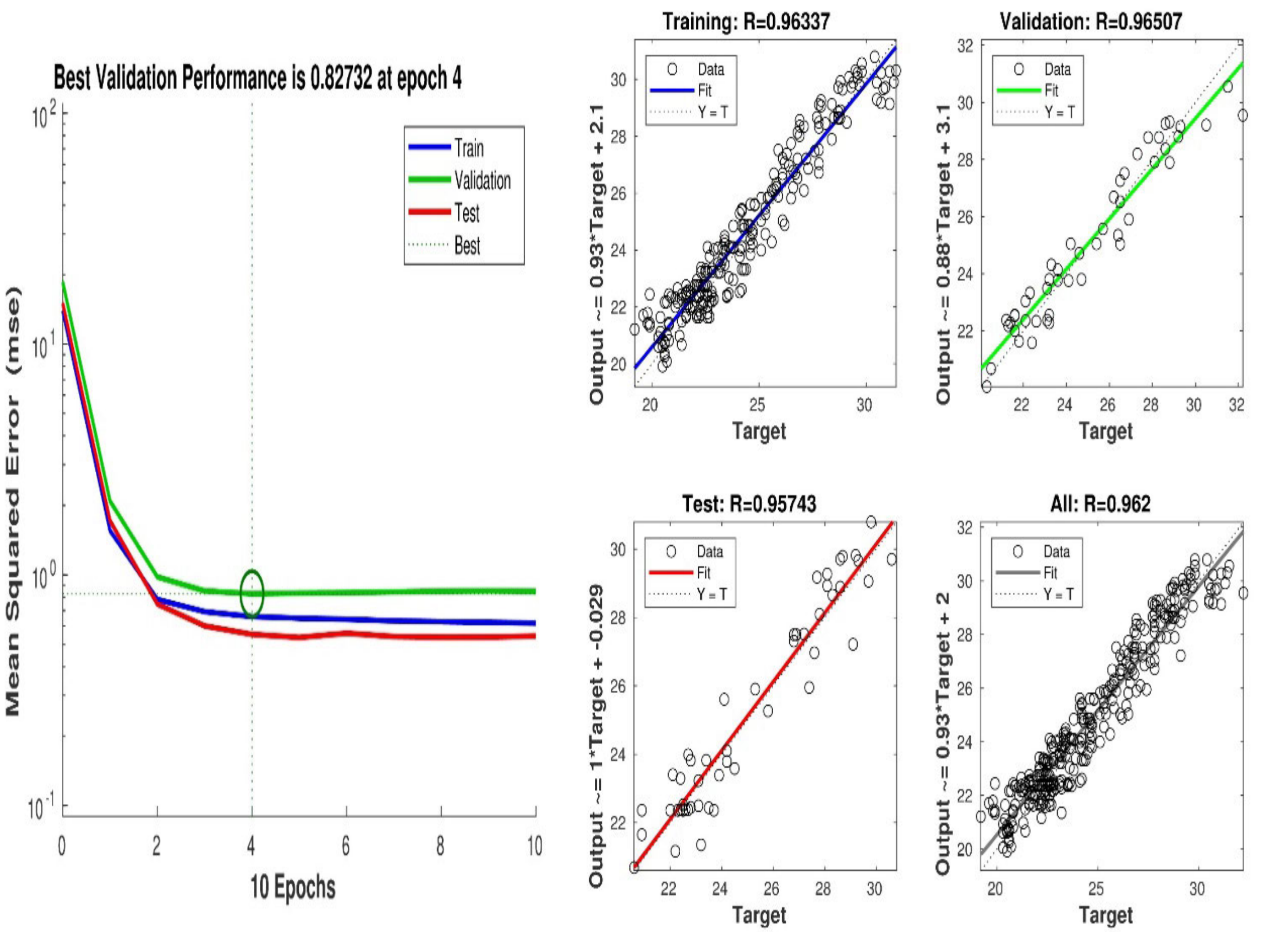

FIGURE 18. MSE and Regression for ANN model for Indoor Temperature with 10 neurons.

performing actual tedious experimental tasks. The thermal comfort of occupants having similar demographic and climatic conditions can be easily predicted without performing subjective analysis.

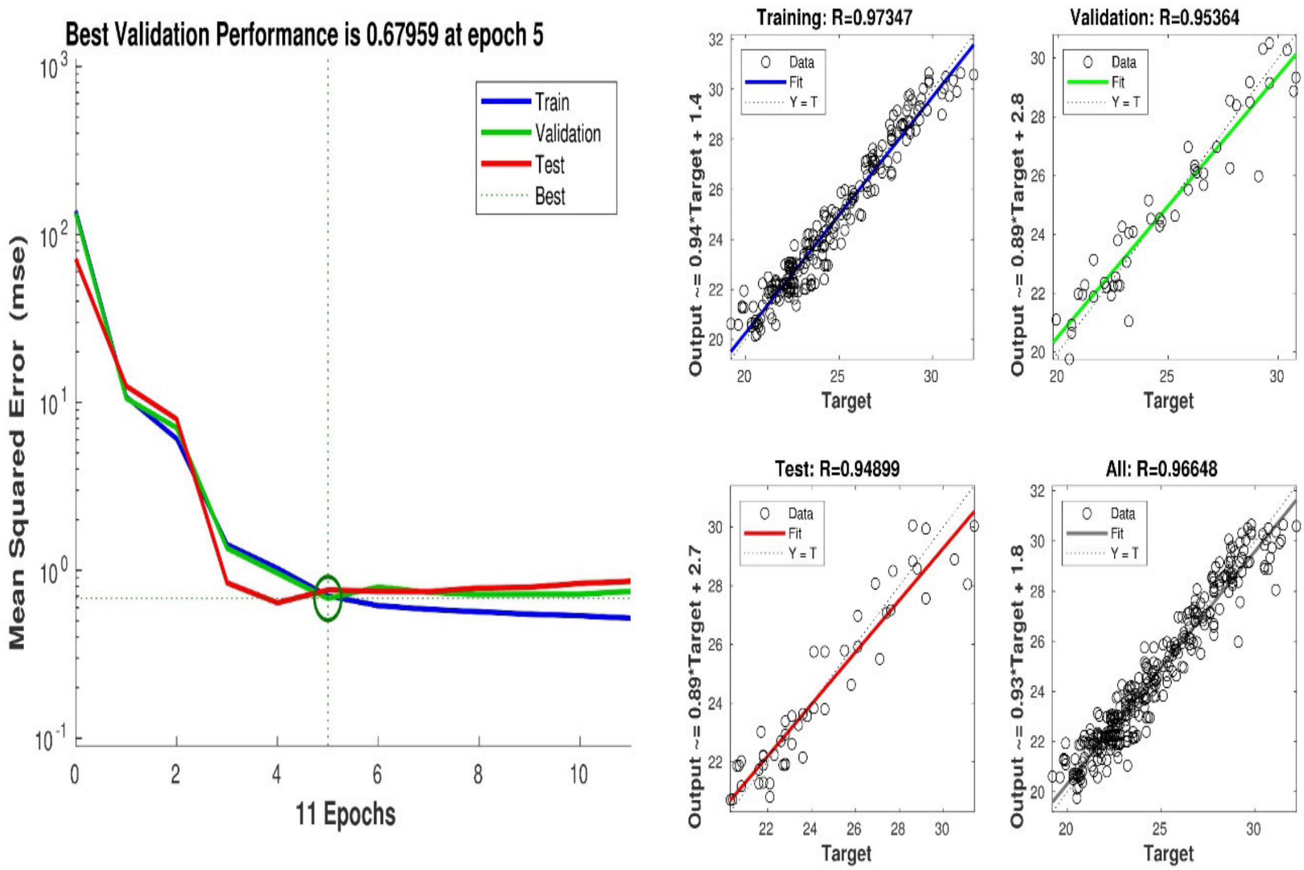

FIGURE 19. MSE and Regression for ANN model for Indoor Temperature with 15 neurons.

V. CONCLUSION

In the current study, a neural network-based intelligent prediction of thermal comfort was made for a real case study of subjects occupying a test room fitted with a thermoelectric air duct (TE-AD) cooling system. The proposed model was applied to predict indoor temperature, PPD, and PMV value for a test room located in Universiti Teknologi PETRONAS, Malaysia. All input and output parameters of the model were determined for this case study. Data were collected during eight-hour experiments for more than two months of hot and humid climatic conditions. A MATLAB based model has been employed for generating suitable datasets for the training and testing of the neural network model. Numerous models were tested and their parameters successfully tuned to identify the best performing ANN model. As per the outcomes, the ANN model based on the Levenberg–Marquardt algorithm was found to be the best performing model. Further, the parameter tuning was achieved on the basis of selected transfer functions and process elements. The prediction ability of the generated neural network models was assessed with a new dataset. For the PMV model, the best results have been obtained at 10 neurons with an MSE of 0.07956 for model M1, and in the case of the PPD model, the best results have been obtained with model M3 at an MSE value of 5.1789 at 10 neurons. In the case of indoor temperature, the best and optimized results have been obtained with model M3 with 15 neurons at an MSE of 0.68959. These models have been used for the calculation of future values for 1-month data. Although the performance of all the models was satisfactorily examined with an unused dataset, the results obtained with the Levenberg-Marquardt (LM) algorithm model showed unmatched performance.

NOMENCLATURE

RH	Relative Humidity (%)
PMV	Predictive Mean Value
PPD	Predicted Percentage of Dissatisfied
HVAC	Heating, Ventilation, and Air Conditioning
ANN	Artificial Neural Network
COP	Coefficient of Performance
TEM	Thermoelectric Module
TE-AD	Thermoelectric Air Duct
MRT	Mean Radiant Temperature, (°C)
MLP	Multilayer Perceptron
MSE	Mean Square Error
M	Model
LM	Levenberg-Marquardt

SYMBOLS

Clo	Clothing and Thermal Insulation
R	Linear Function
v	Uncertainty in Measured Value
T_in	Indoor Temperature, (°C)
T_a	Ambient Temperature, (°C)
T_c	Cold Side of Thermoelectric Module, (°C)
T_H	Hot Side of Thermoelectric Module, (°C)
Y(k)	Output Value
u(k)	Input Value
h	Hidden Neurons
n	Normally Distributed Variable
w	Weights
b	Biases
W	Weight Vector
x	Variable
J	Error Function

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