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Application of Artificial Neural Network for Predicting the Indoor Air Temperature in Modern Building in Humid Region

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Research Article

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ABSTRACT

This work was aimed to apply the artificial neural network (ANNs) for predicting indoor air temperature in modern building, seven hours in advance in humid region, using as inputs only the outdoor air temperature and the last six hourly values of indoor air temperature. The building experiment is built with cement hallow block in the town of Douala in Cameroon, and the experimentation was carried out for six months. Experimental data were used to determine the optimal ANN structure with Levenberg-Marquardt algorithm by using Matlab software. The optimal structure was the multilayer perceptron (MLP) with seven input variables, thirty hidden neurons and one neuron in the output layer. The activation functions were respectively the hyperbolic tangent in the hidden layer and the linear function in the output layer. Moreover, the indoor air temperature results simulated by using the developed ANN model were strongly correlated with the experimental data. These results testified that ANN can be valuable tool for hourly indoor air temperature prediction in particular and others indoor air parameters of building, such as relative humidity, cooling loads.

Keywords: Artificial neural network; building indoor air temperature; MATLAB; thermal behavior.

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1. INTRODUCTION

The mathematical description of thermal behavior of building systems is complex since it involves the modeling of several interconnected subsystems, each one containing long-time constants, non-linearities and uncertainties such as convection coefficients, building material properties etc. Moreover, external unpredicted perturbations, i.e. outdoor air parameters (temperature, relative humidity), soil temperature, radiation effects and other sources of energy, such as people, illuminations and equipments, should also be taken into account (Mendes et al., 2003). The dynamic investigation of the unsteady heat transfer process has focused attention on the problem of the mathematical description. In principle, this knowledge may be obtained by much computational modeling. As an easier alternative, the experimental data may be used to find out a black-box model or an empirical correlation defining the system behavior. The limitation of this approach is that it requires assumption of the functional form of the proposed correlation (Masiuk, 2008). The popular approach to analyze the unsteady and steady heat transfer problems is associated with the availability of non-linear empirical modeling methodologies, such as neural networks, inspired by the biological network of neurons in the brain (Mc Culloch et al., 1943; Minsky et al., 1988; Tawfiq and EI-Amin, 1999; Huang-Chu et al., 2001; Teytaud, 2001; Ou and Achenie, 2005; Mba, 2009).

Artificial neural networks (ANNs), which are increasingly receiving attention in solving complex practical problems, are known as universal function approximators. They are capable of approximating any continuous nonlinear functions to arbitrary accuracy (Cybenko, 1989). Its applications are numerous in various fields including engineering, management, health, biology and even social sciences (Bauer, 1998; Diaz et al., 2001; Kalaitzakis et al., 2002; Imran et al., 2002; Topalli and Erkmen, 2003; Islamoglu, 2003; Gwo-Ching et al., 2004; Yalcinoz and Eminoglu, 2005; Lauret et al., 2008; Jassar et al., 2009). For the identification or analysis of heat transfer problems a neural network approach has been attempted by Thibault and Grandjean (1991), Christtofindes (2001), Alotaibi et al. (2004), Zdaniuk (2006), Ashforth-Frost et al. (1995) and Yilmaz and Atik (2007). Singh et al. (2007) used ANN for calculating thermal conductivity of rock. Many researchers used neural networks for improved performance of built environment (Kreider, 1995; Hepeworth, 2000). Alexiadis et al. (1998) used ANN for the prediction of wind speed at six locations on the islands of the South and Central Aegean Sea in Greece. Some works were carried out on the prediction of surface air temperature in particular and other weather parameters by Njau (1991, 1993). Imran et al. (2002) used ANN for the prediction of hourly mean values of ambient temperature 24 h in advance. This neural network is trained off-line using back propagation and batch learning scheme. The trained neural network is successfully tested on temperatures for years other than the one used for training. It requires one temperature value as input to predict the temperature for the following day for the same hour. Soleimani-Mohseni et al. (2006) used nonlinear ANN models to estimate the operative temperature in a building by using other measurable variables, such as the indoor air temperature, electrical power use, outdoor temperature, time of day, wall temperature and ventilation flow rate.

In the present report, we present an ANN-based approach for predicting the indoor air temperature of the modern building with cement hallow block envelope in humid climate, seven hours in advance, using as inputs only the outdoor air temperature value and the last six hourly values of indoor air temperature.

2. EXPERIMENTAL DETAILS

2.1 Climatic Conditions of Study Area

The work is carried out in the town of Douala, the economic capital of the republic of Cameroon, located at the heart of Africa. This town is 24 km from the sea, on the left bank of the Wouri and dominated by Mount Cameroon, West Africa's highest mountain (4095 m). Douala is situated at 09°44 longitude east and 04°01 latitude south. The height above the sea level is 5 m (Mélingui et al., 1987, 1993; Météo, 2006).

The ambient air temperatures do not vary by an extreme amount. Monthly average of maximum air temperatures during the day are between 27°C and 31.8°C and monthly average of daily minimum air temperature are between 22.4°C and 23.4°C. The highest of the mean maximum air temperatures reaches 31.8°C in February and the lowest of the mean minimum air temperatures is 22.4°C in October. The relative humidity remains constant throughout the year in the range of 68% to 98%. Solar radiation is high. The annual global radiation reaches 4065 kWh/m² per day. The prevailing wind comes from the southwest. It blows mostly between 1.8 and 3.0 meters per second. The precipitation is high. The rainfall reaches 4500 mm per year (Météo, 2006; Mélingui et al., 1987, 1993; Kemajou, 2007).

2.2 Experimental Building

The test building is a household in the town of Douala, built in 1999. The measurements of temperatures are carried out on a modern housing model. The windows are operable but usually remain closed. Building materials used for this housing are cement hallow block with cement coating for an envelope, and aluminium sheet for roofing, with a ceiling of plywood. The room height is 3 m. One bedroom of 15 m² is used to the experimentation.

Instrumentation was used to record the air temperatures in the experimentation area and the outside air temperature. The measurement apparatus was made of the following: a laptop computer equipped with the "DAQ Factory software for the "LABJACK" parameters; a data acquisition apparatus "LABJACK U3"; temperature sensors. Six temperature sensors are installed at the experimentation area. Temperatures are captured hourly for six months, then processed and stored in the computer with the data acquisition system.

2.3 Design Method of ANN Model

The design of ANN follows the method represented in figure 1 below. This method is the same used by Ammar (2007). According to this figure, the implementation of a neural network requires database, neural network architecture, the training algorithm and learning process. Concerning the database, the series of the 4032 experimental values of the two characteristic quantities were obtained, i.e. the outdoor air and the indoor air temperatures. The first month recorded temperatures is presented in figure 2.

The most popular form of ANN is the so called multilayer perceptron (MLP) structure. It has been proved that a multilayer perceptron with a single hidden layer including a sufficient number of neurons can approximate any function with the desired accuracy (Said, 1992; Imran et al., 2002). This structure is chosen.

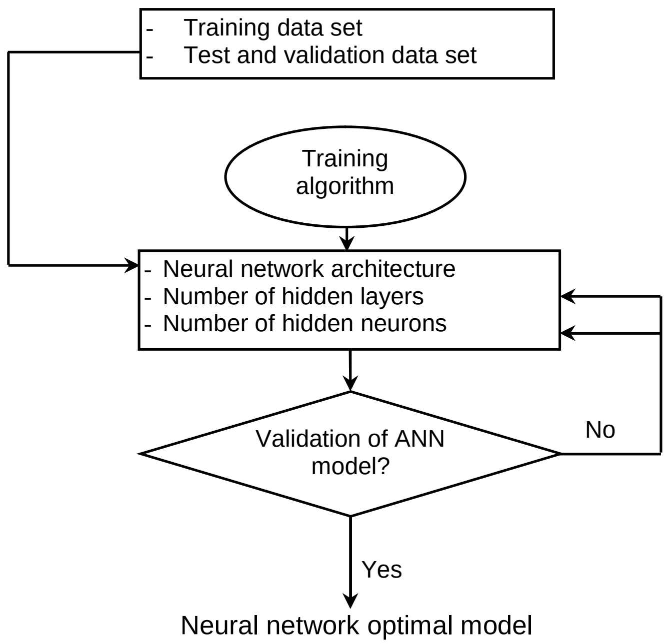

Figure 1: Design method of a neural network

The learning algorithm used is the Levenberg-Marquardt. It is the fastest and ensures the best convergence to a minimum of mean square error (MSE) for function approximation problems (Dreyfus et al., 2002; Rafic, 2006; Howard et al., 2007; Chaabani, 2008).

Table 1: Inputs and outputs of ANN model

Variables		Description
k		Hour
x_0	1	Bias
x_1	TAE (k)	Outdoor air temperature at time k
x_2	TAI (k-1)	Past value of indoor air temperature at time k-1
x_3	TAI (k-2)	Past value of indoor air temperature at time k-2
x_4	TAI (k-3)	Past value of indoor air temperature at time k-3
x_5	TAI (k-4)	Past value of indoor air temperature at time k-4
x_6	TAI (k-5)	Past value of indoor air temperature at time k-5
x_7	TAI (k-6)	Past value of indoor air temperature at time k-6
y_1	TAI (k)	Indoor air temperature at time k

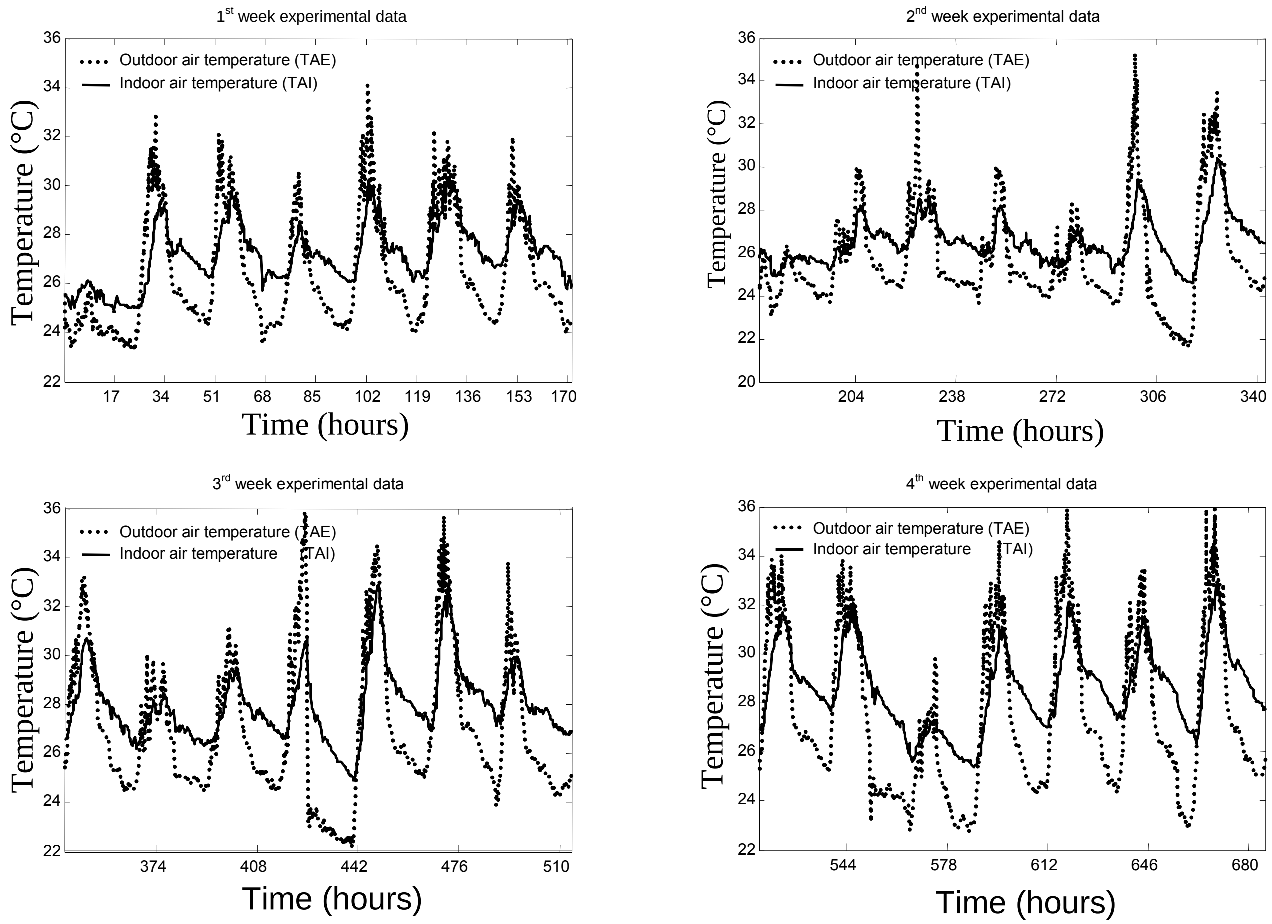

Figure 2: Experimental data for the 1st month

The MLP structure consists of one or several hidden layers and an output layer. The input layer gathers the model's input vector x while the output layer yields the model's output vector y . In our case, the input vector x is given by the hourly values of the variables x_0 to x_7 given in Table 1, and the output vector y consists of only one output y_1, which is the corresponding forecast of the next six hours.

Figure 3 represents the one hidden layer MLP adopted for this work.

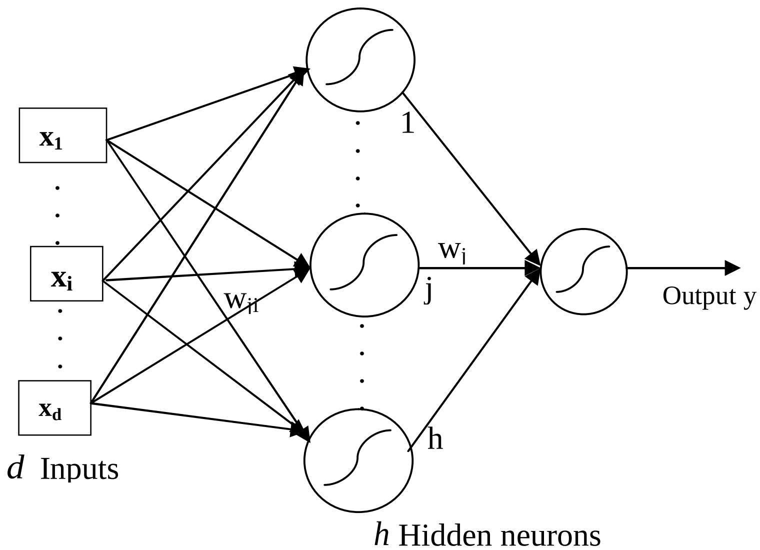

Figure 3: Sketch of a MLP with d inputs and h hidden neurons, in our case, d=7 (see table 1).

The hidden layer is characterized by several non-linear neurons. The non-linear function, i.e. the activation function is usually the tangent hyperbolic function $f(x) = \tanh(x)$. Therefore, an ANN with 7 inputs (see table 1), h hidden neurons and a single output unit defines a non-linear parameterized mapping from an input x to an output y given by the following relationship:

$$y = y(x, w) = \sum_{j=0}^{h} \left[w_j \cdot f\left(\sum_{i=0}^{7} w_{ji} x_i \right) \right], \tag{1}$$

The parameters of the ANN model are given by the weights and biases that connect the layers between them. The ANN parameters, denoted by the parameter vector w, govern the non-linear mapping.

There are two main steps to obtain the ANN optimal model: The learning phase and the generalization phase. During the learning phase, the ANN is trained using a training dataset of N inputs and output examples, pairs of the form $D = \{x_i, t_i\}_{i=1}^{N}$. The vector x contains samples of each of the seven input variables described in table 1. The variable t, also called the target variable, is the corresponding measurement of the temperatures. This phase consist of in adjusting w so as to minimize an error function J , which is usually the sum of square errors between the experimental output t_i and the ANN model output, $y_i = y(x_i;w)$:

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

The second phase is the generalization phase. It consists of evaluating the ability of the ANN to replicate the observed phenomenon, that is to say, to give correct outputs when it is confronted with examples that were not seen during the training phase. Notice that during the phase, the test and validation dataset are used. The performance measure is usually given by the mean square error (MSE):

$$MSE = \sum\left(\frac{e_i^2}{N}\right), \quad (3)$$

Or the root-mean-square error (RMSE):

$$RMSE = \sqrt{\sum\left(\frac{e_i^2}{N}\right)}, \quad (4)$$

The realization of an ANN requires a fairly rigorous methodology. In order to achieve this, a simulation code was developed through Matlab software for learning.

3. RESULTS AND DISCUSSION

Experimental data consisting of hourly indoor air temperature (TAI) and outdoor air temperature (TAE) values of a modern building were collected in humid climate: case of the town of Douala in Cameroon. The ANN model is trained with Levenberg-Marquardt algorithm by software developed using Matlab. The trained model is used to forecast hourly temperatures involving data other than those used for training. The developed model has been trained with 4032 experimental data pairs. Several MLP neural network structures are presented in table 2 below, where k is the discrete time.

Table 2: Number of input and output variables for each MLP structure studied

Cases	Output	Input variables
Case 1	TAI(k)	TAE(k), TAI (k-1), TAI (k-2), TAI (k-3), TAI (k-4), TAI (k-5), TAI (k-6)
Case 2	TAI(k)	TAE(k), TAI (k-1), TAI (k-2), TAI (k-3)
Case 3	TAI(k)	TAE(k), TAI (k-1)

In order to model the experimental data, the number of hidden neurons for each ANN structure presented in table 2 will be obtained by trial and error. So far, no mathematically justifiable method is available for determining the hidden elements. As explained by Haykin (1995), training is started with a minimum number of elements. The number of these elements is constantly increased and re-training of the ANN is continued until satisfactory training is considered as the optimal number. In our case, the root-mean-square errors (RMSE) of three datasets (training set, validation and test sets), of several examples of studied MLP neural network structures are calculated, and some of them, are shown in

Tables 3, 4 and 5. In these tables RMSEL, RMSEV and RMSET represent, respectively the RMSE for the training, the validation and the test sets.

Table 3: Values of RMSE of MLP structure of 90 hidden units for different test initialization parameters with two inputs

Test n°	1	2	3	4	5
RMSEL	7.0 e-0004	7.67e-0004	7.0e-0004	7.0e -0004	7.0e -0004
RMSEV	11.0e-0004	9.21e -0004	12.0e -0004	30.0e -0004	16.0e -0004
RMSET	11.0e-0004	8.51e -0004	9.0e -0004	16.0e -0004	24.0e -0004

Table 4: Values of RMSE of MLP structure of 60 hidden units for different test initialization parameters with two inputs

Test n°	1	2	3	4	5
RMSEL	8.29 e-0004	7.0e-0004	7.94e-0004	7.0e-0004	7.75e-0004
RMSEV	8.89e-0004	9.0e -0004	9.38e -0004	12.0e -0004	9.43e -0004
RMSET	7.91e-0004	10.0e -0004	9.45e -0004	20.0e -0004	7.43e -0004

Table 5: Values of RMSE of MLP structure of 30 hidden units for different test initialization parameters with two inputs

Test n°	1	2	3	4	5
RMSEL	8.0 e-0004	8.17e-0004	8.17e-0004	8.44e-0004	8.34e-0004
RMSEV	11.0e-0004	8.65e -0004	8.98e -0004	8.78e -0004	8.83e -0004
RMSET	10.0e-0004	8.04e -0004	9.27e -0004	9.91e -0004	6.97e -0004

The analysis of root-mean-square error (RMSE) in the tables shows the important effect of the initialization parameters, because for the same number of hidden neurons, RMSE are different by varying the initialization of weights and biases.

The criterion for choosing among these models is the root-mean-square error (RMSET) on the test dataset (Corriou, 1995; Dreyfus et al., 2002; Howard et al., 2007). Notice that MLP neural network structure with seven inputs, 30 hidden neurons with initial parameters corresponding to the test No. 3, has the smallest RMSET (9.27e -0004) with very good root-mean-square errors on the Learning set (8.17e-0004) and validation set (8.98e-0004). This model is the optimal model that allows the best approximation of the building indoor air temperature (TAI).

The comparison of ANN model and experimental results for temperatures are shown in Figure 4.

The results of graphics comparisons showed the similarities between experimental study and ANN model and supported reliability of the model.

The regression line of the output variable TAI for the experiment and ANN testing set is in Figure 5.

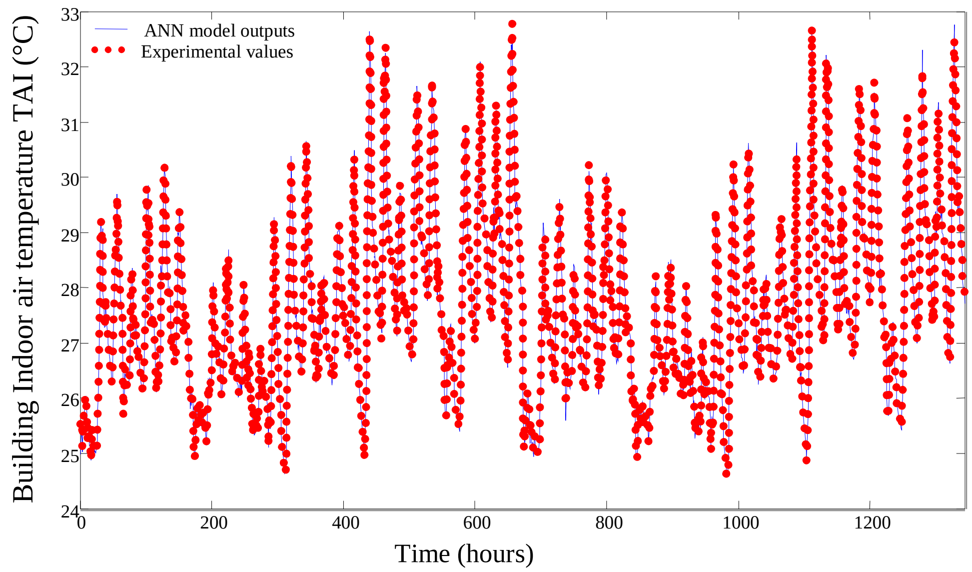

Figure 4: Comparison of experimental values and simulation results on testing data

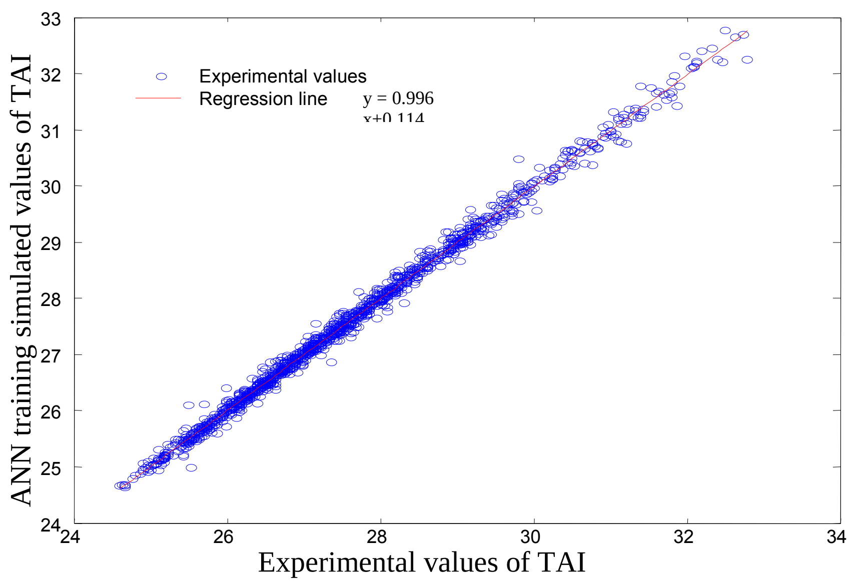

Figure 5: The relationship between experimental results and ANN training simulated values

According to this figure, the square correlation coefficient is $R^2 = 0.998$. As the correlation coefficients get closer to 1, estimation accuracy increases. The estimation results and experimental results are in a good agreement. The deviation between experimental and ANN simulation value is very small and negligible for TAI. This indicates that the obtained model can accurately estimate the modern building indoor air temperature in the humid climate.

4. CONCLUSION

This report presents an ANN used for modern building indoor air temperature prediction, seven hours in advance, in humid climate, using as inputs only the outdoor air temperature and the last six hourly values of indoor air temperature. The results of this investigation show that ANN can effectively model. It is understood that, ANN can be used for modeling of TAI. The biggest advantages of the ANN compared to classical methods are speed of calculations and capacity to learn from examples. In addition, in the building physics domain, the proposed model, compared to others does not require any thermodynamic properties of building materials, solar flux, wind speed, etc. Experimental data were compared with result obtained from ANN and all data were analyzed statistically. When analyses were assessed, value of results obtained from ANN was very close to the experimental results value and therefore, it was seen that the ANN might be used safely. ANN as an alternative method can be used to estimate the indoor air temperature of the building.

COMPETING INTERESTS

Authors have declared that no competing interests exist.

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