Simulation of thermal behavior of residential buildings using fuzzy active learning method

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Abstract
In this paper, a fuzzy modeling technique called Modified Active Learning Method (MALM) was introduced and utilized for fuzzy simulation of indoor and inner surface temperatures in residential buildings using meteorological data and its capability for fuzzy simulation was compared with other studies. The case studies for simulations were two residential apartments in the Fakouri and Rezashahr neighborhoods of Mashhad, Iran. The hourly inner surface and indoor temperature data were accumulated during measurements taken in 2010 and 2011 in different rooms of the apartments under heating and natural ventilation conditions. Hourly meteorological data (dry bulb temperature, wind speed & direction and solar radiation) were measured by a meteorological station and utilized with zero to three hours lags as input variables for the simulation of inner surface and indoor temperatures. The results of simulations demonstrated the capability of MALM to be used for nonlinear fuzzy simulation of inner surface and indoor temperatures in residential apartments.

Keywords: Modified Active Learning Method, fuzzy modeling, residential buildings, Mashhad, indoor temperature, inner surface temperature.

1 Introduction

Simulation of indoor temperature expresses the thermal behavior of buildings. Enough knowledge about thermal behavior of buildings can lead to understanding overall energy performance and optimization of energy consumption. In addition, it is necessary to predict and control indoor temperature for minimization of energy consumption. Therefore simulation of indoor temperature is a prerequisite in management and intelligent control of energy consumption in buildings.

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The indoor temperature in different rooms of a building is the result of complex interactive heat and mass exchange between the interior air and meteorological variables such as solar radiation, wind, air temperature and humidity. White-box (mechanistic, physical or mathematical) models are well known methods for the simulation of indoor temperature; nonetheless these modeling techniques are complicated and need various parameters which should be estimated by calibration and validation techniques. In addition, the models need particular parameters to be determined by experiment [1] such as radiation and convection coefficient, which require a special experimental set up. As a result, the application of white box models is limited for the majority of controlling approaches in energy consumption.

In recent years, employing computational intelligent techniques in miscellaneous applications of energy in buildings is increasing. The black-box and computational intelligent models have simple modeling procedures and are useful for indoor climate simulation when enough in-situ monitored data is available. Seginer et al. [2] and Kok et al. [3] utilized neural networks for greenhouse climate modeling. The ability of neural networks (NN) to model a greenhouse climate was demonstrated in this research. An auto-regressive model with external inputs (ARX) and auto-regressive moving average with external inputs (ARMAX) were utilized for modeling greenhouse temperature under natural ventilation conditions [1] and the indoor temperature of a school [4]. The models were suitable to describe the greenhouse temperature. Linker and Seginer [5] used NN, a hybrid of NN and a physical model for indoor temperature simulation in a greenhouse under HVAC (Heating, Ventilation & Air Conditioning) and found satisfactory results. ARX and neural network ARX (NNARX) were applied for indoor temperature simulation and the results showed that NNARX outperforms ARX [6, 7]. Similarly, Frausto and Pieters [8] utilized NNARX for greenhouse temperature modeling. NN was used for simulation of indoor temperatures in buildings [9, 10]. Thomas and Soleimani-Mohseni [11] compared some linear models (e.g. ARX and ARMAX) with NN for indoor temperature simulation in two buildings. NN showed better results than linear models. Reginato et al. [12] studied the application of the Orthonormal Basis Function (OBF) model for indoor temperature simulation. Alashaary et al. [13] investigated the ability of Adaptive Neuro-Fuzzy Inference System (ANFIS) for indoor temperature modeling in four representative thermal test buildings. They found that ANFIS is capable of indoor temperature modeling. The maximum, minimum and average indoor temperatures in two houses were predicted using some linear models [14]. Mustafaraj et al. [15] evaluated different linear models (ARX, ARMAX, Box-Jenkins (BJ) and Output Error (OE)) for the prediction of the indoor temperature of an office in a modern commercial building. The results demonstrated that all of the investigated linear models provide reasonably appropriate predictions.

One of the computational intelligent techniques is the fuzzy [16] modeling method, which is similar to the human modeling and calculation method and avoids mathematical complexities during the modeling procedure. Although different powerful fuzzy modeling methods have been developed and applied for miscellaneous engineering problems until now (e.g. Mamdani [17]; Takagi and Sugeno [18]; Sugeno and Yasukawa [19]; Tanaka and Sano [20]; Otsubo et al. [21]), the fuzzy models were rarely utilized for indoor temperature simulation and prediction. Bagheri Shouraki and Honda [22] developed a fuzzy modeling technique entitled Active Learning Method (ALM). Taheri Shahrainyi [23] developed new heuristic search, fuzzification and diffuzification methods for the ALM algorithm, and presented a new fuzzy modeling technique entitled Modified Active Learning Method (MALM).

Up until now, MALM has not been utilized for thermal behavior simulation of buildings. In this study, MALM was introduced, utilized and evaluated for the simulation of inner surface and indoor temperature of two residential buildings using meteorological data. That means that only meteorological data were utilized as input variables and the inner surface and indoor temperatures in different rooms of the residential buildings were considered as output variables.
2 MALM

The modeling procedure using MALM is explained here step by step.

Step 1.
Database preparation: Imagine the system under investigation has \( n \) input variables \( (X = \{X_1, \ldots, X_n\}) \) and one output variable \( (Y) \). A database \( (D) \) containing input-output variables is prepared Eq. (2.1).

\[
D = \{ (x_k^m, y^m) \}, m = 1, \ldots, M, k = 1, \ldots, n
\]  

(2.1)

Where, \( x_k^m \) is the \( m \)th member of the \( k \)th variable \( (X_k) \) \( (x_k^m \in X_k \) and \( X_k \in X \) \), \( y^m \) is the \( m \)th member of \( Y \) and \( M \) is the total number of observations.

Step 2.
Dividing the database: Each database must be divided into two smaller databases. In the first iteration of the MALM modeling procedure, there is only one database \( (D) \) and it is divided into two smaller databases. In general, a generated database is expressed as \( D_{qs}^{d,q} \) and it is the \( q \)th database in the \( d \)th iteration and it has been generated by dividing the \( k \)th variable of a bigger database. The bigger database has been divided into two parts (\( s \in \{1,2\} \)) and this database is the \( s \)th part.

When any of the input variables \( (X_k) \) are divided into two parts, then \( D \) is divided into two sub-databases \( (D_{k1}^{11}, D_{k2}^{12}) \). \( D_{k1}^{11} \) and \( D_{k2}^{12} \) are the databases generated by dividing the \( k \)th variable in the first iteration.

\[
D = \{ D_{k1}^{11}, D_{k2}^{12} \}
\]  

(2.2)

\[
D_{k1}^{11} = \{(x_1^t, y^t), t = 1, \ldots, Q^1; l = 1, \ldots, n \text{ if } X_k \leq T_{k1}^{11} \} \tag{2.3}
\]

\[
D_{k2}^{12} = \{(x_1^t, y^t), t = 1, \ldots, Q^1; l = 1, \ldots, n \text{ if } X_k \geq T_{k2}^{12} \} \tag{2.4}
\]

Where, \( Q^1 \) is the number of observations in each database.

In the second iteration, \( D_{k1}^{11} \) is divided into two smaller databases \( (D_{k1}^{21}, D_{k2}^{22}, k' \in \{1, \ldots, n\}) \). Similarly, \( D_{k2}^{12} \) is divided into two smaller databases \( (D_{k1}^{23}, D_{k2}^{24}, k' \in \{1, \ldots, n\}) \). \( D_{k1}^{21} \) and \( D_{k2}^{22} \) are the databases generated by dividing the \( k' \)th variable of \( D_{k1}^{12} \) in the second iteration.

\[
D = \{ D_{k1}^{21}, D_{k2}^{22}, D_{k1}^{23}, D_{k2}^{24} \}
\]  

(2.5)

\[
D_{k1}^{21} = \{(x_1^{t'}, y^{t'}), t = 1, \ldots, Q^2, l = 1, \ldots, n \text{ if } (X_k \leq T_{k1}^{11} \& X_{k'} \leq T_{k1}^{21}) \} \tag{2.6}
\]

\[
D_{k2}^{22} = \{(x_1^{t'}, y^{t'}), t = 1, \ldots, Q^2, l = 1, \ldots, n \text{ if } (X_k \geq T_{k1}^{11} \& X_{k'} \geq T_{k2}^{22}) \} \tag{2.7}
\]

\[
D_{k1}^{23} = \{(x_1^{t'}, y^{t'}), t = 1, \ldots, Q^2, l = 1, \ldots, n \text{ if } (X_k \leq T_{k1}^{11} \& X_{k'} \geq T_{k2}^{22}) \} \tag{2.8}
\]

\[
D_{k2}^{24} = \{(x_1^{t'}, y^{t'}), t = 1, \ldots, Q^2, l = 1, \ldots, n \text{ if } (X_k \geq T_{k1}^{11} \& X_{k'} \leq T_{k2}^{22}) \} \tag{2.9}
\]

Where, \( Q^2 \) is the number of observations in each database. In general, in Eq. (2.3) – (2.4) and Eq. (2.6) – (2.9), \( T_{k1}^{dq} \) and \( T_{k2}^{dq} \) are the percentile values bigger and smaller than the median of \( X_k \) in the \( D_{ks}^{d-1,q+1} \) database, respectively. It implies that the fuzzy dividing is applied here. The typical values of \( T_{k1}^{dq} \) and \( T_{k2}^{dq} \) are third and first quantiles of \( X_k \), respectively.

This algorithm is iterated and the \( D \) is divided into more small databases. In general, \( D \) in the \( d \)th iteration is divided into \( 2^d \) small databases.

Which \( X_k \) is the best one to divide into a database?

For determination of the best option, all of the possible dividing options are performed. Hence, for dividing the \( D_{qs}^{d,q} \) into two smaller databases, \( n \) possible options are performed and \( 2n \) databases are
generated. The data in each generated database is divided into \( n \) one-variable databases. Thus when the \( j \)th variable is divided into two small databases, \( 2n \) one-variable databases \( (S) \) are generated. 

\[
S_{ij}^t = \{(x_i^t, y_i^t)\}, \quad i = 1, \ldots, n, \; t = 1, \ldots, Q^d, \; s = 1, 2
\]  

\( Q^d \) is the number of \((x, y)\) points in the one-variable database. 

The relationship between \( X_i \) and \( Y \) \((\hat{Y}_i = f^i_j(X_i), i = 1, \ldots, n)\) in all of \( S_{ij}^t \) is calculated by a fuzzy interpolation technique called IDS (Ink Drop Spread) \[22\]. Similarly, the relationship between \( X_i \) and \( Y \) \((\hat{Y}_i = g^i_j(X_i), i = 1, \ldots, n)\) in all of \( S_{ij}^t \) is calculated. The accuracy of \( f^i_j \) and \( g^i_j \) functions for the estimation of output \((Y)\) is evaluated. Consequently, \( f^i_j \) and \( g^i_j \) \((z & z' \in \{1, \ldots, n\})\) are determined as the best one-variable functions with the lowest errors, respectively. Consider \( e^j \) as the total error of output \((Y)\) estimation in \( D_{ks}^{dq} \) by \( f^i_j \) and \( g^i_j \). Then \( e^j \) for \( j = 1, \ldots, n \) is calculated and the minimum value in \( \{e^1, \ldots, e^n\} \) is determined. Consider \( e^k' \) as the minimum. Consequently, the input variable corresponding to the minimum error \((X_k')\) is the best variable for dividing \( D_{ks}^{dq} \) into two smaller databases \((D_{k'1}^{d+1}, D_{k'2}^{d+1})\) and \( f^{k'}(X_{z}) \) and \( g^{k'}(X_{z'}) \) are the best one-variable functions for the estimation of output in the two generated databases and \( e(f^{k'}(X_{z})) \) and \( e(g^{k'}(X_{z'})) \) are their corresponding errors, respectively. 

**Step 3.**

Rule-base generation: In the first iteration of the MALM algorithm, \( D \) is divided into two databases (See Eq. (2.2) – (2.4)) and two one-variable functions \((f^k(X_{z}) \) and \( g^k(X_{z'})\)) are determined and utilized for the output estimation in two databases. Therefore, the rule-base can be expressed as Eq. (2.11). 

\[
\begin{align*}
\text{If} \; & X_k \leq T_{k1}^{11} \text{ Then } \hat{Y}_1 = f^{k1}(X_z) \\
\text{If} \; & X_k \geq T_{k2}^{12} \text{ Then } \hat{Y}_2 = g^{k1}(X_{z'})
\end{align*}
\]  

(2.11)

In the second iteration, each generated database in the first iteration is divided into two databases. Accordingly, four databases are generated (See Eq. (2.5) – (2.9)) and four one-variable functions \((f^{k1}(X_{z}), g^{k1}(X_{z'}), f^{k2}(X_{z}), g^{k2}(X_{z'}))\) are developed for the output estimation. Therefore, the rule-base can be expressed as Eq. (2.12): 

\[
\begin{align*}
\text{If} \; & (X_k \leq T_{k1}^{11} \; \& \; X_{k'} \leq T_{k1}^{21}) \text{ Then } \hat{Y}_1 = f^{k1}(X_z) \\
\text{If} \; & (X_k \leq T_{k1}^{12} \; \& \; X_{k'} \geq T_{k1}^{22}) \text{ Then } \hat{Y}_2 = g^{k1}(X_z) \\
\text{If} \; & (X_k \geq T_{k2}^{11} \; \& \; X_{k'} \leq T_{k2}^{21}) \text{ Then } \hat{Y}_3 = f^{k2}(X_z) \\
\text{If} \; & (X_k \geq T_{k2}^{12} \; \& \; X_{k'} \geq T_{k2}^{22}) \text{ Then } \hat{Y}_4 = g^{k2}(X_z)
\end{align*}
\]  

(2.12)

Consequently, the rule-bases with 8, 16, 32, … rules are generated in the third, fourth, fifth, … iterations, respectively. In general, the number of rules in a rule-base is equal to \(2^d\) \((d \) is the number of iterations). 

**Step 4.**

Fuzzification and defuzzification: Fuzzy dividing has been performed in Step 2, thus the rules in each rule-base overlap and the membership functions should be defined for input variables. Implementation of fuzzy modeling using trapezoidal membership functions is very straightforward and easy; hence this membership function is applied here. We define a fuzzy membership function as \(A_{k5}^{dq}(X_k)\). In general, when a variable is divided into two parts for each part a trapezoidal membership function is defined \((A_{k1}^{dq}(X_k)\) and \(A_{k2}^{dq}(X_k))\). \(A_{k1}^{dq}(X_k)\) and \(A_{k2}^{dq}(X_k)\) are defined as Eq. (2.13) and (2.14).
The studied residential buildings are located in the Rezashahr and Fakouri neighborhoods of Mashhad (Figure 1) (hereinafter called Rezashahr and Fakouri buildings). Mashhad is the capital city of Khorasan-e-Razavi province and is the second most populated city in Iran. Mashhad is located in an arid climate in the northeastern part of Iran where the outdoor temperature can reach up to 40°C in the summer and down to -5°C or less in the winter [24]. The thermal gradient between indoor and outdoor temperature highly influences energy consumption in Mashhad. The studied apartments are located on the top floor of these five-storey residential buildings. The studied apartments have 3 bedrooms facing north, a kitchen facing west, and a dining and living rooms facing south. The height of buildings is about 15m (3m per story). The area of apartments is about 220 m². Photographs of the studied apartments are presented in figure 2. The Rezashahr and Fakouri buildings were constructed with conventional materials (hollow clay block) and insulated materials (3D panels), respectively.
The walls of the Rezashahr and Fakouri buildings are exhibited in Figures 3a and 3b, respectively. The walls of the Rezashahr building are made of hollow clay block (200*205*104 mm) which includes six hollows in three rows and two columns. One side of the hollow clay block has been covered with 25 mm of cement mortar as an external wall covering. The other side of the hollow clay block has been covered with 20 mm of gypsum mortar and finally covered with 5mm of gypsum plaster as internal wall covering (Figure 3a). The walls of the Fakouri building are made of 40 mm polystyrene and both sides of the polystyrene layer are covered with 35mm of armed cement mortar. The inner side of the walls is covered with 20 mm of gypsum mortar and finally covered with 5mm gypsum plaster (Figure 3b). The overall heat transfer coefficients (U) of the walls of the Rezashahr and Fakouri buildings were calculated by Taheri Shahraein [25] and were about 2.2 and 0.9 W/(m².ºK), respectively.

BES-01 and BES-02 (accuracy: ±0.5 ºC) are the data loggers which have been utilized for inner surface and indoor temperature measurements, respectively. The measurements were performed in the bedrooms (northwest & northeast bedrooms), kitchen and living room. The measurements were performed during the summers of 2010 and 2011 and winter of 2011. The winter measurements were under heating and the summer measurements were under natural ventilation conditions. The measurements of inner surface and indoor temperature were performed on an hourly scale. The data loggers were calibrated before the measurements by the method presented by Taheri Shahraein [25]. Mashhad Meteorological Station measured hourly air temperature, wind speed & direction and solar radiation (direct, diffuse and total radiation) concurrent with the inner surface and indoor temperature measurements in the residential buildings.
Figure 2: Images of Rezashahr (left hand) and Fakouri (right hand) buildings

Figure 3: Complete sections of the walls of studied buildings in details, a) Hollow clay block wall of Rezashahr Building (left hand), b) Insulated wall (3D-Panel) of Fakouri building (right hand)

4. Algorithm of study

The algorithm of study has been presented in figure 4. The steps of figure 4 are described here.
Step 1: Acquiring the meteorological data and selection of appropriate input variables for thermal behavior

Step 2: Measurements of inner surface and indoor temperatures as output variables.

Step 3: Generation of inputs-outputs databases

Step 4: Dividing each database to training and testing

Step 5: Training of MALM for temperature modeling

Step 6: Testing of the trained MALM models and selecting the best MALM models.

Step 7: Comparing the results of temperature modeling in this study with other studies.

Figure 4: The algorithm of study.

Step 1:
After the measurements of meteorological data during the study periods, it is necessary to select appropriate meteorological data as input variables for temperature behavior modeling of apartments. In this study, these input variables were selected according to previous studies. The meteorological data which have been used as input variables in other studies were often outdoor temperature, wind speed & direction, solar radiation, cloudiness of sky and humidity (e.g. Frausto et al [1]; Linker and Seginer [5]; Frausto and Pietro [8]; Moreno et al. [4]; Reginato et al. [12]; Lu and Viljanen [10]). The cloudiness of sky influences the values of direct and indirect radiation; therefore, direct and indirect radiations were utilized instead of cloudiness in this study. Frausto et al. [1] demonstrated that outdoor humidity is an ineffective input variable for the building temperature modeling, thus outdoor humidity is not utilized as an input variable in this study. Finally, among the meteorological data, hourly air temperature, wind speed, wind direction and diffuse, direct and total solar radiation were selected as appropriate input variables.

Step 2:
The inner surface and indoor temperature are measured in the northeast and northwest bedrooms, kitchen and living room of the Fakouri and Rezashahr apartments during the study period.
Step 3:
The inputs-output databases for modeling are created by utilizing temperature measurements in buildings as output variables (step 2) and meteorological data measurements as input variables (step 1). In total, 22 inputs-output databases are created for some of the rooms in the two buildings under different ventilation conditions. Eleven databases were created for inner surface temperature modeling (Table 1) and eleven databases were created for indoor temperature modeling (Table 2). Each database is composed of 25 input variables and one output variable. In each database, the input variables for modeling are hourly air temperature, humidity, wind speed, wind direction, diffuse radiation, direct radiation, total radiation, wind speed and wind direction in time of $t$, $t-1$, $t-2$, and $t-3$ and the time of $t$ (The range of $t$ is between 1 and 24 hrs) and the output variable is hourly inner surface or indoor temperature in time of $t$.

Step 4:
Each database is randomly divided into two databases for training and testing temperature behavior models. About 65% and 35% of the data in each database are considered as training and testing databases, respectively. The numbers of training and testing data in inner surface and indoor temperature modeling databases are presented in Table 1 and Table 2, respectively.

Step 5:
MALM is utilized for simulation of inner surface and indoor temperatures in different rooms of the Rezashahr and Fakouri buildings under natural ventilation and heating conditions using training databases.

Step 6:
After the training of MALM under different fuzzy rules, it is necessary to select the best number of fuzzy rules or the best trained MALM model. In this step, the trained MALM models are tested using test databases. The test procedure is performed based on specific goodness-of-fit criteria. The utilized statistical goodness-of-fit criteria in this study are Mean Bias Error (MBE), Mean Absolute Error (MAE), coefficient of determination ($R^2$), Root Mean Square Error (RMSE) and Mean Absolute of Percentage Error (MAPE). The equations of these goodness-of-fit criteria are presented in Table 3. Finally, the best 11 MALM models for inner surface temperature modeling are determined. Similarly, 11 MALM models for indoor temperature modeling are determined.

Step 7:
The results of developed temperature models in this study are compared with other similar studies on temperature behavior modeling and the MALM performance is evaluated.
Table 1: Eleven databases for inner surface temperature simulation with the number of training and test data in each database

<table>
<thead>
<tr>
<th>Building</th>
<th>Condition</th>
<th>Room</th>
<th>Nr. Of Training data</th>
<th>Nr. Of Test data</th>
</tr>
</thead>
<tbody>
<tr>
<td>Fakouri</td>
<td>Heating</td>
<td>NE bedroom</td>
<td>900</td>
<td>470</td>
</tr>
<tr>
<td></td>
<td>Heating</td>
<td>NW bedroom</td>
<td>960</td>
<td>510</td>
</tr>
<tr>
<td></td>
<td>Heating</td>
<td>Kitchen</td>
<td>960</td>
<td>500</td>
</tr>
<tr>
<td></td>
<td>Heating</td>
<td>Living room</td>
<td>200</td>
<td>110</td>
</tr>
<tr>
<td>Rezashahr</td>
<td>Natural ventilation</td>
<td>NE bedroom</td>
<td>685</td>
<td>340</td>
</tr>
<tr>
<td></td>
<td>Heating</td>
<td>NE bedroom</td>
<td>1000</td>
<td>460</td>
</tr>
<tr>
<td></td>
<td>Heating</td>
<td>NW bedroom</td>
<td>950</td>
<td>510</td>
</tr>
<tr>
<td></td>
<td>Heating</td>
<td>Kitchen</td>
<td>970</td>
<td>500</td>
</tr>
<tr>
<td></td>
<td>Natural ventilation</td>
<td>Kitchen</td>
<td>720</td>
<td>320</td>
</tr>
<tr>
<td></td>
<td>Heating</td>
<td>Living room</td>
<td>970</td>
<td>500</td>
</tr>
<tr>
<td></td>
<td>Natural ventilation</td>
<td>Living room</td>
<td>700</td>
<td>340</td>
</tr>
</tbody>
</table>

Table 2: Eleven databases for indoor temperature simulation with the number of training and test data in each database

<table>
<thead>
<tr>
<th>Building</th>
<th>Condition</th>
<th>Room</th>
<th>Nr. Of Training data</th>
<th>Nr. Of Test data</th>
</tr>
</thead>
<tbody>
<tr>
<td>Fakouri</td>
<td>Natural ventilation</td>
<td>NE bedroom</td>
<td>80</td>
<td>45</td>
</tr>
<tr>
<td></td>
<td>Heating</td>
<td>NE bedroom</td>
<td>900</td>
<td>470</td>
</tr>
<tr>
<td></td>
<td>Heating</td>
<td>NW bedroom</td>
<td>960</td>
<td>510</td>
</tr>
<tr>
<td></td>
<td>Heating</td>
<td>Kitchen</td>
<td>960</td>
<td>500</td>
</tr>
<tr>
<td></td>
<td>Heating</td>
<td>Living room</td>
<td>940</td>
<td>460</td>
</tr>
<tr>
<td>Rezashahr</td>
<td>Natural ventilation</td>
<td>NE bedroom</td>
<td>685</td>
<td>336</td>
</tr>
<tr>
<td></td>
<td>Heating</td>
<td>NE bedroom</td>
<td>1000</td>
<td>460</td>
</tr>
<tr>
<td></td>
<td>Heating</td>
<td>NW bedroom</td>
<td>950</td>
<td>510</td>
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<td></td>
<td>Heating</td>
<td>Kitchen</td>
<td>970</td>
<td>500</td>
</tr>
<tr>
<td></td>
<td>Natural ventilation</td>
<td>Kitchen</td>
<td>720</td>
<td>320</td>
</tr>
<tr>
<td></td>
<td>Heating</td>
<td>Living room</td>
<td>940</td>
<td>500</td>
</tr>
</tbody>
</table>

Table 3: The equations of goodness of fit criteria, utilized in this study

<table>
<thead>
<tr>
<th>Goodness-of-fit criteria</th>
<th>Equations</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean Bias Error (MBE)</td>
<td>[ \frac{1}{n} \sum_{i=1}^{n} (O_i - S_i) ]</td>
</tr>
<tr>
<td>Mean Absolute Error (MAE)</td>
<td>[ \frac{1}{n} \sum_{i=1}^{n}</td>
</tr>
<tr>
<td>Mean Absolute Percentage Error (MAPE)</td>
<td>[ \frac{1}{n} \sum_{i=1}^{n} \frac{</td>
</tr>
<tr>
<td>Root Mean Square Error (RMSE)</td>
<td>[ \sqrt{\frac{1}{n} \sum_{i=1}^{n} (O_i - S_i)^2} ]</td>
</tr>
</tbody>
</table>

\( n \) is the number of observation data, \( O_i \) and \( S_i \) are the observed and simulated inner surface or indoor temperature of \( i \)th data, respectively.
5 Results and discussion

The time delay due to the thermal mass is known as time lag. Thicker and more resistive materials need more time for heat transfer and these materials have high time lag. For instance, according to the time lag of the building’s walls, the peak daytime temperature will reach the internal surface of the building in the evening. One of the prerequisites for all of the modeling is the question of how many time delays of input variables should be used as input variables for modeling. To answer this question, the time lag of the studied buildings should be determined. Taheri Shahraein [25] utilized experimental and simulation approaches for the retrieval of time lag for the Rezashahr and Fakouri buildings. The results of time lag determination by the experimental approach are presented in Table 4. Taheri Shahraein [25] simulated the time lag in two studied buildings using K-Value software and the results of the time lag simulations are presented in Table 4.

<table>
<thead>
<tr>
<th>Building</th>
<th>Condition</th>
<th>Room</th>
<th>MBE</th>
<th>MAE</th>
<th>RMSE</th>
<th>R²</th>
<th>MAPE</th>
<th>Nr. Of fuzzy rules</th>
</tr>
</thead>
<tbody>
<tr>
<td>Fakouri</td>
<td>Heating</td>
<td>NE bedroom</td>
<td>2:40</td>
<td>2:25</td>
<td>2:25</td>
<td>2:05</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Heating</td>
<td>NW bedroom</td>
<td>2:40</td>
<td>2:25</td>
<td>2:25</td>
<td>2:05</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Heating</td>
<td>Kitchen</td>
<td>2:40</td>
<td>2:25</td>
<td>2:25</td>
<td>2:05</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Heating</td>
<td>Living room</td>
<td>2:40</td>
<td>2:25</td>
<td>2:25</td>
<td>2:05</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Rezashahr</td>
<td>Natural ventilation</td>
<td>NE bedroom</td>
<td>2:40</td>
<td>2:25</td>
<td>2:25</td>
<td>2:05</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Heating</td>
<td>NE bedroom</td>
<td>2:40</td>
<td>2:25</td>
<td>2:25</td>
<td>2:05</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Heating</td>
<td>NW bedroom</td>
<td>2:40</td>
<td>2:25</td>
<td>2:25</td>
<td>2:05</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Heating</td>
<td>Kitchen</td>
<td>2:40</td>
<td>2:25</td>
<td>2:25</td>
<td>2:05</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Heating</td>
<td>Living room</td>
<td>2:40</td>
<td>2:25</td>
<td>2:25</td>
<td>2:05</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

According to the findings of Taheri Shahraein [25], the time lag in the studied buildings is between two and three hours. Therefore, the meteorological data with zero to three hours lags (t, t-1, t-2 & t-3) were utilized as input variables to MALM models in this study. Although the thermal properties of each building envelope were not used explicitly in the simulations, the effects of these parameters have been considered implicitly by MALM. These parameters express how the outdoor parameters influence the inner surface and indoor temperatures. When inner surface or indoor temperature and outdoor parameters were utilized in the black box modeling, it means that the thermal properties of each building envelope have been considered implicitly.

The MALM was trained and tested using 11 training and testing databases for modeling inner surface temperature. Then the best-developed MALM models for different rooms of the apartments under natural ventilation and heating conditions were determined in the testing step. The goodness of fit criteria for the best MALM models developed for the 11 studied databases are presented in Table 5. For example, figures 5a and 5b exhibit the time series of measured and modeled inner surface temperatures in the testing step in the living rooms of the Rezashahr and Fakouri buildings, respectively.
Similarly, the goodness of fit criteria for the best MALM models developed for indoor temperature modeling of the 11 studied databases by the test databases are presented in Table 6. For example, figures 6a and 6b exhibit the time series of measured and modeled indoor temperatures in the testing step in the living rooms of the Rezashahr and Fakouri buildings, respectively.

Table 6: The goodness of fit criteria of the best developed MALM models for indoor temperature modeling with the number of fuzzy rules in the best models

<table>
<thead>
<tr>
<th>Building</th>
<th>Condition</th>
<th>Room</th>
<th>MBE</th>
<th>MAE</th>
<th>RMSE</th>
<th>$R^2$</th>
<th>MAPE</th>
<th>Nr. Of fuzzy rules</th>
</tr>
</thead>
<tbody>
<tr>
<td>Rezashahr</td>
<td>Natural ventilation</td>
<td>NE bedroom</td>
<td>0.4</td>
<td>1.1</td>
<td>1.6</td>
<td>0.79</td>
<td>3.9</td>
<td>64</td>
</tr>
<tr>
<td>Heating</td>
<td>NE bedroom</td>
<td>0.13</td>
<td>1.0</td>
<td>-</td>
<td>0.87</td>
<td>5.4</td>
<td>64</td>
<td></td>
</tr>
<tr>
<td>Heating</td>
<td>NW bedroom</td>
<td>-0.1</td>
<td>0.85</td>
<td>1.2</td>
<td>0.61</td>
<td>4.6</td>
<td>128</td>
<td></td>
</tr>
<tr>
<td>Heating</td>
<td>Kitchen</td>
<td>-0.2</td>
<td>0.7</td>
<td>1.0</td>
<td>0.79</td>
<td>4.5</td>
<td>32</td>
<td></td>
</tr>
<tr>
<td>Rezashahr</td>
<td>Natural ventilation</td>
<td>NE bedroom</td>
<td>0.1</td>
<td>0.8</td>
<td>1.0</td>
<td>0.91</td>
<td>2.6</td>
<td>128</td>
</tr>
<tr>
<td>Heating</td>
<td>NE bedroom</td>
<td>-0.13</td>
<td>1.0</td>
<td>-</td>
<td>0.87</td>
<td>5.4</td>
<td>64</td>
<td></td>
</tr>
<tr>
<td>Heating</td>
<td>NW bedroom</td>
<td>-0.1</td>
<td>0.85</td>
<td>1.2</td>
<td>0.61</td>
<td>4.6</td>
<td>128</td>
<td></td>
</tr>
<tr>
<td>Heating</td>
<td>Kitchen</td>
<td>-0.2</td>
<td>0.7</td>
<td>1.0</td>
<td>0.79</td>
<td>4.5</td>
<td>32</td>
<td></td>
</tr>
<tr>
<td>Fakouri</td>
<td>Natural ventilation</td>
<td>NE bedroom</td>
<td>-0.2</td>
<td>1.3</td>
<td>1.7</td>
<td>0.68</td>
<td>4.5</td>
<td>64</td>
</tr>
<tr>
<td>Heating</td>
<td>NE bedroom</td>
<td>-0.05</td>
<td>0.8</td>
<td>1.1</td>
<td>0.63</td>
<td>3.9</td>
<td>32</td>
<td></td>
</tr>
<tr>
<td>Heating</td>
<td>NW bedroom</td>
<td>0.07</td>
<td>1.0</td>
<td>1.3</td>
<td>0.66</td>
<td>5.2</td>
<td>64</td>
<td></td>
</tr>
<tr>
<td>Heating</td>
<td>Kitchen</td>
<td>-0.24</td>
<td>1.1</td>
<td>1.4</td>
<td>0.65</td>
<td>5.8</td>
<td>128</td>
<td></td>
</tr>
<tr>
<td>Heating</td>
<td>Living room</td>
<td>0.07</td>
<td>0.7</td>
<td>0.95</td>
<td>0.87</td>
<td>3.7</td>
<td>64</td>
<td></td>
</tr>
</tbody>
</table>

Figure 5: Time series of measured and modeled inner surface temperature in testing step for living room under heating condition, a) Rezashahr Building, b) Fakouri building
MALM is able to determine the suitable variables for modeling among the input variables and it removes the unsuitable variables. For example, MALM has developed a fuzzy model with 8 fuzzy rules for simulation of inner surface temperature of NE bedroom in Fakouri building (See Table 5). Eq. (5.16) presents these 8 fuzzy rules.

\[
\begin{align*}
\text{if } X_1 \leq 7.4 \land X_{13} \leq 4.74 \land X_{19} \leq 2.74 & \Rightarrow \hat{Y}_1 = f_1(X_{13}) \\
\text{if } X_1 \leq 7.4 \land X_{13} \leq 4.74 \land X_{19} \geq -8.8 & \Rightarrow \hat{Y}_2 = f_2(X_{13}) \\
\text{if } X_1 \leq 7.4 \land X_{13} \geq -0.16 \land X_{19} \geq 5.7 & \Rightarrow \hat{Y}_3 = f_3(X_{19}) \\
\text{if } X_1 \leq 7.4 \land X_{13} \geq -0.16 \land X_{19} \geq 1.6 & \Rightarrow \hat{Y}_4 = f_4(X_{19}) \\
\text{if } X_1 \geq 0.54 \land X_{13} \leq 8.65 \land X_{19} \leq 5.85 & \Rightarrow \hat{Y}_5 = f_5(X_{13}) \\
\text{if } X_1 \geq 0.54 \land X_{13} \leq 8.65 \land X_{19} \geq 1.87 & \Rightarrow \hat{Y}_6 = f_6(X_{13}) \\
\text{if } X_1 \geq 0.54 \land X_{13} \geq 2.6 \land X_{19} \leq 9.69 & \Rightarrow \hat{Y}_7 = f_7(X_{13}) \\
\text{if } X_1 \geq 0.54 \land X_{13} \geq 2.6 \land X_{19} \geq 3.72 & \Rightarrow \hat{Y}_8 = f_8(X_{13}) 
\end{align*}
\]

(5.16)

Where, \( X_1, X_{13} \) and \( X_{19} \) are the first, 13\textsuperscript{th} and 19\textsuperscript{th} input variables which are air temperature in time \( t \), \( t-2 \) and \( t-3 \), respectively. \( f_1 \ldots f_8 \) are implicit one-variable functions. These function have been determined by fuzzy interpolation technique. According to the Eq. (5.16), the rules overlap, thus fuzzy dividing has been applied for the temperature simulation.

Eq. (5.16) implies that the air temperature in time \( t \), \( t-2 \) and \( t-3 \) are suitable variables for inner surface temperature modeling in Fakouri building and only these variables have been used in simulation. The other variables (22 variables) has been removed. In addition, Eq. (5.16) shows that air temperature in time \( t-2 \) and \( t-3 \) are more suitable than air temperature in time \( t \). In the other words, MALM is able not only to determine the suitable input variables but also to rank the suitable variables.

Here, the results of this study are compared with some other similar studies.

Frausto et al. [1] simulated the indoor temperature of a greenhouse in Belgium under natural ventilation conditions using ARX and ARMAX. They used climate data from a typical reference year for Belgium as input variables for ARX and ARMAX and utilized simulated values of indoor temperature by physical model as the output variables. When the utilized input variables for modeling were outside air temperature, solar radiation and cloudiness of sky, the R2 values of developed ARX and ARMAX models for different seasons were in the range of 0.66-0.98 and 0.29-0.98, respectively. The range of R2 values of MALM models for indoor temperature simulation under natural ventilation is 0.68-0.91 (Table 6). According to the Frausto et al. [1] results, the MALM indoor temperature modeling results are reasonable and satisfactory.

Linker and Seginer [5] simulated the indoor temperature of a greenhouse under HVAC conditions using the neural networks. The results showed that the least RMSE of the neural networks simulations is about 1.3 °C. According to Table 6, the results of MALM indoor temperature simulations under heating condition are very similar to the results from Linker and Seginer (2004).

Moreno et al. [4] simulated indoor temperature of a room (area=16 m\(^2\)) in the graduate building of the engineering school at Queretaro State University. The meteorological data were acquired by the instruments installed outside the studied room. The modeling was performed by ARX and ARMAX under HVAC conditions. The best R2 values of developed ARX and ARMAX models were about 0.91 and 0.89, respectively. The best R2 value of MALM models developed under heating conditions is about 0.86 (see Table 6). In this study, the utilized meteorological data were acquired by Mashhad Meteorological station, which is located 15.0 and 10.4 km from the Fakouri and Rezashahr buildings respectively. Many of the meteorological parameters have spatial variations. Hence, the meteorological data measured in Mashhad station have some differences from these parameters around the studied building. Utilization of measured meteorological data in a station far from studied buildings is one of the reasons for deviations of modeling results from observed data. Achievement to R2=0.86 with these meteorological data implies that MALM has presented appropriate results in comparison with the Moreno et al. [4] results.
Reginato et al. [12] simulated the indoor temperature of a residential building under HVAC conditions using the OBF modeling technique and the result showed that the RMSE of modeling is about 1.34 ºC. Therefore, the MALM and OBF modeling techniques have presented similar results (see Table 6). In addition, MALM simulated the indoor temperature with MPAE, RMSE and MAE values less than 5.2%, 1.7 ºC and 1.3 ºC, respectively (Table 6). The results of MALM and its comparison with similar studies demonstrated that it is an appropriate generic computational intelligent technique for indoor temperature simulation.

The results of indoor temperature and inner surface temperature modeling by MALM are very similar in total, but MALM simulated the inner surface temperature slightly better than indoor temperature. MALM simulated the inner surface temperature with MPAE, RMSE and MAE values less than 4.8%, 1.3 ºC and 1.0 ºC, respectively (Table 5). Although the number of studies on the inner surface temperature simulation by black box models using meteorological data is limited to such an extent that makes it hard to compare the results of the present study with similar studies, the results of inner surface modeling by MALM and our findings about MALM indoor temperature modeling nevertheless imply that MALM is also a practical modeling technique for inner surface temperature modeling. The results demonstrated that MALM is applicable for the thermal behavior of buildings with conventional (Rezashahr building) and insulated (Fakouri building) construction methods.
6 Conclusion

In this study, a new fuzzy modeling technique called Modified Active Learning Method (MALM) was applied for the simulation of thermal behavior of two residential buildings using meteorological data. The results demonstrated its capability for performing inner surface and indoor temperature simulations. Thermal behavior simulation of the two studied buildings was performed with less than 5.2% error. In addition, MALM is able to determine the suitable input variables for simulation. The comparison of MALM results with other similar studies demonstrated that the MALM has appropriate performance for thermal behavior simulation of buildings with conventional and insulated construction methods under heating and natural ventilation conditions. Hence, MALM has the merit to be introduced as an appropriate fuzzy modeling technique for thermal behavior simulation of residential buildings.

Acknowledgments

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