

## ESTIMATION OF INDOOR RELATIVE HUMIDITY USING ANFIS AND BPNN: A CASE STUDY FROM ESKISEHIR, TURKEY

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**Abstract:** Evaluation of building energy efficiency necessitates systematically designed experimental studies since the design parameters should be validated with real life data. In this scope, it is a well known fact that indoor thermal comfort conditions are thoroughly important for design. However, collection of data may be time-consuming and expensive. Because necessary data is collected after construction of the building, determination or prediction of these parameters can be useful in design stage. These parameters can also be used for back-calculation of energy efficiency parameters. In this study, adaptive neuro-fuzzy inference systems (ANFIS) and back-propagation neural networks (BPNN) were employed to predict the indoor thermal comfort conditions. Data used in this study is collected from a residential building in Eskisehir, Turkey. Three hobo dataloggers were placed in three rooms of different locations in the building. The data concerning indoor temperature, relative humidity and dew point was systematically collected. A novel approach was adopted in evaluation of data: data collected from two rooms were used for prediction of relative humidity in the third room. It was concluded that ANFIS and BPNN are useful tools for estimating indoor thermal comfort conditions using data collected from same environment.

**Key words:** thermal comfort; residential building; ANFIS; BPNN

## ПРОЦЕНА НА РЕЛАТИВНА ВЛАЖНОСТ НА ВНАТРЕШЕН ПРОСТОР СО УПОТРЕБА НА МОДЕЛИТЕ ANFIS И BPNN: СТУДИЈА ЗА СЛУЧАЈ ОД ESKISEHIR, ТУРЦИЈА

**Апстракт:** За оценувањето на ефикасноста на електричната енергија во зградите е потребно да се направат систематски осмислени експериментални студии, бидејќи параметрите на проектирање треба да бидат валидирани со податоци од реалниот живот. Во таа насока, добро познат факт е дека условите за топлински комфорт во затворен простор се многу важни за проектирањето. Сепак, собирањето на податоци може да одземе многу време и да биде скапо. Со оглед на тоа што потребните податоци се собираат по изградба на зградата, утврдувањето или предвидувањето на овие параметри може да биде корисно во фазата на проектирање. Овие параметри можат да се искористат и за пресметување назазад на параметрите на енергетската ефикасност. Во оваа студија беа користени моделите ANFIS (адаптивни невро-фазни системи) и BPNN (неврални мрежи со обратно распространување на грешката) за предвидување на условите на термален комфорт на внатрешен простор. Податоците користени во оваа студија се собрани од станбена зграда во Ескишехир, Турција. Три хобо уреди за прибирање на мерни податоци беа сместени во три соби на различни локации во зградата. Систематски беа собрани податоци за внатрешната температура, релативната влажност и точката на оросување. Беше усвоен нов пристап во оценувањето на податоците на податоците: податоците собрани од две соби беа употребени за предвидување на релативната влажност на третата соба. Се дојде до заклучок дека ANFIS и BPNN се корисни алатки за оценување на условите на топлински комфорт на внатрешен простор при користење на податоци собрани од истата средина.

**Клучни зборови:** топлински комфорт; станбена зграда; ANFIS; BPNN

## INTRODUCTION

Thermal comfort is an important issue for all buildings nowadays since expectations of occupants from indoor conditions are increasing. When thermal comfort is neglected during design, indoor environmental conditions can pose risk to human health in a long period [1]. Parameters related to indoor environment including relative humidity is essential for evaluation of thermal comfort in buildings. This parameter is frequently required in calculation of thermal comfort based on standards such as ASHRAE 55-2004 [2] and ISO 7730 [3]. It has also a significant influence on human physiological response and thermal sensation [4]. Most of the studies show that the relative humidity in indoor environments influences the incidence of respiratory infections and allergies [5]. In addition, it has a role in determination of climate control strategies in warm climates [6]. For that reasons, data concerning thermal comfort should be collected for different purposes. In this way, sophisticated instruments, simulation tools including EnergyPlus and DesignBuilder, calculation or prediction by mathematical models are alternative ways to collect valuable data.

## BACKGROUND

Several parameters (building material properties, geometrical information about building, weather data, indoor gains, etc.) are necessary for calculation of thermal comfort. For this aim, several studies on prediction of indoor environmental parameters by use of several methods such as back-propagation neural network (BPNN) and adaptive neuro-fuzzy inference system (ANFIS) was carried out. In this scope, Ghazali [1] developed a predictive model to forecast indoor environmental parameters using Artificial Neural Network (ANN) technique. Results indicated that twelve ANN models with the best structure were developed to predict indoor temperature, humidity and air velocity. Benjamin et al. [7] used a neural network for air quality prediction model in a sensitive area of Ujjain city in India. The best model was developed with minimum percentage error of 0.332. Thomas and Soleimani-Mohseni [8] defined different black-box prediction models for the indoor environment in two buildings. The results for both buildings showed that accurate temperature predictions were taken from non-linear ANN-models.

Based on the brief summary of past studies, a different approach was made. This study presents

an investigation into development of a suitable model using the BPNN and ANFIS that could be used to predict relative humidity in a room of residential building, based on measured data in two other rooms: indoor temperature, relative humidity and dew point per hour in addition months (June, July, August, and September). The results seem to be promising: these methods provided great benefits in prediction of relative humidity, using data from other structural divisions of different indoor and outdoor thermal conditions.

## MATERIALS AND METHODS

### *Climatic conditions of study area*

This study is carried out using data obtained in a residential building in Eskisehir city, Turkey. The city is located at 39.78 latitude and 30.52 longitude and 798 meters above sea level. In Eskisehir, annual average temperature is 10.9°C. The coldest month of the year is January with average temperature of -2°C. The coldest days and frost action are generally observed from second half of December till first half of February. The minimum temperatures range between -10°C and -25°C during this period. The hottest period is observed during June, July and August. The highest mean monthly air temperature is between 30°C and 40°C from July to August. Temperature differences between night and day are substantial, which ranges between 12°C and 29°C. Winter is snowy and rainy. Annual average precipitation is 378.9 kg/m<sup>3</sup> [9].

### *Information about building in consideration*

Selected building is a household located in Eskisehir (Figure 1). Its ground floor was built in 1956. Afterwards, first floor was reconstructed in 1980. Total floor area of household is 170 m<sup>2</sup>. It had no thermal insulation but it was renovated in 2004 and thermal insulation was applied on external walls with 4 cm XPS then roof was treated with glass wool of 10 cm thickness. Temperature, relative humidity and dew point temperature were measured in entrance, living room, and buffer zone of first floor with HOBO RH/Temp/Light/External data logger during the five months (06 June 2009 – 25 September 2009) at intervals of 5 minutes. The measuring accuracy of HOBO data logger is ±0.7 °C for temperature and ±%5 for relative humidity. Data loggers are placed on the walls at a height of 1.5 m from the ground. Living conditions in house during the measurement were not restricted to reflect real life situation.

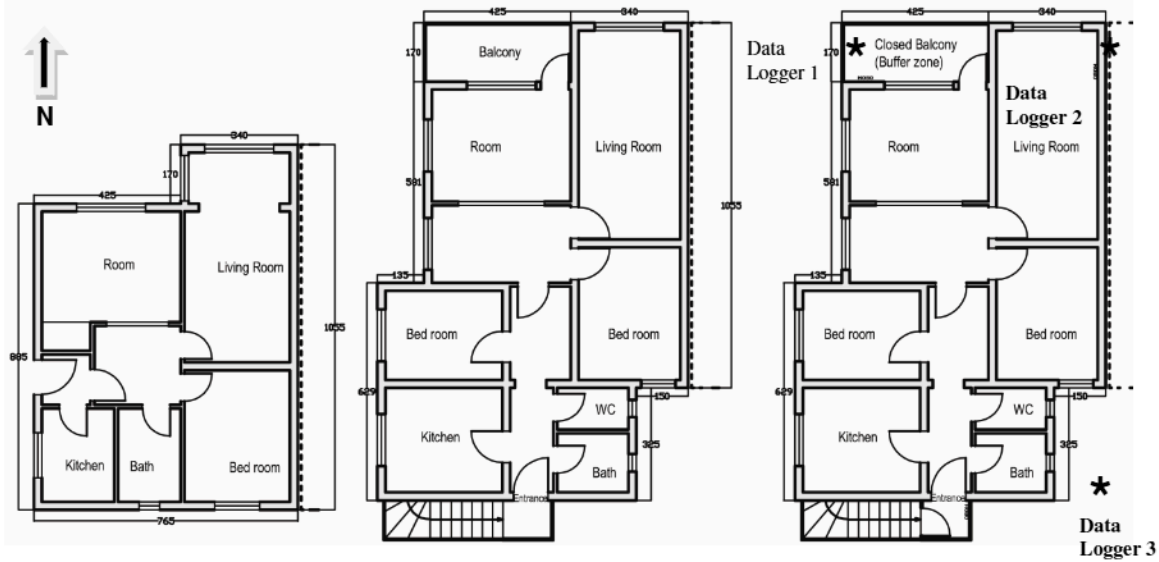


Fig. 1. Floor plans of selected building including locations of data loggers [10].

**SOFT COMPUTING METHODS FOR PREDICTIVE PURPOSES**

Two well-known methods, namely BPNN and ANFIS are employed to estimate the relative humidity. A short description of the methods are given below.

*Back-propagation neural networks*

Artificial neural networks were firstly introduced in 1943 by McCulloch and Pitts [11]. The idea behind these networks was constituting a mathematical model similar to parallel data proc-

essing and learning ability of neurons in human brain. Basically, an artificial neural network constitutes a nonlinear relationship between multidimensional input and output spaces. These networks are widely used for clustering, optimization, simulation and prediction purposes [12]. Several methods are available for learning in an artificial neural network including competitive learning, Boltzmann learning and back propagation learning algorithms. Multi layer back propagation neural networks (BPNN) are of the first choice, and Figure 2 shows a typical BPNN structure.

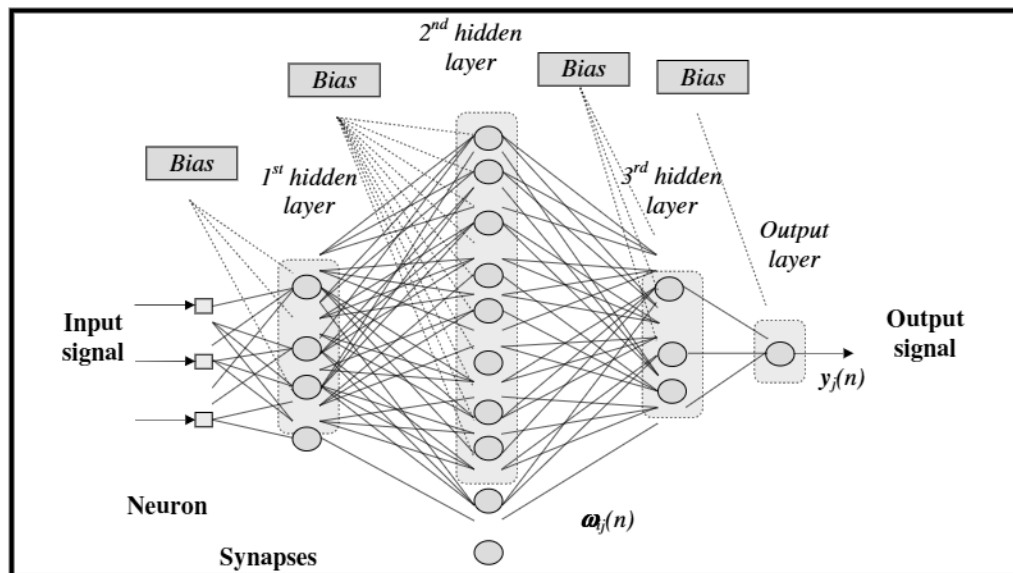


Fig. 2. A typical back propagation neural network structure.

During the learning process, input signal ( $x_j$ ) at all nodes are multiplied by synaptic weights ( $\omega_j$ ) after consecutive iterations, and the constant bias value ( $b_j$ ) is added to the result. The resulting value is filtered using a transfer function ( $\phi$ ), for calculation of the output of that neuron. Among all the transfer functions, the most frequently used are logistic and hyperbolic tangent. Mathematically speaking, the output of a neuron can be calculated as:

$$y_j = \phi \left( \sum x_j w_{ji} + b_j \right). \quad (1)$$

BPNN uses an iterative approach adjust the weights and bias values, and an error energy function is used to end the iterations. In the last phase, trained network can be used to calculate the inputs for given outputs, for prediction or validation purposes.

*Adaptive neuro-fuzzy inference systems*

Adaptive neuro-fuzzy inference system (ANFIS), which was firstly introduced by Jang in 1993,

is another alternative for establishing nonlinear relationships between input and output space [13, 14]. In other words, this method is a quite reasonable tool for prediction. Basically, the method trains membership function variables using a hybrid learning algorithm composed of least squares method and back propagation gradient descent algorithm. As can be inferred from its name, the method utilizes a combination of neural network and fuzzy inference system. The method is based on the Takagi-Sugeno inference model [15]. ANFIS uses a hybrid learning algorithm to determine related parameters of Sugeno-type fuzzy inference systems. Based on Figure 3, for the first-order Sugeno fuzzy model, a typical rule set with two fuzzy if-then rules can be expressed as:

If  $x$  is  $A_1$  and  $y$  is  $B_1$  then

$$f_1 = p_1x + q_1y + r_1 \quad (2)$$

If  $x$  is  $A_2$  and  $y$  is  $B_2$  then

$$f_2 = p_2x + q_2y + r_2 \quad (3)$$

Weighted averages of the individual rule outputs are used to calculate output  $f$ . Details of the calculation procedure can be found elsewhere [16].

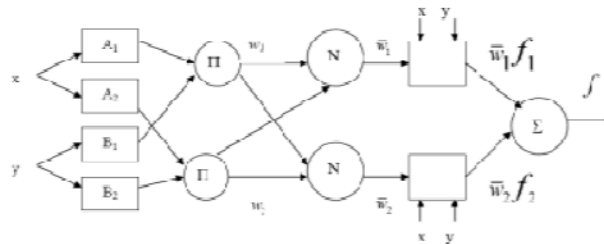


Fig. 3. A typical Sugeno ANFIS structure [15].

RESULTS

ANFIS and BPNN were used to model the data obtained from three data loggers. Temperature, dew point and absolute humidity were selected as inputs and relative humidity was selected as the output. A different approach was adopted here: we used three data loggers located in different positions of the same level and the data obtained from two (Hobo1 and Hobo2) are used to question if the recordings obtained from third one (Hobo3) can be predicted or not. Acquired in a certain period, 57354 recordings were obtained by Hobo1 and Hobo2, and this data is used for training. 28677 recordings were obtained by Hobo3, and this data is used for testing the performance of established ANFIS and BPNN structures.

A simple architecture of 3×10×1 is selected for NN model. It should be noted that, the data obtained from hobo3 is divided into two parts for validation and testing. Mean squared error (MSE) calculated during training is given in Figure 4. It should be noted that, the MSE value calculated here is extremely low, and this will boost up to success of the NN architecture, although a very low number of hidden neurons is selected. Besides, error histogram comprising a statistical approach to the difference among targets and outputs are given in Figure 5. It is clear that, the targets are concentrated at a very narrow range in the vicinity of zero.

The scatter plots considering training, validation, testing and all data sets are given in Figure 6. It is clear that there underlies an almost perfect

relationship among input and outputs and this extremely simple architecture can map the relationship among inputs and outputs. MSE values calculated from training, validation and testing data sets are  $1.55 \times 10^{-3}$ ,  $1.83 \times 10^{-3}$  and  $2.29 \times 10^{-3}$ , respectively.

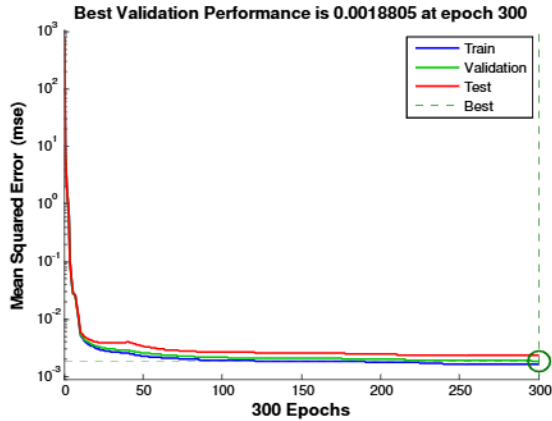


Fig. 4. Mean squared error obtained during training.

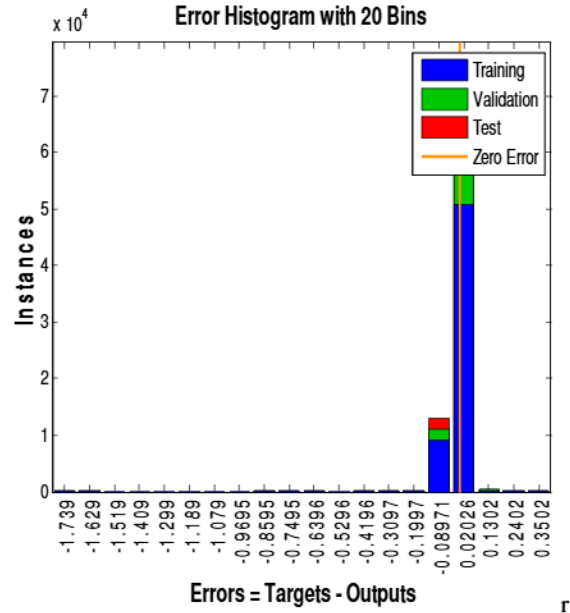


Fig. 5. Error histogram

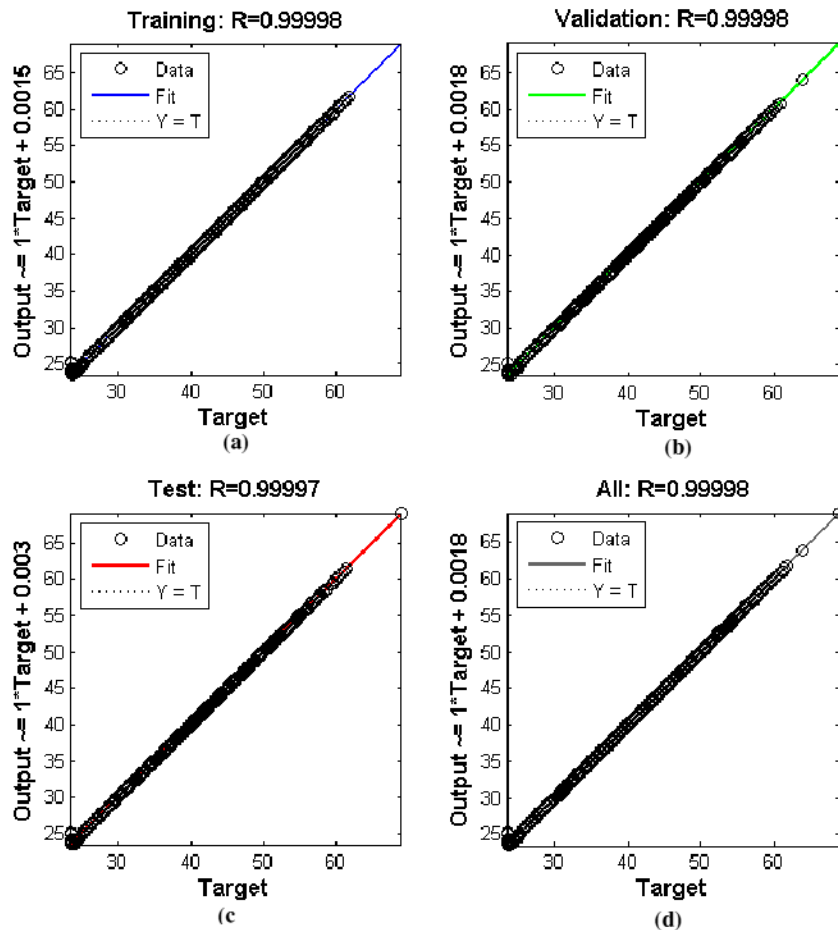


Fig. 6. Regression approach to simulated and real values of relative humidity. a) Training; b) Validation; c) Testing; d) All data

A Sugeno-type fuzzy inference system was designated (Figure 7). In Figure 7, inputs 1, 2 and 3 and output are temperature, dew point, absolute humidity and relative humidity, respectively. The

input parameters were instructed to this inference system and obtained relative humidity values were compared with actual relative humidity values.

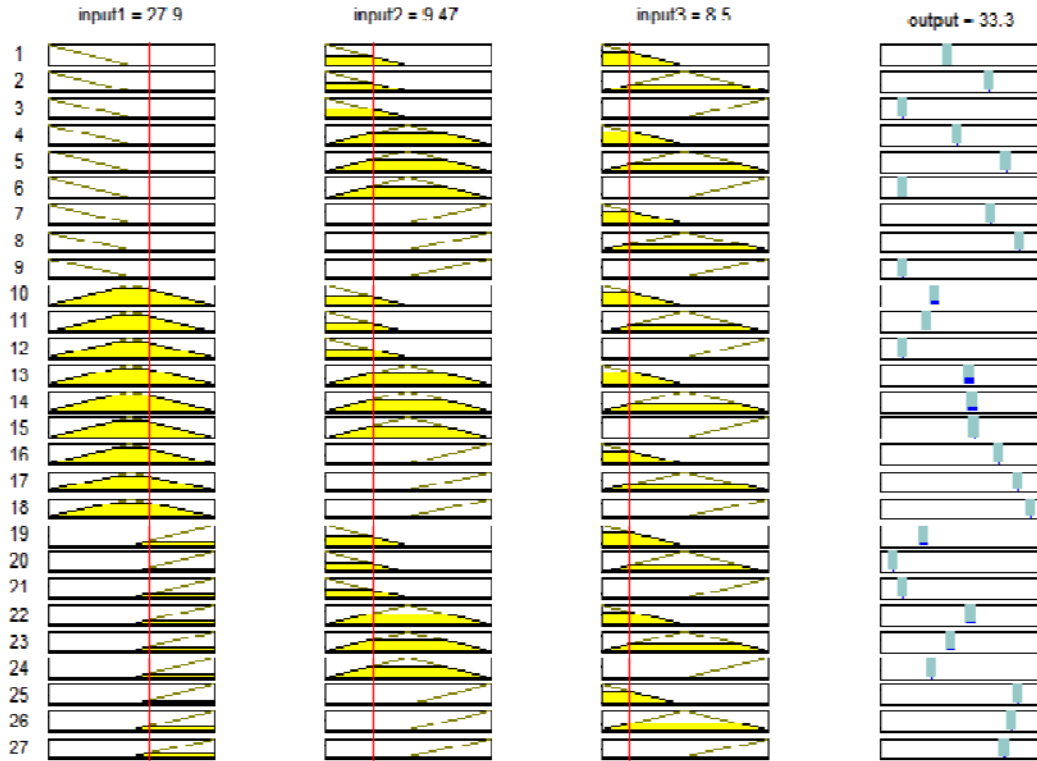


Fig. 7. Sugeno type inference system with three inputs (input 1: temperature, input 2: dew point; input 3: absolute humidity; output: relative humidity)

Comparisons of ANFIS outcomes and actual values of uncompensated relative humidity are given in Figure 8. ANFIS almost perfectly models the uncompensated relative humidity parameter.

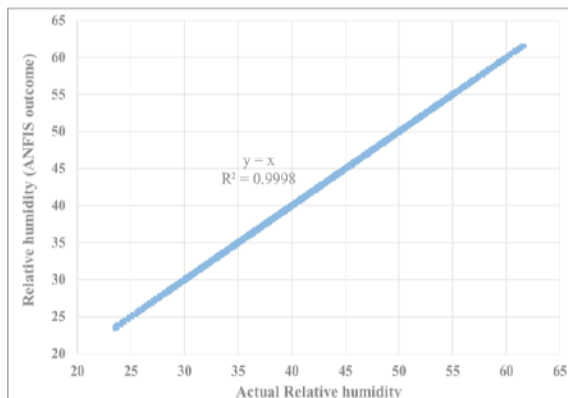


Fig. 8. The scatter plot and linear trend line describing the relationship between real and ANFIS outcomes of relative humidity

## CONCLUSIONS

In this study, ANFIS and BPNN are employed to model the uncompensated relative humidity value by use of temperature, dew point and absolute humidity parameters. A different approach was adopted: Using data obtained from two data loggers located in two different locations at the same level, relative humidity data on the third logger was predicted using soft computing techniques. Following are the outcomes of this study:

1. Performances of ANFIS and BPNN were superior in prediction of the relative humidity parameter. The scatter plots among calculated and real values concluded coefficient of determination ( $R^2$ ) values greater than 0.99.

2. Relative humidity parameter can be estimated using the data obtained from a single data logger or different data sources may be used for prediction of this parameter, for a specific building.

3. The results of this study should be improved using data obtained from different buildings under different climatic conditions.

## REFERENCES

- [1] GHAZALI S. B.: *Prediction of indoor environmental parameters for naturally ventilated building using artificial neural Network: a reflection of outdoor parameters*. Master thesis. Faculty of Civil and Environmental Engineering, Universiti Tun Hussein Onn Malaysia, 2015.
- [2] ANSI / ASHRAE Standard 55 – 2004: Thermal environmental conditions for human occupancy (2004).
- [3] ISO 7730, Moderate thermal environments – Determination of the PMV and PPD indices and specification of the conditions for thermal comfort, International Organization for Standardization, 1994.
- [4] Li B., Tan M., Liu H., Ma X., Zhang W.: Occupant's perception and preference of thermal environment in free-running buildings in China. *Indoor Built Environ*, **19** (4), 405 (2010).
- [5] Alsmo T., Alsmo C.: Ventilation and relative humidity in Swedish buildings. *J of Env. Protect*, **5**, 1022 (2014).
- [6] Li B., Yu W., Liu M., Li N.: Climatic strategies of indoor thermal environment for residential buildings in Yangtze River Region, China. *Indoor Built Environ*, **20** (1), 101 (2014).
- [7] Benjamin N., Sharma S., Pendharker U., Shrivastava J. K.: Air quality prediction using artificial neural network. *Int J Chem Stud*, **2** (4), 07 (2014).
- [8] Thomas B., Soleimani-Mohseni M.: Artificial neural network models for indoor temperature prediction: investigations in two buildings. *Neural Comp App*, **16**, 81 (2007).
- [9] Eskisehir Chamber of Industry: Organized Industrial Zone. [http://www.eosb.org.tr/eng/social\\_indicators/climate\\_2.html](http://www.eosb.org.tr/eng/social_indicators/climate_2.html). (2016).
- [10] Yildiz Y., Özbalta T. G., Eltez A.: Energy-Saving Retrofitting of Houses in Cold Climates, *J. of Thermal Sci Techn*, **34** (1), 53 (2014).
- [11] McCulloch W. S., Pitts W.: A logical calculus of the ideas immanent in nervous activity, *Bull Math Biophysics*, **5**, 115 (1943).
- [12] Haykin S.: *Neural Networks, A comprehensive foundation*, 2<sup>nd</sup> Ed., Prentice-Hall, New Jersey, 1998.
- [13] Jang J. S. R.: Anfis: Adaptive-network-based fuzzy inference systems. *IEEE Trans Syst Man Cybernetics*, **23**, 665 (1993).
- [14] Jang J. S. R., Sun C. T.: Neuro-fuzzy modeling and control. *Proceedings of the IEEE*, **83**, 378 (1995).
- [15] Takagi T., Sugeno M.: Fuzzy identification of systems and its applications to modeling and control, *IEEE Trans Syst Man Cybernetics*, **15** (1), 116 (1985).
- [16] Inan G., Goktepe A. B., Ramyar K., Sezer A.: Prediction of sulfate expansion of PC mortar using adaptive neuro-fuzzy methodology, *Build Environ*, **42** (3), 1264 (2007).