Adaptive neuro-fuzzy based inferential sensor model for estimating the average air temperature in space heating systems

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Commissioning
Subtractive clustering

ABSTRACT

The heating systems are conventionally controlled by open-loop control systems because of the absence of practical methods for estimating average air temperature in the built environment. An inferential sensor model, based on adaptive neuro-fuzzy inference system modeling, for estimating the average air temperature in multi-zone space heating systems is developed. This modeling technique has the advantage of expert knowledge of fuzzy inference systems (FISs) and learning capability of artificial neural networks (ANNs). A hybrid learning algorithm, which combines the least-square method and the back-propagation algorithm, is used to identify the parameters of the network. This paper describes an adaptive network based inferential sensor that can be used to design closed-loop control for space heating systems. The research aims to improve the overall performance of heating systems, in terms of energy efficiency and thermal comfort. The average air temperature results estimated by using the developed model are strongly in agreement with the experimental results.

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1. Introduction

The inferential sensing technology was originally developed to improve the control of chemical and biological processes [1,2]. Inferential sensing allows difficult to measure process parameters to be inferred from other easily made measurements [3,4]. All inferential sensors are based on an inferential modeling module that represents the dynamics between the inputs, or easily measurable variables, and the output, or undetectable variables. Listed below are some commonly used approaches for the development of the inferential modeling module:

- Physical model
- Neural network
- Fuzzy logic
- Adaptive neuro-fuzzy inference system

Despite considerable success in chemical and biological engineering, the inferential sensing and control techniques have not been popularly used in building automation. Some researchers began to investigate the benefit of incorporating the inferential sensing technique with conventional building control schemes [5–9]. These conclude that both the energy efficiency and the indoor environment quality of the built environment can be significantly improved if the conventional building control schemes are enhanced by the inferential sensors.

Recent research demonstrates that inferential sensing is used for estimating the average air temperature in multi-zone heating systems [6]. The estimated temperature provides a closed-loop boiler control scheme (see the feedback loop through dashed line in Fig. 1); as in the absence of an economic and technically reliable method for measuring the overall comfort level in the built environment, the boilers are normally controlled to maintain the supply water temperature (see the solid feedback loop in Fig. 1). Liao and Dexter developed a simplified physical model of multiple-zone space heating systems and incorporated it with conventional boiler controller to design an inferential control scheme. The physical model based inferential sensor intends to estimate the time-dependent value of the average air temperature, which consequently, are difficult to be commissioned.

Long-term performance of this scheme can be optimized if the water temperature can be changed according to the heating load appropriately with a resolution of only 5 °C [6]. Therefore, it seems unnecessary to maintain the high accuracy required by the physical-model based inferential sensor. This study aims to make contributions to solve the above said problem. The paper presents the development, the commissioning with short-term monitoring...
2. Application of ANFIS to inferential sensing

In recent years, artificial intelligence (AI) based techniques have been proposed as alternatives to traditional statistical ones in many scientific disciplines. Fuzzy logic was introduced by Zadeh [10] as a mathematical way to represent ambiguity and vagueness. For the last two decades fuzzy logic has been extensively applied to the built environment, to improve the performance and to reduce energy consumption [11–14]. Santamouris [15] reviewed the applications of fuzzy logic in building technology, in terms of improvement of indoor comfort and energy conservation. At the same time many researchers used neural networks for improved performance of built environment [16,17]. Soleimani-Mohseni et al. [18] 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.

On the other hand, new AI techniques have been developed, which is known as “soft computing”. These techniques aim at integrating powerful artificial intelligence methodologies such as neural networks and fuzzy inference systems. While fuzzy logic performs an inference mechanism under cognitive uncertainty, neural networks posses exciting capabilities such as learning, adaption, fault-tolerance, parallelism and generalization [19]. To enable a system to deal with cognitive uncertainties in a manner more like humans, one may incorporate the concept of fuzzy logic into the neural networks [20]. Since Jang proposed the ANFIS [21], its applications are numerous in various fields including engineering, management, health, biology and even social sciences. Specially, the literature has several articles on the application of ANFIS to automatic control, robotics, nonlinear regression, system identification, adaptive signal processing, decision making, quality control, medicine, pattern recognition and inventory control [22]. ANFIS is claimed to be a universal approximator to represent highly nonlinear functions more powerfully than conventional statistical methods [23].

Kelly et al. [24] designed a neural fuzzy controller that allows for the combination of the qualitative knowledge in fuzzy rules and the learning capabilities of neural networks. This method offered two unique features, namely the ability to eliminate human decision making and enhance the learning capability. The results of this paper show that the neural fuzzy controller, developed using ANFIS as part of the control system, successfully learns to control a second order plant autonomously after a short training time, gives better control than the conventional PID, and corresponds with the change made to the original plant.

Singh et al. [25] used ANFIS for calculating the thermal conductivity of rock. Thermal conductivity, a complex rock parameter, is predicted using simple rock parameters like P-wave velocity, porosity, bulk density, uniaxial compressive strength of rock, as input parameters to ANFIS.

Nomenclature

<table>
<thead>
<tr>
<th>Symbol</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>$T_{avg}$</td>
<td>average air temperature in built environment (°C)</td>
</tr>
<tr>
<td>$T_0$</td>
<td>external temperature (°C)</td>
</tr>
<tr>
<td>$Q_{col}$</td>
<td>solar radiation (W)</td>
</tr>
<tr>
<td>$Q_{in}$</td>
<td>energy consumption, calculated on the basis of control signal fire (W)</td>
</tr>
<tr>
<td>$Q_d$</td>
<td>energy released by radiators (W)</td>
</tr>
<tr>
<td>$C_1$</td>
<td>total thermal capacity of air in the building (J/°C)</td>
</tr>
<tr>
<td>$C_{e1}$</td>
<td>total thermal capacity of the internal layer of building envelope (J/°C)</td>
</tr>
<tr>
<td>$C_{e2}$</td>
<td>total thermal capacity of the external layer of the building envelope (J/°C)</td>
</tr>
<tr>
<td>$T_{e1}$</td>
<td>lumped temperature of the internal layer of the building envelope (°C)</td>
</tr>
<tr>
<td>$T_{e2}$</td>
<td>lumped temperature of the external layer of the envelope (°C)</td>
</tr>
<tr>
<td>$K_2$</td>
<td>total heat transfer coefficient from the internal air to the internal layer of the building envelope</td>
</tr>
<tr>
<td>$K_3$</td>
<td>total heat conductance from the internal air to the outside through infiltration</td>
</tr>
<tr>
<td>$K_4$</td>
<td>total heat conductance from the internal layer to the external layer of building envelope</td>
</tr>
<tr>
<td>$K_5$</td>
<td>total heat transfer from the external layer of building envelope to the outside</td>
</tr>
<tr>
<td>$\alpha$</td>
<td>constant determining the portion of the solar radiation that into the building</td>
</tr>
<tr>
<td>$\beta$</td>
<td>constant determining the portion of energy released from a radiator through convection</td>
</tr>
<tr>
<td>$\tau_0$</td>
<td>time constant of boiler (s)</td>
</tr>
<tr>
<td>$E$</td>
<td>overall error function for training algorithm (°C)</td>
</tr>
<tr>
<td>$\gamma$</td>
<td>ANFIS network parameter</td>
</tr>
<tr>
<td>$\eta$</td>
<td>learning rate for hybrid learning algorithm</td>
</tr>
<tr>
<td>$k$</td>
<td>step size of learning rate</td>
</tr>
</tbody>
</table>

Fig. 1. Block diagram representation of closed-loop boiler control scheme.

Fig. 2. ANFIS architecture.
The paper presents the use and effectiveness of ANFIS for inferential sensor model development, which estimates the average air temperature in the buildings that heated by a hydraulic heating system. The paper is organized as follows. In Section 3 the technical background is reviewed for the ANFIS structure. Section 4 will discuss the development and commissioning process for the ANFIS model. The model validation and simulation results are presented in Section 5. Finally, conclusions are given and future work is discussed.

3. Theoretical survey

3.1. Fuzzy modeling and ANFIS

Fuzzy inference is a method that interprets the values in the input vector and assigns values to the output by means of some set of fuzzy “IF-THEN” rules:

\[
\text{IF } x \text{ is } A \text{ THEN } y \text{ is } B
\]  

(1)
where \( A \) and \( B \) are fuzzy sets, e.g., “low”, “high”. Each fuzzy set is characterized by appropriate membership functions that map each element to a membership value between 0 and 1. The IF part (antecedent) and THEN part (consequent) of a rule can have multiple parts linked by Boolean operators (AND, OR) which have counterpart fuzzy operations (MIN, MAX).

A fuzzy inference system consists of a “rule base” containing fuzzy rules, a “database” defining the membership functions of the fuzzy sets, and a “reasoning mechanism” which performs the inference procedure. Among various fuzzy inference systems, Takagi-Sugeno’s system is more suitable for sample-data based fuzzy modeling [26,27], in which the output of each rule is a predetermined function of input variables. To give an example, in first-order Sugeno model with two inputs \((x_1, x_2)\), the \(i\)th rule is described as

\[
\text{IF } x_1 \text{ is } X_{1i}; \text{ AND } x_2 \text{ is } X_{2i} \text{ THEN } y_i = p_{i,0} + p_{i,1}x_1 + p_{i,2}x_2
\]

where the uppercase variable \( X \) stands for the fuzzy sets corresponding to the domain of each linguistic label, and \( p_i \) is a set of adjustable parameters. The final output, \( y \), is the weighted average of each rule, expressed as,

\[
y = \sum u_i y_i
\]

where \( u_i \) is the weight of the \( i \)th rule.

On the other hand, a neural network structure consists of a number of nodes connected through directional links. Each node is characterized by a node function with fixed or adjustable parameters. The optimum parameter values of the network are determined through a training process. The basic learning rule is a well-known back-propagation method which seeks to minimize some measure of error, usually a sum of squared differences between a network’s outputs and desired outputs.

The functionality of nodes in ANFIS, as a five-layered feed-forward neural structure (Fig. 2) can be summarized as follows:

- **Layer 1**: Nodes are adaptive; membership functions (MFs) of input variables are used as node functions, and parameters in this layer are referred to as antecedent or premise parameters.
- **Layer 2**: Nodes are fixed with outputs representing the firing strengths of the rules.
- **Layer 3**: Nodes are fixed with outputs representing normalized firing strengths.
- **Layer 4**: Nodes are adaptive with node function given by Layer 1 for a first-order model, and with parameters referred to as defuzzifier of consequent parameters.
- **Layer 5**: The single node is fixed with output equal to the sum of all the rules’ outputs.

### 4. ANFIS model building and model commissioning

This work is an attempt to illustrate the utility and effectiveness of a soft computing approach in handling the modeling and control of the built environment. A physical model for estimating the average air temperature in multi-zone heating systems is developed by Liao and Dexter [7]. The overall average air temperature \( T_{\text{avg}} \) in the building is estimated based upon the information available to the boiler plant, including the external temperature.

<table>
<thead>
<tr>
<th>( Q_{\text{in}} ) (W)</th>
<th>( Q_{\text{out}} ) (W)</th>
<th>( T_{\text{in}} ) (°C)</th>
<th>( T_{\text{avg}} ) (°C)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Min.</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Max.</td>
<td>14253</td>
<td>15024</td>
<td>12252</td>
</tr>
<tr>
<td>Mean</td>
<td>8652</td>
<td>9509</td>
<td>1535</td>
</tr>
<tr>
<td>SD</td>
<td>2687</td>
<td>2452</td>
<td>2552</td>
</tr>
</tbody>
</table>

**Table 1** Statistical analysis between training and testing data set of different inputs and output.

**Fig. 5.** Testing data for ANFIS (February 2000: day 1 to day 21).
(T₀), and solar radiation (Q_{SOL}) and the boiler control signal (Fire) that are used to calculate the power consumption Q_{in}. The relationship between the output T_{avg} and three inputs Q_{in}, Q_{SOL} and T₀ is governed by a set of first-order differential equations [7]. There are nine relevant parameters that need to be commissioned using short-term monitoring data before the inferential sensor can be used.

The physical-model based inferential sensor fails to function properly if quality of commissioning data is not good or if the optimization process used for commissioning terminated at local extremes. This paper presents an inferential sensor model based upon ANFIS.

4.1 Model structure

This section explains the development of the ANFIS based inferential sensor model to compute the average temperature in the multi-zone heating system. The three inputs for the model are Q_{in}, (derived from boiler control signals), Q_{SOL}, T₀ and the output is T_{avg}. The ANFIS model structure with three inputs, developed in this work, is shown in Fig. 3.

Selection of fuzzy inference system (FIS) structure is the major concern when designing an ANFIS to model a specific target system. Various types of FIS are reported in the literature [26] and each is characterized by their consequent parameters only. In this project the ANFIS structure is generated by subtractive clustering method. The first-order Sugeno model is preferred as an interface system for its simplicity [27].

The subtractive clustering method, proposed by Chiu [28], clusters the data points in an unsupervised way by measuring the potential of data points in the feature space. When there is not a clear idea of how many clusters should be used for a given data set, it can be used for estimating the number of clusters and cluster centers. Subtractive clustering assumes that each data point is a potential cluster center and calculates the potential for each data point based on the density of surrounding data points. The data point with highest potential is selected as the first cluster center, and the potential of data points near the first cluster center is destroyed. Then data points with the highest remaining potential as the next cluster center and the potential of data points near the new cluster center is destroyed. The influential radius is critical for determining the number of clusters. A smaller radius leads to many smaller clusters in the data space, which results in more rules, and vice versa. Hence it is important to select the proper influential radius for clustering the data space.

After clustering the data space, the number of fuzzy rules and premise fuzzy MFs are determined. Then the linear square's estimate is used to determine the consequent parameters in the output MFs, resulting in a valid FIS.

4.2 Training and testing ANFIS

Experimental data obtained from a laboratory heating system is used for training and testing of the developed model. The laboratory heating system was monitored in a EU CRAFT project [29]. The laboratory is located in Milan, Italy. The laboratory is a three-story building with one zone at each floor. Multiple sensors were used to
monitor the air temperature in each zone and their algebraic average was treated as the representative measurement of the room temperature in the zone. Because each zone has the same floor area, the building air temperature is represented by the algebraic average of the air in all three zones.

A gas meter was used to monitor the energy consumption $e$, where

$$ e = [e(1) \ e(2) \ \ldots \ e(N_e)] $$

and $e(i) \ [i = 1 \ldots N_e]$ is the total gas consumption recorded at the $i$th time step, $N_e$ is the total number of samples [8].

Therefore, the input $Q_{in}$ is given by

$$ Q_{in}(j) = (e(j + 1) - e(j))/\Delta t $$

where $\Delta t$ is the sampling interval.

The other two inputs, $T_0$ and $Q_{SOL}$, were monitored regularly by a metrological station next to the laboratory. The model is commissioned using six days of the experimental data for a month (Fig. 4) and the rest of the three weeks of data is used as the testing data (Fig. 5).

Statistical consistency is made between training and testing data sets as given in Table 1. Care has been taken so that the range of the data set used for testing is the same as the range of the training data set so that when the data set is given to the network for testing, the network should be already trained by that range of data during training process.

Design parameters have been used to create an initial membership function matrix using Gaussian functions described by the following equation:

$$ \mu_i(x) = \exp \left\{ - \left( \frac{x - c_i}{a_i} \right)^2 \right\} $$

(5)

where $c_i$ and $a_i$ are membership function parameters that changes its shape.

Each input variable is characterized by four Gaussian MFs, thus the total number of antecedent parameters is 12. The rule base contains four rules of first-order Sugeno type.

The network is trained by a hybrid learning algorithm to update the parameters [23]. The training phase is a process to determine optimum parameter values to successfully fit the training data. Each epoch consists of a forward pass and a backward pass. In the forward pass of the hybrid learning algorithm, node output goes forward until layer 4 and consequent parameters are identified by the least-square method. In the backward pass, the error signals propagate backward and premise parameters are updated by the gradient descent method. The learning algorithm for the network parameters is discussed in Section 4.2.1.

4.2.1. Learning of network parameters

The overall error function of the network is expressed as follows:
\[ E = \frac{1}{N} \sum_{i=1}^{N} E_i^2 = \frac{1}{N} \sum_{i=1}^{N} (\bar{T}_{\text{avg}} - T_{\text{avg}})^2 \]  

(6)

where \( N \) is the total number of entries in a given training data set, \( \bar{T}_{\text{avg}} \) is experimental output and \( T_{\text{avg}} \) is ANFIS predicted output. If \( \gamma \) is a parameter of the network, then simplifying equation (6) further,

\[ \frac{\partial E}{\partial \gamma} = \sum_{i=1}^{N} \frac{\partial E_i}{\partial \gamma} \]  

(7)

Accordingly, the updated formula for the parameter \( \gamma \) is

\[ \Delta \gamma = -\eta \frac{\partial E}{\partial \gamma} \]  

(8)

In equation (8), \( \eta \) is a learning rate and is given by

\[ \eta = \frac{k}{\sqrt{\sum \left( \frac{\partial E}{\partial \gamma} \right)^2}} \]  

(9)

where \( k \) is the step size, the length of each gradient transition in the parameter space.

4.3. Commissioning results

The developed model has been trained with 1800 data pairs for 60 epochs. Training error graph is shown in Fig. 6. Long-term testing error has been calculated at various steps of commissioning to determine the optimized value of short-term training error. Fig. 7 shows that 0.314 °C of training error gives minimum long-term error of 0.2188 °C. After training, the MFs assume a different form and Fig. 8 presents a comparison between the building air temperature measured and estimated during commissioning period.

5. Simulation results and model validation

Various statistical indices are proposed in the literature to check the predictive performance of the models [7,30]. In this study model performance is measured using the root mean-square error (RMSE) and is defined as,

\[ \text{RMSE} = \sqrt{\frac{1}{N} \sum_{i=1}^{N} (o_i - p_i)^2} \]  

(10)

where \( o_i \) and \( p_i \) are the observed and predicted values of the parameter to be measured, for sample \( i \), \( N \) is total number of samples in the test set.

The strong agreement between measured and estimated temperature values in Fig. 8 indicates that it is possible to tune the model so that it can represent the real situation during the commissioning period. Fig. 9 presents the comparison for the testing data. Good agreement can be observed. This indicates that the model used in the estimator is correctly structured and can accurately estimate the building air temperature.

Eight different sections of the experimental data obtained from laboratory heating system were selected as different test data sets. For training data RMSE is 0.314 °C. Table 2 gives the values for RMSE for different testing data sets. Testing data sets I to VI are for year 2000 and testing data sets VII and VIII are for year 2001. Test data set II is only for day 1–day 21.

Fig. 10 shows the performance of physical model based inferential sensor model. Experimental data is same as that for ANFIS based model. The RMSE for physical model based inferential sensor is 0.54 °C [7]. With ANFIS based inferential sensor model, error has improved to 0.22 °C.

The model presented in this paper can be used to build a soft-sensor. The soft-sensor can estimate the average air temperature in multi-zone heating systems based on the information available to the boiler plant. The soft-sensor is then used to close the feedback loop (dashed line in Fig. 1) from the thermal comfort in the building.

\[ \text{Table 2} \]

RMSE (°C) for different testing data sets.

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</thead>
<tbody>
<tr>
<td>RMSE (°C)</td>
<td>0.3542</td>
<td>0.2188 (Fig. 9)</td>
<td>0.2092</td>
<td>0.3671</td>
<td>0.4982</td>
<td>0.2175</td>
<td>0.5782</td>
<td>0.3459</td>
</tr>
</tbody>
</table>

Fig. 10. Comparison of experimental output and Physical model output.
to the control of boilers. Liao and Dexter presented an inferential control scheme [7]. Performance of the scheme is investigated using simulation. It was found that the control scheme can significantly improve the overall long-term performance of heating systems compared with the conventional boiler controllers.

Limited extra hardware is required for the implementation of the control scheme as the model needs only three variables to be measured. The data about two of the variables, $Q_{SOl}$ and $T_o$, is available from weather information stations. Although the engineering cost will be higher than the conventional open-loop control scheme, but this scheme can significantly improve the energy efficiency and thermal comfort in the built environment. The quantitative analysis in terms of operating cost, installation cost, and increase in energy efficiency and thermal comfort will be presented in other papers.

6. Conclusion

Inferential sensors can be a very effective tool to estimate the average air temperature in multi-zone heating systems. It can provide a rational basis to improve the overall performance of heating systems. In this study, a new methodology based on neural fuzzy method has been proposed to estimate the average air temperature. Based on the results presented the following conclusion can be drawn:

1. The ANFIS model can be commissioned using hybrid learning algorithm. Training data can be obtained through a short-term monitoring of the system.
2. Simulation results obtained using the model, are very close to experimental results. Highest possible RMSE is 0.5782 °C.

The following work is being undertaken to further develop the inferential control schemes using developed model and extend applications:

1. To test the performance of the model in the inferential control scheme.
2. To investigate the scope for improvement of energy efficiency and thermal comfort in built environment.
3. To investigate the applicability of the model for cooling systems.

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