

Original Article

Outdoor Temperature Estimation Using ANFIS for Soft Sensors

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ABSTRACT

In recent years, several studies using smart methods and soft computing in the field of HVAC systems have been provided. In this paper, we propose a framework which will strengthen the benefits of the Fuzzy Logic (FL) and Neural Fuzzy (NF) systems to estimate outdoor temperature. In this regard, Adaptive Neuro Fuzzy Inference System (ANFIS) is used in effective combination of strategic information for estimating the outdoor temperature of the building. A novel versatile calculation focused around ANFIS is proposed to adjust logical progressions and to weaken the questionable aggravation of estimation information from multisensory. Due to ANFIS accuracy in specialized predictions, it is an effective device to manage vulnerabilities of each experiential framework. The NF system can concentrate on measurable properties of the samples throughout the preparation sessions. Reproduction results demonstrate that the calculation can successfully alter the framework to adjust context oriented progressions and has solid combination capacity in opposing questionable data. This sagacious estimator is actualized utilizing Matlab and the exhibitions are explored. The aim of this study is to improve the overall performance of HVAC systems in terms of energy efficiency and thermal comfort in the building.

Keywords: Soft Sensor; ANFIS; Neuro Fuzzy; Outdoor Temperature; Soft Computing

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1. Introduction

During the last two decades, soft Computing in sensor, according to the inference measurement capability has attracted a lot of attention in the field of science and industry^[1]. The sensors which are so-called soft sensors, are essential and valuable replacement for the old hardware to configure new systems^[2]. Soft Sensors are kinds of computer programs that are in use such a relatively inexpensive alternative in hard sensors. Because traditional hard sensors cannot deal with human observation scenarios, but soft sensors can. They are predictive models used to infer the vital process variables difficult and measure in broad range of engineering fields^[3,22,23,29,34]. There are two kinds of soft sensors including physical model based and data-driven soft sensors. Physical model based soft sensors involve 1) first principle-based soft sensors, 2) gray model-based soft sensors, and 3) hybrid model-based soft sensors^[23,24]. Today measurement of necessary parameters online is very costly, difficult, and time-consuming, so the soft sensors use a combination of process data recorded from other sensors and soft sensor techniques are used to estimate the quality of the product and other key indicators widely that can't be measured online by the hard sensors. They are called data-driven soft sensors which often employ multiple adaptive mechanisms and exploit historical databases to deal with non-stationary conditions. They are usually inferential soft sensor which provides the real-time valuable information that

is necessary for effective quality control^[17,18,23,25,26,39].

Data-driven soft sensor is used to estimate the process variables in the situation. They provide good conditions, because variables cannot be measured by classical instruments due to economic constraints or lack of measurement technology or often because of lack of space and environmental conditions. In addition, when the hard sensor is broken or due to maintenance or replacement removed, the data-driven soft sensor can be used as a backup sensor^[3]. Also the data-driven soft sensor is used as an online measurement tool to monitor and control industrial and non-industrial process data^[4,30,31,32].

Today, the soft sensors are benefits such as cost reduction and great improvement of precision^[36], so commonly using measurement sensors of the average temperature is impractical, because its wiring and instrumentation are very expensive to install and maintain^[37]. Data-driven soft sensor can be used for short-term and long-term measurements in prediction or estimation of the air temperature for a long time. Data-driven soft sensor can be implemented with experimental models such as the Principal Component Regression (PCR), Kalman Filter (KF), Kernel Learning Methods (KLM), Kernel Principal Component Analysis (KPCA), Principal Component Analysis (PCA), Support Vector Machines (SVM), Bayesian approaches, Artificial Neural Networks (ANNs), Fuzzy Logic (FL), and Neural Fuzzy (NF). According to a comparison between the NF, ANN and FL models used to determine temperature in data-driven soft sensors^[5,26,27,28,35,38], we resulted that for a thermal sensor, NF model is an appropriate and accurate model for acting. Over the past decades, significant advances have been used in the field of FL and Neural Networks (NNs). A combination of FL and NNs creates a system that has a high learning of thought, reasoning and defines such an improvement tool to determine uncertain behavior of dynamic and complex systems. This model has the advantage of specialized knowledge of fuzzy systems and training capability of the ANNs^[5,6,19,20].

Since Jang has raised NF, its applications have increased in various fields, including engineering, health management, biology and social science. In the background of his research is seen many articles

employed for ANFIS application in automatic control, robotics, nonlinear regression, nonlinear system identification, adaptive signal processing, decision-making, medical quality control, pattern recognition, mapping and list control. NF method claims that it is a general prediction method for nonlinear functions and has more power than conventional statistical methods^[7,21].

ANFIS system functions, including fast and accurate learning, is able to generalize well, explain and express fuzzy rules greatly and adapt the available data and expertise, and make them appropriate for a wide range of scientific and engineering applications^[6]. Today, the Internet of Things (IoT) is an economic revolution which includes the main actors such as data volume and the immediacy. But, the IoT world generates huge amounts of data, known as a “dark data”, because they are generated but never analysed^[29], hence data-driven soft sensors can make such a data useable and meaningful information. In fact, data-driven soft sensors can play important role in IoT infrastructure. These sensors must be updated due to deal trade between the process variables which have time-varying behaviors^[33].

Some studies have used from data-driven soft sensors of NF model on various topics related to HVAC systems, because ANFIS based inferential model represents the dynamics of the targeted system. These data-driven soft sensors are called adaptive soft sensors and use adaptation methods to avoid model degradation in soft sensors. These soft sensors are called adaptive soft sensors^[22,32]. In a research, an inferential sensor based on the modeling of the Adaptive Neuro Fuzzy (ANF) system, estimates the average of the air temperature in several parts used HVAC systems. This paper outlines the analytical performance-based adaptive inferential sensor network which can be used to design adaptive closed loop control of HVAC systems. The structure of ANFIS can be used to model the specific target system. The ANFIS design is produced using subtractive clustering and due to the simplicity, first order Sugeno model has been used such as an interface system. Although, construction and design costs are more than open-loop control, but this plan can significantly improve efficiency and thermal comfort of the building^[7].

In another research, NN and inferential sensor based on NF hybrid model have been compared for HVAC systems. Here, the average estimation of the air temperature in the building has been presented by means of NN models and ANFIS based on inferential sensor. In this study, three different models of inferential sensor: ANFIS-SUB, ANFIS-GRID and integer NN have been compared in HVAC systems with each other. ANFIS-SUB model estimates the average of the air temperature in the environment accurately and give the best results. Integer NN model has the lowest precision^[8].

In another article with the rules of physics as a model of ANF inferential sensor, the sensor has been proposed for predicting indoor temperature in heating systems and its operating have been compared with non-physical rules based on ANFIS model in estimating the indoor temperature. ANFIS sensor based on physical rules, has the higher prediction in estimating indoor temperature of the building, so the control signals are more consistent in heating systems and can be effective in improving energy efficiency in the heating systems especially improving energy efficiency, logically^[9].

ANFIS, as a platform that upgrades the capacity to consequently learn and adjust, has been utilized via specialists within different design frameworks^[10,11]. Also, there are numerous investigations of the requisition of ANFIS for estimation and constant recognizable proof of numerous distinctive frameworks^[12,13]. Fuzzy Inference System (FIS) is the principle center of ANFIS. FIS is focused on skill based on “If-then” rules and can subsequently be utilized to anticipate the conduct of numerous questionable frameworks. FIS preference is that it does not oblige information of the underlying physical process as a precondition for its provision. In this way, ANFIS incorporates the FIS into a back-proliferation taking in calculation of neural system.

In this article it is endeavored by soft computing principle i.e. ANFIS to structure an effective information combination method for the outdoor temperature

estimation of the building. So, a novel versatile calculation focused on ANFIS is proposed to alter framework of the thermal sensors to adjust context oriented progressions and constrict the unverifiable aggravation of estimation information from multisensory and be updated according to its weight. Utilizing a given info/yield information set, ANFIS develops a FIS whose enrollment capacity parameters are tuned by a half system, back propagation calculation and minimum squares strategy^[14–16,30]. In this model, when new data set is arrived from hard sensors, it will be trained and aggregated into adaptive inferential soft sensor according to its weight. The recreation results indicate that the novel calculation proposed in this paper has higher exactness and strength and how to use and the performance is given. Therefore, section 2 offers materials and methods, section 3 presents result and discussions and finally section 4 provides conclusion.

2. Materials and Methods

2.1 ANFIS Model

In this paper, ANFIS structure is employed to estimate outdoor temperature of the building (**Figure 1**). The structural planning comprises two parts: 1) indoor temperature sensors (hard sensors) and 2) soft sensor. 4 hard sensors collect indoor temperature during 24 hours from 4 rooms (**Figure 2**). Then the data values of these sensors are sent to soft sensor. Soft sensor has two parts: 1) ANFIS section and 2) display for outdoor temperature. In ANFIS, the quality of trading and testing data have an important role in determination of soft sensor performance. Training must be performed after extracting desired features from the NF signal^[17,18], thus adaptive noise cancellation method based on the estimation and subtraction of the noise from the signal is used that is one of the most useful methods^[19–22]. Then, trained data without cancelation noise and after noise cancellation of the indoor temperature, will be reformed by suitable track-to-track combination calculation, and then outdoor temperature will be announced via ANFIS and displayed.

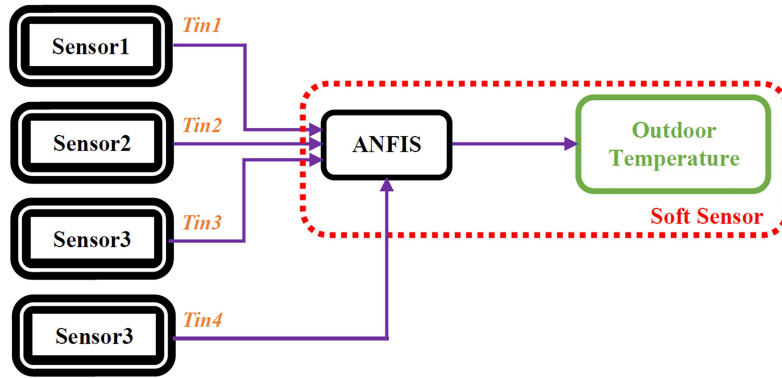


Figure 1. The architecture of the algorithm based on ANFIS.

In this paper, ANFIS is a key section of the proposed structural planning. Also, the certain computation of the hard sensors will impact the last combination result. The modeling of this paper is performed for a residential building with area of 450 square meters in the northern city of Mashhad, built in 1976. This building is next to other buildings and is located in south-north direction and has windows with 4 rooms. Experimental data obtained from temperature

sensors located in 4 rooms for collecting data from the 21 May to 2 April 2015 for 12 days during 24 hours per day (**Figure 2**). Therefore, ANFIS has 4 inputs: the indoor temperature of the room 1 (Tin1), the indoor temperature of the room 2 (Tin2), the indoor temperature of the room 3 (Tin3) and the indoor temperature of the room 4 (Tin4) which are in °C. and outdoor temperature obtained from www.weather.com. These experimental data are used for training and testing here.

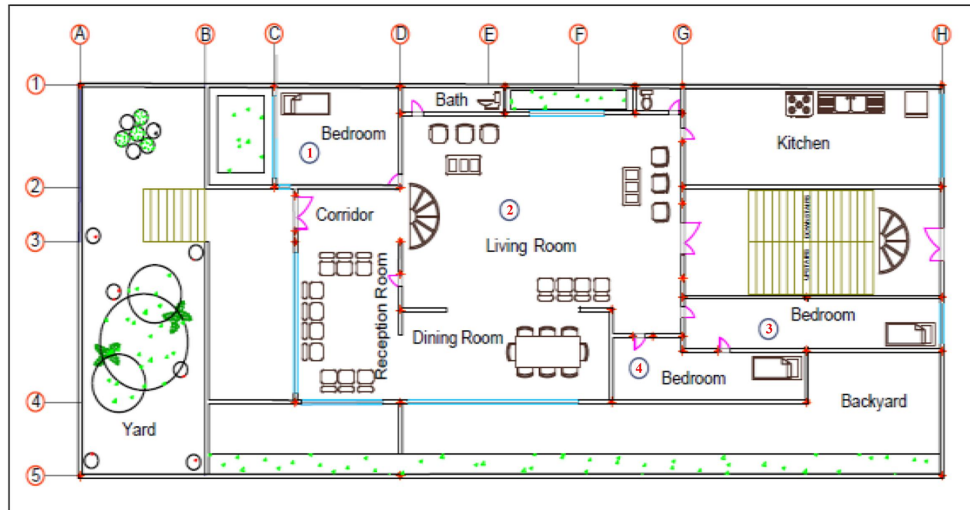


Figure 2. Selection of four building rooms for outdoor temperature test.

ANFIS has five layers totally to perform various node functions. It uses a hybrid learning mode for learning and tuning parameters in FIS. The least square error approach is applied to update the resulted parameters in the forward pass and back them to the backward pass. So, the resulted parameters are fixed in the backward pass and gradient descent method is employed to update the given parameters. Each of the forward and backward pass completed, is called epoch.

The given and resulted parameters are recalled for FIS and Membership Functions (MF) by forward and backward repetition. If there are m MFs for each input variable and n input variables for the problem, the total number of fuzzy rules will be m^n . In this study, the total number of fuzzy rules is $8^4 = 4096$, but we use 3 MFs. Here, the real outdoor temperatures have been collected the site www.weather.com from the 21 May to 2 April 2015 for 12 days during 24 hours per day. Two

dimensional exhibitions of the real outdoor temperatures are shown in **Figure 3**.

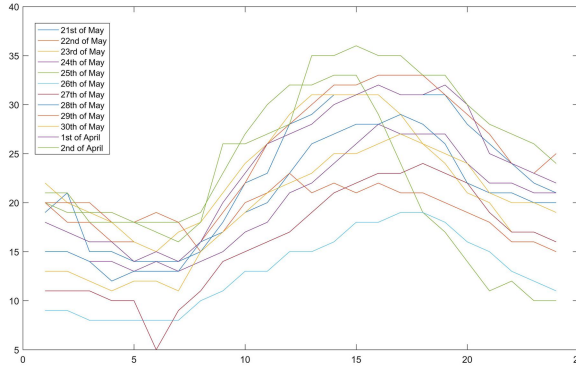


Figure 3. Real outdoor temperatures for 12 days during 24 hours.

FIS is the main core of ANFIS. FIS is based on expertise expressed in terms of ‘IF–THEN’ rules and can thus be employed to predict the behavior of many uncertain systems. The advantage of FIS is that it does not require the knowledge of the underlying physical process as a precondition for its application. Thus ANFIS

integrates the FIS with a back propagation learning algorithm of NN. FIS has three conceptual components: a rule base, which contains a selection of fuzzy rules; a database, which defines the MFs used in the fuzzy rules; and a reasoning mechanism, which performs the inference procedure upon the rules and the given facts to derive a reasonable output or conclusion.

Intelligent systems combine knowledge, technique and methodologies from various sources. They possess human-like expertise within a specific domain, adapt themselves, and learn better in changing environments. In ANFIS, NNs recognize patterns, and are adapted for environments. ANFIS is tuned with a back propagation algorithm based on the collection of input/output data. In this study ANFIS algorithm in MATLAB was used for the entire process of training and evaluation of FIS. **Figure 4** shows the ANFIS structure of this study. In this work, the first-order Sugeno model with four inputs and fuzzy IF-THEN rules of Takagi and Sugeno’s type is used.

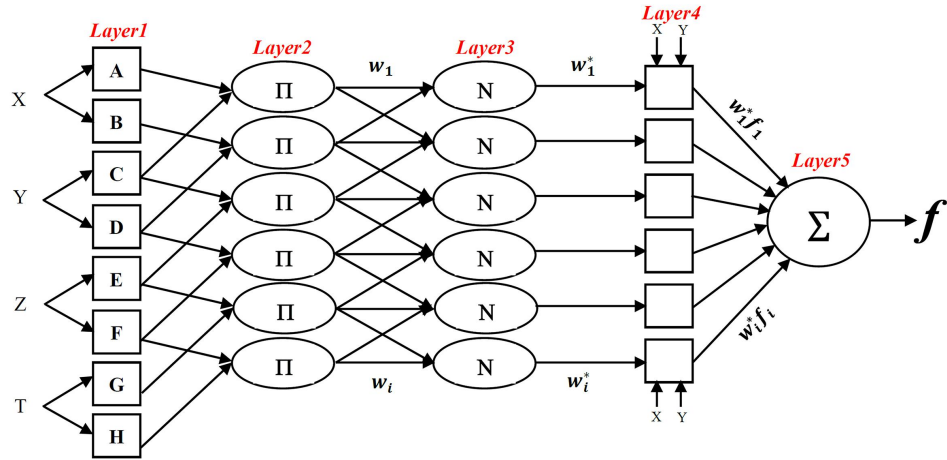


Figure 4. ANFIS structure with three inputs.

2.2 Model Evaluation

NF is the combination of FL and ANN^[20] whose fuzzy system is better. It relies on specialize knowledge lower (**Figure 5**)^[9]. NF is a method in which vector input values are given ad then using some conditional fuzzy rules, output values are considered (Eq. 1).

$$\text{if } x \text{ is } A \text{ then } y \text{ is } B \quad (1)$$

In equation 1, A and B are fuzzy sets. Each of fuzzy set are known by MF. MFs give each component, rules of Takagi and Sugeno’s type are widely used for

value between 0 and 1. The first and second sections of the condition can include different parts. These parts are joined with each other with Boolean operators such as AND/OR and equivalent to maximum and minimum fuzzy operation. A NF system is based on fuzzy rules and database in which membership of fuzzy set, is introduced. After that, it has an inference mechanism which performs inferential process. Takagi and Sugeno’s system are suitable for fuzzy modeling based on data sample between various fuzzy systems. Fuzzy IF-THEN interpretation of efficiency, high applied calculation and

optimized and compatible methods between FIS models^[4]. Each of the rules are determined such input

values. For example, in first degree of Sugeno's model with two inputs X_1 and X_2 , the i rule is as equation 2.

$$\text{if } X_1 \text{ is } X_{1,i} \text{ AND } X_2 \text{ is } X_{2,i} \text{ THEN } Y_i = P_{i,0} + P_{i,2}X_1 + P_{i,2}X_2 \quad (2)$$

In equation 2, X shows fuzzy sets corresponding to each linguistic labels and P_i is a set of adjustable parameters. The final output, Y , is weighting average of each rule as equation 3.

$$Y = \sum w_i Y_i \quad (3)$$

Where w_i is the i th rule. On the other hand, ANN has some nodes joined to each other with direct link. Each of the nodes are known due to a node which is a function of adjustable or fixed parameters. The optimized values can determine through training. Training rule is a backward method. This rule minimizes the measurement criteria and usually includes the sum of square of difference between network output and desired output. In NF model, the performance of the nodes is such a forward structure with 5 layers where are defined here:

Layer 1: Adaptive nodes that MF of the input values are used such as the functions of these nodes. The parameters of this layer are known as the first or primary parameters.

Layer 2: Fixed nodes whose outputs show the power of the use of these rules (Eq. 4).

$$O_{2,k} = \mu_{A_i}(X) * \mu_{B_j}(Y) \quad (4)$$

Layer 3: Fixed nodes whose outputs show the normalizing power of the drive. The participation ratio of each rule to the participation degree is as follow (Eq. 5).

$$O_{3,i} = \bar{w}_i = \frac{w_i}{\sum_{k=1}^4 w_k} \quad (5)$$

Layer 4: Adaptive nodes which calculate the output of each node using resulted parameters. It is defined as below (Eq. 6).

$$O_{4,i} = \bar{w}_i f_i = p_i x_i + q_i x_2 + r_i \quad (6)$$

Layer 5: The output node whose output is equal to the sum of the all output rules.

$$O_{5,i} = \bar{w}_i f_i = \frac{\sum_{i=1}^4 w_i f_i}{\sum_{i=1}^4 w_i} \quad (7)$$

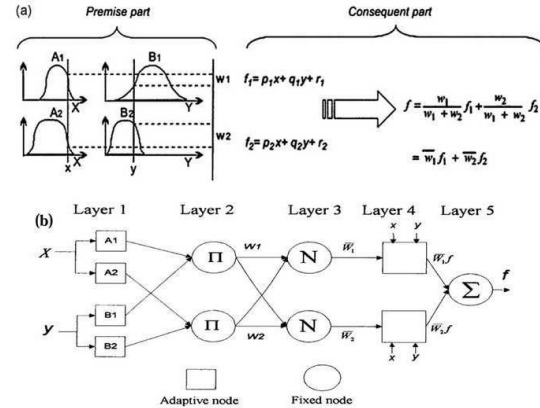


Figure 5. (a) FL in ANFIS. (b) ANN in ANFIS^[21,40].

In the forward pass of the ANFIS algorithm, functional signals go forward until Layer 4 and the consequent parameters are identified by the least squares estimate. In the backward pass, the error rates propagate backwards and the premise parameters are updated by the gradient descent.

3. Results and Discussion

In this paper, we use from temperature data and the output data for training. Then, we generate initial FIS. After training we tune initial FIS. Then, the output is evaluated by input data and tuned FIS. Also, we cancel the noise of temperature data one by one. So, the input signals are measured and canceled from input. We want to have an error comparison between the output without noise and with noise with real output. Here, the output is the outdoor temperature.

3.1 Nonlinear Noise Cancellation

In this part of the study, we explore and correct the noise which occurs from interfering with any of the indoor temperature sensor inputs and can influence on calculation of the outdoor temperature. At first, we compute the noise of any inputs alone with the programming and then we cancel all the three noise together on program. Here, adaptive nonlinear noise cancellation using the FL functions has been simulated. Outdoor temperature signal cannot be measured without

an interference signal, n_2 , which is generated from another noise source, n_1 , e.g. Tin1, Tin2, Tin3 and Tin4 via a certain unknown nonlinear process.

The **Figure 6** shows the inputs with noise source and inputs without noise (Tin1, Tin2, Tin3 and Tin4).

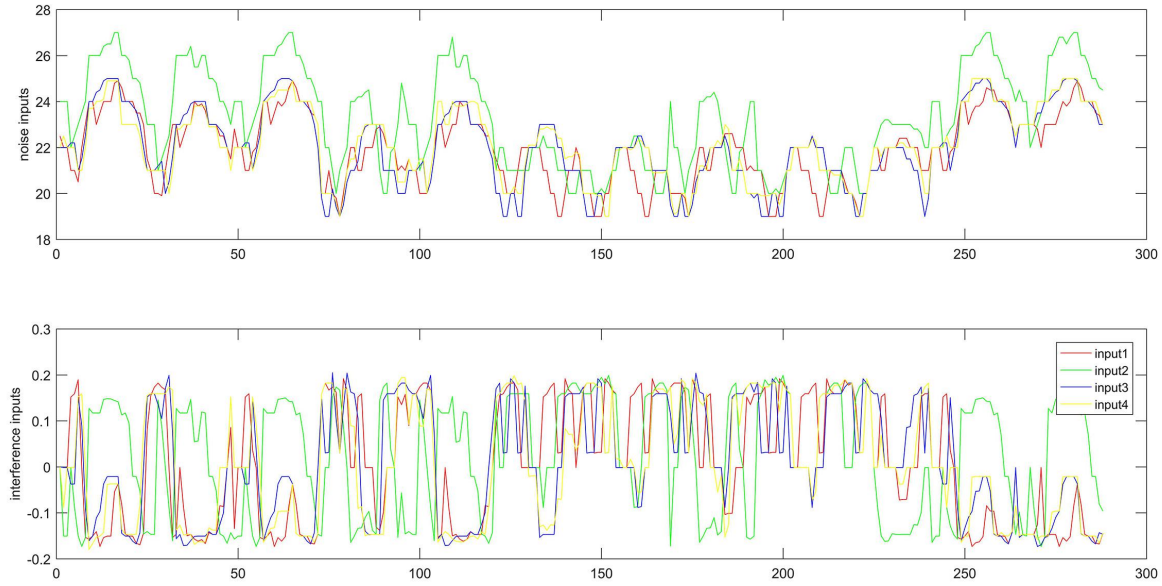


Figure 6. Temperature inputs with noise (above) and without noise (below).

The interference/noise signal n_{2k} that appears in the input signal is assumed to be generated via an unknown nonlinear equation like:

$$n_{2k} = 4 * \frac{\sin(n_{1k}) * n_{1-k}}{[1 + n_{1-k}^2]} \quad (8)$$

Note that n_{1k} is related to temperature input and n_{1-k} is the inference signal. The noise measures with

equations 8 and 9 during 288 hours. **Figure 7** illustrates the noise results of our original source.

$$x = \sin(40 / (time + 0.01)) \cdot time = 1:288 \quad (9)$$

$$m_i = x' + n_{2k} \quad (10)$$

Where m_i is the measured noise signal of each temperature input.

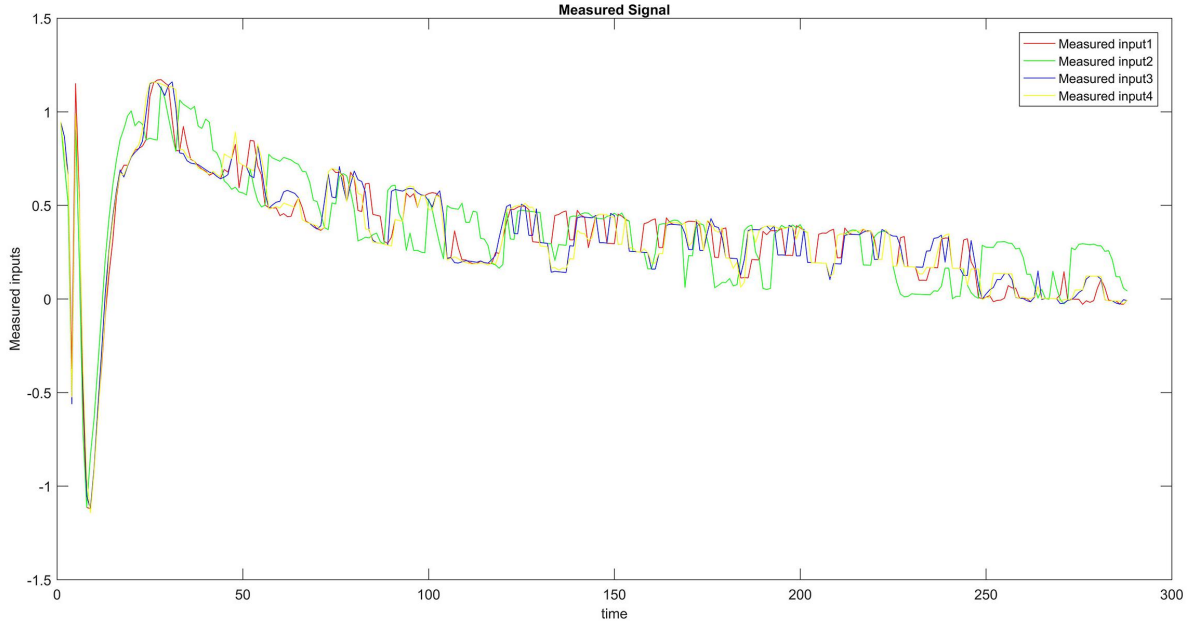


Figure 7. Measured noise signal input.

Then, we cancel this noise from the estimated output (Eq. 11).

$$Output_{With\ canceled\ noise} = Output_{estimated} - \sum_{i=1}^k m_i$$

(11)

Figures 8 and 9 show the estimated output and estimated output with canceled noise.

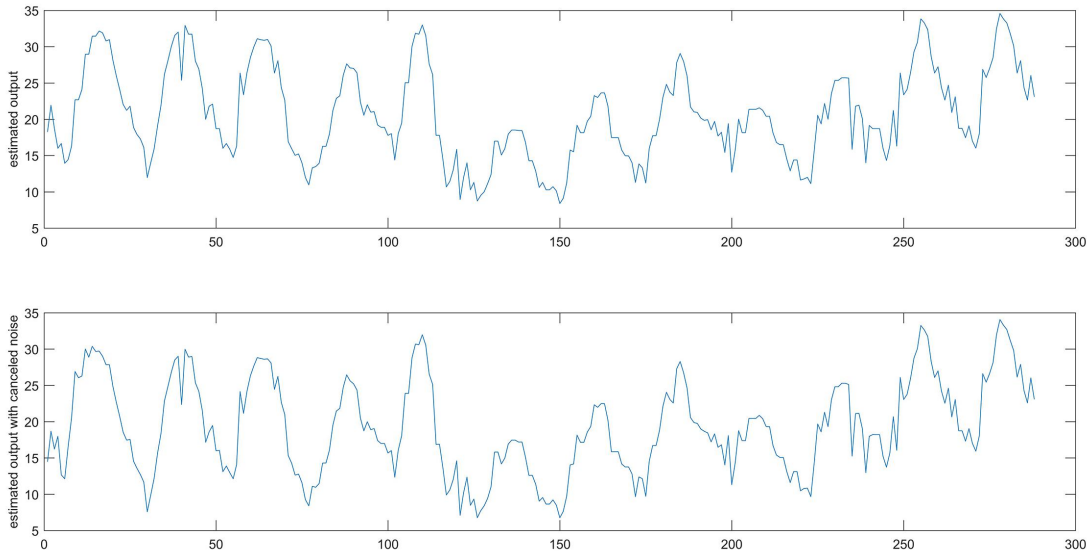


Figure 8. Estimated outdoor temperature (above) and with canceled noise (below).

Figure 9 shows the real outdoor temperature, temperature with canceled noise together. estimated outdoor temperature and estimated outdoor

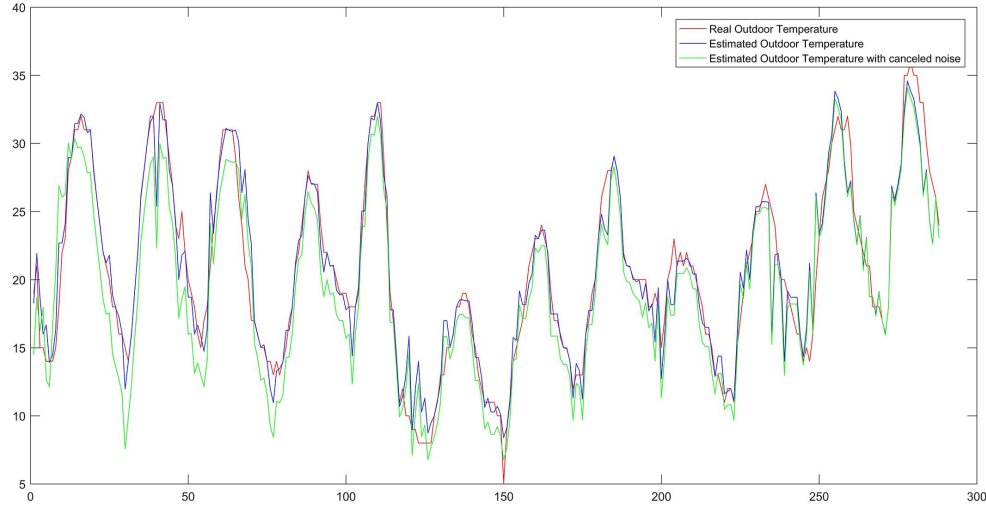


Figure 9. Real outdoor temperature (red color), estimated outdoor temperature (blue color) and estimated outdoor temperature with canceled noise (green color).

3.2 Error Discussion

As a data-driven model, the ability of the ANFIS to make reasonable estimations is mostly dependent on input parameter selection for training. In this study, three bell-shaped membership functions are used for each input during the training procedure, and the training procedure lasts 50 epochs. We have 5 temperature inputs for training including 4 temperature data from hard sensors and outdoor temperature from online database. So, adequate consideration of the factors controlling the system studied is crucial to developing a reliable network. The ANFIS information data have been given in **Table 1**. For this experiments, we use 50% of the data to train, 20% to validate and 30% to test samples.

Table 1. ANFIS information data

Number of nodes: 193
Number of linear parameters: 405
Number of nonlinear parameters: 36
Total number of parameters: 441
Number of training data pairs: 288
Number of checking data pairs: 0
Number of fuzzy rules: 81

To estimate the error and the accuracy of the proposed model for estimated outdoor temperature and

estimated outdoor temperature with canceled noise, three errors are determined: Root Mean Square Error (RMSE), Mean Absolute Error (MAE) and Mean Squared Error (MSE) (Eqs. 12-14) (**Table 2**).

$$RMSE = \sqrt{\frac{1}{N} \sum_{i=1}^N (O_i - P_i)^2} \quad (12)$$

$$MAE = \frac{1}{N} \sum_{i=1}^N |O_i - P_i| \quad (13)$$

$$MSE = \frac{1}{N} \sum_{i=1}^N (O_i - P_i)^2 \quad (14)$$

Where O_i and P_i are the real outdoor temperature and estimated outdoor temperature, respectively, and N is the number of output data.

Table 2. Accuracy comparison of ANFIS model with RMSE, MAE and MSE

Statistical Methods	Estimated outdoor temperature	Estimated outdoor temperature with canceled noise
RMSE	1.95	2.69
MAE	1.19	2.13
MSE	3.81	7.28

4. Conclusion

In this study, a data-driven soft sensor model was developed in MATLAB with ANFIS for the estimation of building outdoor temperature. Simulations are run in MATLAB and the results are observed on the corresponding output blocks. The main advantages of the ANFIS scheme are: computationally efficient, well-adaptable with optimization and adaptive techniques. ANFIS can also be used with systems handling more complex parameters. Another advantage of ANFIS is its speed of operation, which is much faster than in other control strategies. The results show that hard sensors must not be located adjacent to noise, because the accuracy of them decreases, so this data-driven soft sensor model without noise has an accurate result. Hence, this model can be considered as a very useful and cost-efficient tool for estimating the outdoor air temperature. This model can be used in automatic systems especially in the HVAC systems to improve energy efficiency. It is likewise conceivable to be connected to numerous fields including coordinated route, sign transforming, picture handling, and deficiency identification, and so on. Future work is using unsupervised algorithm for this goal.

Conflict of Interest

There is no conflict of interest.

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