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Area temperature system monitoring and computing based on adaptive fuzzy logic in wireless sensor networks

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ABSTRACT

The many subfields in the wireless sensor networking literature include data fusion, data aggregation, remote environmental monitoring, sensing (temperature, pressure speed) and various military applications. The distance between sensor nodes can be measured by a Received Signal Strength Indicator (RSSI). This study proposes both average and adaptive fuzzy logic algorithms for computing temperature in a monitored area. The main advantages of these methods are their simplicity and accuracy and better than the standard Manadni fuzzy logic method. Finally, comparison of the two methods in terms of root mean square error shows that the adaptive fuzzy logical algorithm with RSSI is better than average fuzzy logical algorithm for computing monitoring area temperature.

1. Introduction

Wireless sensor networks (WSNs) have attracted research interest in recent years because of their many potential applications, including military target tracking and surveillance [1,2], natural disaster relief [3], biomedical health monitoring [4,5], hazardous environment exploration and seismic sensing [6]. In military target tracking and surveillance, applications of WSNs include intrusion detection and identification. Specific examples include spatially correlated and coordinated detection of troop and tank movements. Sensor nodes can also sense and detect environmental change in disaster forecasting. Biomedical applications include surgical implant sensors for monitoring patients. For seismic sensing, *ad hoc* sensor deployment along a volcanic area can detect earthquakes and eruptions. A wireless sensor network includes numerous small, energy-constrained nodes. The basic components of a sensor node include a single or multiple sensor modules, a wireless transmitter–receiver module, a computational module and a power supply module. These nodes are usually small and inexpensive to allow deployment on a large scale. These sensors usually have a wireless link that can be used to extract the information captured by the sensor. A sensor node has a small micro-controller and an energy source, usually a battery. In order to meet the objective of these sensors, resources in terms of energy, memory, computational speed and bandwidth are severely constrained. The sensors use each other to transport data to a monitoring entity. Because each sensor has a limited energy supply, the sensors must conserve energy if the network is to operate for a long time. Currently, most sensors are wired. Although most sensors are wired, wireless sensors provide significant advantages. Low-cost sensors and communication networks enable quick and inexpensive deployment of wired sensor networks.

Wireless Sensor standards have been developed to minimize energy consumption, which is a key design requirement. The standard defines the functions and protocols needed for sensor nodes to interface with various networks. The following paragraph describes the ZigBee standard in detail. ZigBee is a simple, low cost, low power wireless communication technology used in embedded applications to define the higher layer communication protocols built on the IEEE 802.15.4 standards for WSN. ZigBee devices can form mesh networks consisting of hundreds or even thousands of devices. ZigBee devices use very little power and can operate on a cell battery for many years. The three ZigBee devices are the coordinator, which initiates network formation, stores information and bridges networks; routers, which link groups of devices and provide multi-hop communication across devices, and end devices, which consist of sensors, actuators and controllers that collect data and communicate only with the router or coordinator. The ZigBee standard was adopted in June 2005.

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In 1965, Zadeh introduced fuzzy set and fuzzy logic theory to solve problems involving knowledge expressed in vague, linguistic terms. A crisp set is a collection of elements in which some elements either do or do not belong to a set. In a crisp set, the elements in a set are unambiguous. In a fuzzy set, however, each element has a graded membership in the real interval [0,1]. That is, membership is not an absolute. Fuzzy set theory can be defined as a collection of elements in a universe of information in which the boundary of the set contained in the universe is ambiguous, vague and otherwise fuzzy.

Fuzzification is the process of transforming crisp values into fuzzy linguistic variables. The membership function associates a grade with each linguistic variable. The number of membership functions and their initial values are selected based on process knowledge and intuition. A membership function has value between 0 and 1 over a crisp variable interval.

The benefit of fuzzy logic is its use in constructing mathematical models that are more robust than those constructed using classical mathematical models for plant parameter changes.

The four parts in the main configuration of the fuzzy logic controller are fuzzification, inference engine, rule base and defuzzification. Initially, a fuzzification process converts the controller input into linguistic fuzzy variables that describe input behavior. The dynamic behavior of the fuzzy system is described by a set of linguistic description rules (IF–THEN rules). These rules describe the relation between the linguistic inputs and the output variables of the fuzzy system based on expert knowledge of system behavior. This set of linguistic IF–THEN rules for describing the system are usually given in the following form:

IF (a set of conditions are satisfied) **THEN** (a set of consequences can be inferred)

For example, **IF** (x_1 is A_1 AND x_2 is A_2, . . ., x_d is A_d) **THEN** (y is B_1).

An inference mechanism then calculates the degree to which the input data matches the condition of the fuzzy rules. It also obtains a conclusion by matching and combining all inferred rules. Finally, the defuzzification process maps the fuzzy rule outputs to a crisp (single) point.

The motivation of this study is to develop a novel fuzzy logic algorithm for computing temperature in a monitored area of a WSN. The objective is to use fuzzy logic algorithm to compute area temperature based on known information about deployment nodes. Area temperature was monitored by calculating root mean square error (RMSE). To our knowledge, this study is the first to apply fuzzy logic for simple and accurate area temperature monitoring. The contribution of this paper is to design both rules and inference of the fuzzy logic system. The main advantage of the proposed method is that it directly uses values of the temperatures in the reference points to calculate the outputs, allowing the number of rules to be reduced.

This paper is organized as follows: the next section discusses the related literature and the motivation for the study. Section 3 describes the experiment setup for the temperature computing system. Section 4 describes the proposed method. Section 5 presents some experimental results and discussion. Section 6 presents concluding remarks.

2. Related literature

Wireless sensor networks have attracted research interest because of their many potential applications, including environmental and habitat monitoring, industrial process control, infrastructure security [7], and transportation automation. Demirbas [8] presented a feasibility study of wireless sensor networks for monitoring large public buildings and proposed several directions for research in using WSNs for event detection. In [9], a fuzzy inference system was proposed for detecting fires in aircraft dry bays and engine compartment fire detection systems. Proposed fire detection system used image analysis technique. Histogram and successive frame subtraction data statistical measures enable the use of fuzzy if–then rules to compute the probability of a fire. In [10,11], a neural network and fuzzy inference system was proposed for detecting fires by transmitting multi-sensor data to the user through RS 232 cable.

A fuzzy controller module design creates a Knowledge Base consisting of concept information in a Data Base and Rules Base. The Knowledge Base has a static data structure with a predefined size and installed content. The Knowledge Base structure should be defined before starting the application work. The Data Base contains fuzzy set information such as linguistic terms used in fuzzy rules. To simplify a calculation, each fuzzy set membership function is presented as a piecewise-linear function with three or four points. The point count depends on whether the membership function is triangular or trapezoidal. Moreover, medical applications of fuzzy set theory have been developed to address uncertainty when making decisions. Thus, fuzzy sets have attracted interest in their potential use in modern information technology, production techniques, decision making, pattern recognition, diagnostics, data analysis, etc. [12–15].

Neuro-fuzzy systems are fuzzy ANNs that validate their properties (fuzzy sets and fuzzy rules) by processing data samples. Neuro-fuzzy systems connect the power of the two paradigms: fuzzy logic and ANNs, by using the mathematical properties of ANNs to tune rule-based fuzzy systems [16–18].

Some basic scientific categories are medical information, anatomy, pathology, forensic medicine, genetics, physiology, pharmacology, and education. Fuzzy logic was first applied in medical informatics in the early 1970s. Recent work in fuzzy controllers has focused on stability, self-organizing, and synergies among computing techniques such as neural networks and genetic algorithms. The potential use of fuzzy logic for managing and retrieving information was discussed by Chiodo et al. [19]. Recently, a decision support system running across the World-Wide Web was designed by McCall and Petrovski [20]. The client server contains a database of treatment information that are optimized using genetic algorithms; the system is currently undergoing trials in the United Kingdom. Two recent studies by Sadegh-Zadeh [21,22] developed a fuzzy theory for health, illness, and disease; an extensional-recursive scheme for defining the controversial notion of disease is also proposed to support the proposed concept of fuzzy disease. Comparison of performance for a space fault detection application with Takagi–Sugeno–Kang (TSK) [23,24] and Mandani-type fuzzy inference systems was proposed in [25]. The experiment results show that the TPK method has smoother transitions than Mandani method. For control of a simple dynamic process with fuzzy algorithms was proposed in [26] used Mandani method to handle nonlinear system.

Studies of fuzzy distance measurement by WSN based on RSSI include [27], which proposed a fuzzy inference system trained by adaptive neural-fuzzy inference system to map RSSI into correct T–R distance and performed experiments to confirm its feasibility. A WSN with a multi-sensor data fusion algorithm fuzzy logic for fire detection is proposed in [28]. By improving the reliability and accuracy of sensed information, the proposed method minimizes the false alarm rate. One ZigBee Personnel Location system proposed in [29] used a fuzzy logical model to reduce uncertainty in the RSS character matrix. Extending the lifetime of the energy constrained wireless sensor networks is a crucial challenge in sensor network research [30], which proposed an interval type-2 fuzzy logic method to improve this problem. Fuzzy logic rules in [31] adjusted the mutation rate and crossover rate of the genetic

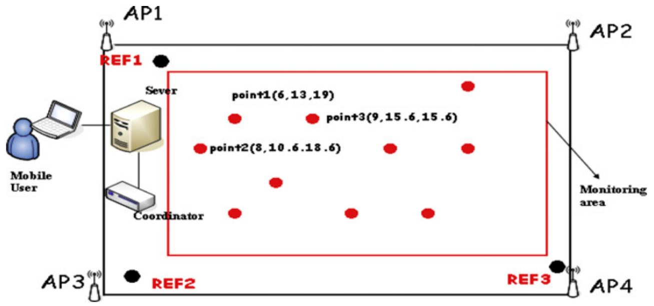


Fig. 1. Experiment setup for temperature computing system. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

algorithm according to best fitness, average fitness and variance in fitness. The proposed adaptive genetic algorithm with fuzzy logic method performs better than a standard GA method does in terms of solving convergence problems. Three techniques used in soft computing [32] are genetic algorithm, fuzzy logic algorithm and neuro computing. Hybrid soft computing techniques reportedly outperform other methods. A two-phase learning method for fuzzy article neural networks introduced in [33] demonstrated better performance compared to methods using basic genetic algorithms. In [34], fuzzy technique was used to evaluate performance in terms of similarity to ideal solution approach based on modified performance ratio and an efficient fuzzy distance measurement. The authors also used this method to rank fuzzy closeness and fuzzy numbers for improved accuracy. In [35–37], the authors overcome complex uncertain concept with fuzzy set theory was used to evaluate linguistic vagueness.

3. Experiment setup for temperature computing system

The experimental area was a room with dimensions 30 m (L) × 40 m (W) × 15 m (H). The monitored area in this study was delineated by four ZigBee access points inside, coordinator, sever, three reference points and ten unknown test points (red block in Fig. 1). The temperatures at all 13 points are transmitted to the coordinator. The mobile user can compute temperature at ten points in red black for monitoring area when collecting data from the coordinator. First, only the temperature of unknown points 1, 2 and 3 of the ten points are computed. Fig. 1 depicts the distances from all points d_1 to REF1, d_2 to REF2 and d_3 to REF3. The temperatures at the three reference points are T_1, T_2 and T_3.

Fig. 2 shows that WSN node devices in this study included sensing units, processing units, transceiver units and power units. Their functions were as follows:

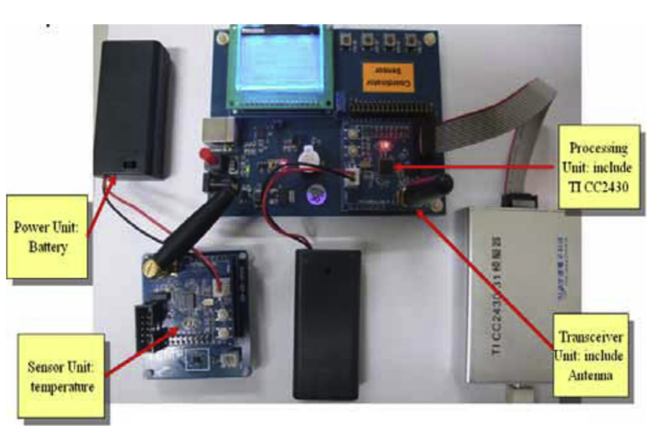


Fig. 2. Sensor nodes in proposed temperature computing system.

(1) Sensing unit. Includes sensor and the analog-to-digital converter for detecting and collecting environmental data, which are represented using analog signals. The analog-to-digital converter then converts the analog signals into digital data and sends the data to the processing unit. The sensing unit provides data for temperature, humidity, ultraviolet light and illumination.
(2) Processing unit. Contains a unit for processing data according to the pre-defined program codes and a unit for storing the collected environmental data.
(3) Transceiver unit. Communicates between the sensor devices.
(4) Power unit. Provides electrical power to WSN.

4. The fuzzy logical algorithm for computing temperature system

4.1. System architecture for this system

The WSN technologies are based on Received Signal Strength Indicator (RSSI) and distance measurements. In [23], a novel distance measuring technology based on RSSI and fuzzy inference dramatically improved the precision of distance measurements between transmitter and receiver. Generally, the longer the distance between transmitter and receiver, the lower the receiving power of the receiver provided by RSSI on RF chip. The relationship between RSSI and distance can be determined by the following formula based on Friis transmission equation:

$$\text{RSSI} \quad [\text{dBm}] = -(10 \times n \times \log_{10}(d) + A) \tag{1}$$

where initial signal strength A describes the absolute value of RSSI at a distance of 1 m to the transmitter. The signal propagation coefficient n shows the signal damping.

Fig. 3 shows the three parts of the fuzzy logic system for computing test point temperature: the main parameters of this system are the fuzzy rules for input variables, membership function for distance, and correlation coefficients of $\mu_A(d_i)$. Finally, each fuzzy rule for test point temperature is an output variable. However, choosing the correlation coefficients and membership functions was the main objective of this study. The distances between reference points and test points are classified as very close, close, medium, far, and very far. The fuzzy membership functions generally include Sigmoid-shaped function, Gaussian-shaped function, triangle-shaped function, trapezoid-shaped function, S-shaped function and Z-shaped function or combination of them. The Friis transmission equation confirms the assertion that the longer the distance between test points used as reference (T–R), the lower the correlation coefficient. Therefore, the system has five rules.

(1) If T–R distance is very far, then correlation coefficient is very small.
(2) If T–R distance is far, then correlation coefficient is small.
(3) If T–R distance is medium, then correlation coefficient is moderate.
(4) If T–R distance is close, then correlation coefficient is large.
(5) If T–R distance is very close, then correlation coefficient is very large.

The correlation coefficients depend on distances between reference points and test points. Fig. 4 shows that correlation coefficients calculated for the proposed fuzzy logic system with different membership function for distance. Therefore, correlation coefficients were used to fix for fast and simple temperature calculations instead of using a function for that. Because the distance between the test points and reference points for membership function of

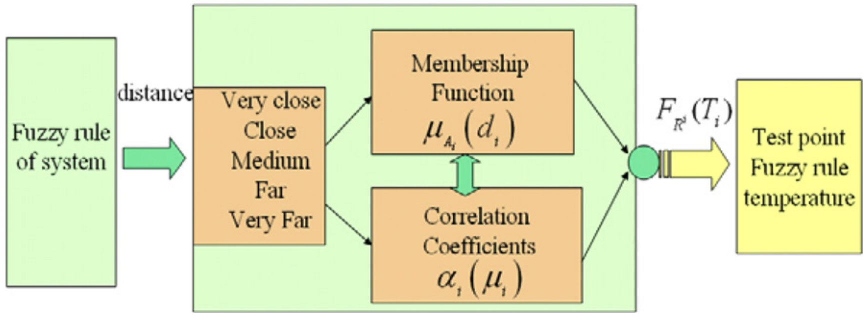


Fig. 3. Fuzzy logic for temperature computing system.

fuzzy logic temperature computing system have five levels. (Very close, Close, Medium, Far and Very far.) Those values are between 0 and 1 which divided into five equal portions and were calculated by averaging, which were assigned values of 0.1, 0.3, 0.5, 0.7, and 0.9 from the smallest to the largest, respectively and not arbitrary for this system.

The fuzzy inference system has fuzzy rules (IF antecedent THEN consequent) derived from either an expert Knowledge Base or from system input–output learning. Gaussian, triangle, trapezoid and Sigmoid functions are the most common membership functions. The Gaussian function has good local approximation ability for the radial basis function (RBF) neural network. In the back-propagation network (BPN), the Sigmoid function has a better ability of finding the global optimum. In this study, choosing the membership functions for input variables based on the advantages of RBF and BPN. The Z-shaped (Very close), S-shaped (Very far) and Gaussian membership functions (Close, Medium, Far) are therefore used as variables to simplify the computations and to obtain an RMSE better than that of other membership functions in the fuzzy logical temperature computing system. As described above, the appropriate membership function and correlation coefficient are obtained. Finally, based on the flowchart, the test point transfer function with fuzzy rule for temperature is defined as $F_{Rj}(T)$.

$$F_{Rj}(T) = \frac{\sum_{i=1}^{3} T_i \mu_A(d_i)\alpha(\mu_i)}{\sum_{i=1}^{3} \mu_A(d_i)\alpha(\mu_i)} \tag{2}$$

where T_i is the temperature of ith reference point; d_i is the distance between test point and ith reference point; $\mu_A(d_i)$ is membership function of d_i; $\alpha(\mu_i)$ is correlation coefficient of the $\mu_A(d_i)$.

4.2. The fuzzy logic algorithm for this system

The must commonly used fuzzy inference technique is Mandani method. The Mandani method is also called Maximum–Minimum Composition.

Max–min composition is defined as follow:

$$\mu_{MoN}(u, w) = \cup_v(\mu_M(u, v) \cap \mu_N(v, w)) \tag{3}$$

In terms of use, the Mandani is more widely used, mostly because it provides reasonable results with a relatively simple structure, and also due to the intuitive and interpretable nature of the rule base.

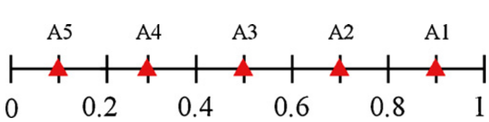


Fig. 4. The correlation coefficients were calculated by averaging between 0 and 1.

For fuzzy logic (FL), the operators min, max and complement correspond to and, or and not, and defined as:

$$\mu_{A\cap B}(u) = \min(\mu_A(u), \mu_B(u)) \tag{4}$$

$$\mu_{A\cup B}(u) = \max(\mu_A(u), \mu_B(u)) \tag{5}$$

$$\mu_{\overline{A}}(u) = 1 - \mu_A(u) \tag{6}$$

According to (4) and (5), we can also display (3) as the follow:

$$\mu_{MoN}(u, w) = \max_v \min(\mu_M(u, v), \mu_N(v, w)) \tag{7}$$

A fuzzy control model for this system is established with the distances between sensors nodes as input variables and each fuzzy rule for test point temperature as output variable.

The input/output fuzzy relations rule R_j as the follow:

$$R_j = (d_{1k} \times d_{2k} \times d_{3k}) \times T_{ref} \tag{8}$$

where d_1, d_2, d_3 is the distance between test point and reference points 1, 2, and 3; T_{ref} is the temperature at the reference point and $k = 1, 2, \ldots, 5$.

Fuzzy relationship matrix R is composed of n fuzzy relation rules for this system

$$R = \bigcup_{i=1}^{n} R_j \tag{9}$$

There are many kinds of defuzzification methods, usually maximum membership and centroid techniques are used. In practice, defuzzification is done using center gravity method. It is given by the following formula:

$$y^* = \frac{\sum_{i=1}^{n} \mu_A(y) \times y dy}{\sum_{i=1}^{n} \mu_A(y) dy} \tag{10}$$

where $\mu_A(y)$ is the membership function of set A and $y = (d_1 \times d_2 \times d_3) \times R$

In the proposed fuzzy logical algorithm temperature computing system, the distances between the sensor nodes are input fuzzy variables, and the temperature in the monitored area is the output variable. This study directly calculates the monitoring point temperature based on information about deployment of reference points. The monitoring point temperature can be show as:

$$T_{\text{output}} = \sum_{i=1}^{n} \frac{T_i}{W_{oi}} \tag{11}$$

where W_{oi} is the affect weight between reference i and output point; n is reference points and in this study $n = 3$

The membership functions for each input variable are defined as “Very Close”, “Close”, “Medium”, “Far” and “Very Far” (on short VC, C, M, F, VF) ($A1$, $A2$, $A3$, $A4$ and $A5$, respectively). Fig. 5 shows the membership graph of the distances between sensor nodes for

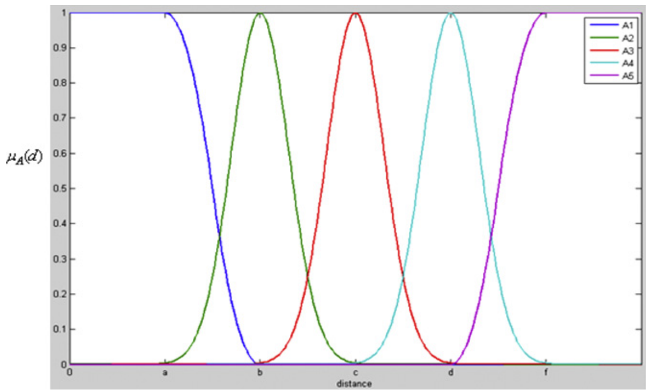


Fig. 5. Membership functions for d_i.

the input variables. The membership functions $A1$, $A2$, $A3$, $A4$ and $A5$ are as follows:

$\mu_{A1}(d_i)$: Z-shaped function

The calculation for this function is

$$\mu_{A1}(d_i)=\begin{cases}1 & \text{for} \quad d_i \le a\\ 1-\dfrac{2(d_i-a)^2}{(a-b)^2} & \text{for} \quad d_i > a \quad \text{and} \quad d_i \le \dfrac{a+b}{2}\\ \dfrac{2(b-d_i)^2}{(a-b)^2} & \text{for} \quad d_i > \dfrac{a+b}{2} \quad \text{and} \quad d_i \le b\\ 0 & \text{for} \quad d_i > b\end{cases} \tag{12}$$

$\mu_{A2}(d_i)$, $\mu_{A3}(d_i)$, $\mu_{A4}(d_i)$: Gaussian-shape function

Those functions are given as

$$\begin{aligned}\mu_{A2}(d_i)&=e^{-((d_i-b)^2/2\sigma^2)}\\ \mu_{A3}(d_i)&=e^{-((d_i-c)^2/2\sigma^2)}\\ \mu_{A4}(d_i)&=e^{-((d_i-d)^2/2\sigma^2)}\end{aligned} \tag{13}$$

where b, c, d: mean of membership function; σ: standard deviation of membership function; $\mu_{A5}(d_i)$: S-shaped function.

The function is formulated as:

$$\mu_{A5}(d_i)=\begin{cases}0 & \text{for} \quad d_i \le d\\ \dfrac{2(d_i-d)^2}{(f-d)^2} & \text{for} \quad d \le d_i \le \dfrac{d+f}{2}\\ 1-\dfrac{2(d_i-d)^2}{(f-d)^2} & \text{for} \quad \dfrac{d+f}{2} \le d_i \le f\\ 1 & \text{for} \quad d_i > f\end{cases} \tag{14}$$

Fig. 6 shows the correlation coefficient of this temperature computing system. For example, if the input variable is VC ($A1$), then the correlation coefficient value (0.9) is the weighting for $A1$.

Consider the following example: $a < d_1 < b$, $b < d_2 < c$, $d < d_3 < f$. According to the membership functions for d_i (Fig. 5), the d_1 is either "Very close" ($A1$) or "Close" ($A2$), d_2 is either "Close" ($A2$) or "Medium" ($A3$) and d_3 is either "Far" ($A4$) or "Very far" ($A5$). Therefore, the system has $8 = 2^3$ fuzzy rules. Table 1 shows the fuzzy logic rule system.

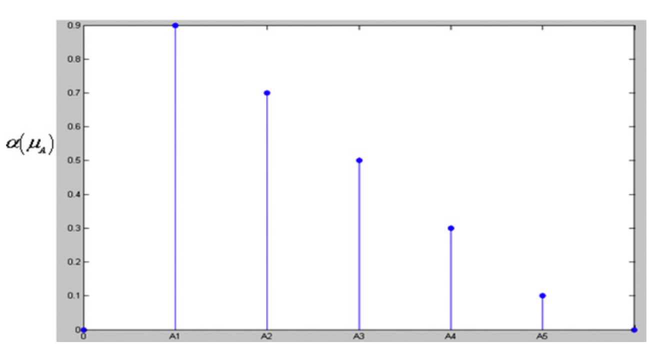


Fig. 6. Correlation coefficient of input variables.

Table 1
Rules for fuzzy logic system.

Rule number	Antecedent 1	Antecedent 2	Antecedent 3
1	Very Close	Close	Far
2	Very Close	Close	Very Far
3	Very Close	Medium	Far
4	Very Close	Medium	Very Far
5	Close	Close	Far
6	Close	Close	Very Far
7	Close	Medium	Far
8	Close	Medium	Very Far

The fuzzy if–then rules in this temperature computing system are as follows.

Where the distances from all points d_1 to REF1, d_2 to REF2 and d_3 to REF3. The temperatures at the three reference points are T_1, T_2 and T_3.

$$\begin{aligned}&\mu_{d_1A1}=\mu_{A1}(d_1),\quad \mu_{d_1A2}=\mu_{A2}(d_1),\quad \mu_{d_2A2}=\mu_{A2}(d_2),\\ &\mu_{d_2A3}=\mu_{A3}(d_2),\quad \mu_{d_3A4}=\mu_{A4}(d_3),\quad \mu_{d_3A5}=\mu_{A5}(d_3),\\ &\alpha_1=0.9,\quad \alpha_2=0.7,\quad \alpha_3=0.5,\quad \alpha_4=0.3,\quad \alpha_5=0.1\end{aligned}$$

R^1: **IF** d_1 is very close **and** d_2 is close **and** d_3 is Far **THEN** Temperature is T_{R^1}

$$T_{R^1}=\frac{T_1\mu_{d_1A1}\alpha_1+T_2\mu_{d_2A2}\alpha_2+T_3\mu_{d_3A4}\alpha_4}{\mu_{d_1A1}\alpha_1+\mu_{d_2A2}\alpha_2+\mu_{d_3A4}\alpha_4} \tag{15}$$

R^2: **IF** d_1 is very close **and** d_2 is close **and** d_3 is Very Far **THEN** Temperature is T_{R^2}

$$T_{R^2}=\frac{T_1\mu_{d_1A1}\alpha_1+T_2\mu_{d_2A2}\alpha_2+T_3\mu_{d_3A5}\alpha_4}{\mu_{d_1A1}\alpha_1+\mu_{d_2A2}\alpha_2+\mu_{d_3A5}\alpha_4} \tag{16}$$

R^3: **IF** d_1 is very close **and** d_2 is medium **and** d_3 is Far **THEN** Temperature is T_{R^3}

$$T_{R^3}=\frac{T_1\mu_{d_1A1}\alpha_1+T_2\mu_{d_2A3}\alpha_3+T_3\mu_{d_3A4}\alpha_4}{\mu_{d_1A1}\alpha_1+\mu_{d_2A3}\alpha_3+\mu_{d_3A4}\alpha_4} \tag{17}$$

R^4: **IF** d_1 is very close **and** d_2 is medium **and** d_3 is Very Far **THEN** Temperature is T_{R^4}

$$T_{R^4}=\frac{T_1\mu_{d_1A1}\alpha_1+T_2\mu_{d_2A3}\alpha_3+T_3\mu_{d_3A5}\alpha_5}{\mu_{d_1A1}\alpha_1+\mu_{d_2A3}\alpha_3+\mu_{d_3A5}\alpha_5} \tag{18}$$

R^5: **IF** d_1 is close **and** d_2 is close **and** d_3 is Far **THEN** Temperature is T_{R^5}

$$T_{R^5}=\frac{T_1\mu_{d_1A2}\alpha_2+T_2\mu_{d_2A2}\alpha_2+T_3\mu_{d_3A4}\alpha_4}{\mu_{d_1A2}\alpha_2+\mu_{d_2A2}\alpha_2+\mu_{d_3A4}\alpha_4} \tag{19}$$

R^6: **IF** d_1 is close **and** d_2 is close **and** d_3 is Very Far **THEN** Temperature is T_{R^6}

$$T_{R^6}=\frac{T_1\mu_{d_1A2}\alpha_2+T_2\mu_{d_2A2}\alpha_2+T_3\mu_{d_3A5}\alpha_5}{\mu_{d_1A2}\alpha_2+\mu_{d_2A2}\alpha_2+\mu_{d_3A5}\alpha_5} \tag{20}$$

R^7: **IF** d_1 is close **and** d_2 is medium **and** d_3 is Far **THEN** Temperature is T_{R^7}

$$T_{R^7}=\frac{T_1\mu_{d_1A2}\alpha_2+T_2\mu_{d_2A3}\alpha_3+T_3\mu_{d_3A4}\alpha_4}{\mu_{d_1A2}\alpha_2+\mu_{d_2A3}\alpha_3+\mu_{d_3A4}\alpha_4} \tag{21}$$

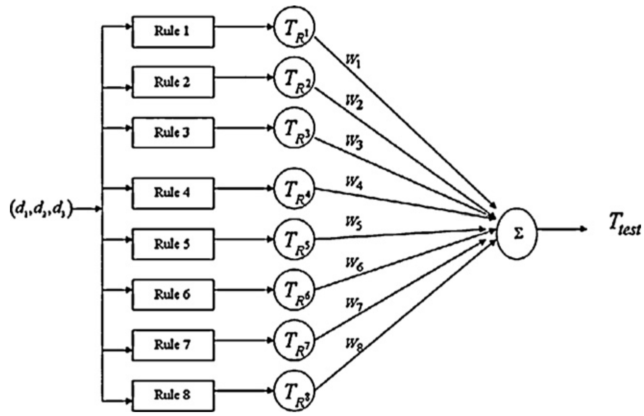


Fig. 7. Weights for computing temperature using fuzzy rules.

R^8: **IF** d_1 is close **and** d_2 is medium **and** d_3 is Very Far **THEN** Temperature is T_{R^8}

$$T_{R^8} = \frac{T_1\mu_{d_1A2}\alpha_2 + T_2\mu_{d_2A3}\alpha_3 + T_3\mu_{d_3A5}\alpha_5}{\mu_{d_1A2}\alpha_2 + \mu_{d_2A3}\alpha_3 + \mu_{d_3A5}\alpha_5} \quad (22)$$

Fig. 7 illustrates the fuzzy rule weight from computing the test point temperature. The rules in the flowchart are weighted as W_1, W_2, W_3, W_4, W_5, W_6, W_7 and W_8.

This section compares the fuzzy logic algorithm with the average and adaptive methods.

According to (15)–(22) and Fig. 6, the test point temperature can be computed by

$$T_{\text{test}} = \sum_{j=1}^{8} T_{Rj} W_j \quad (23)$$

When the weight of each rule is the same for computing temperature system,

$$T_{\text{test}} = \frac{\sum_{j=1}^{n} T_{Rj}}{n} \quad (24)$$

Where n is the total number of fuzzy rules; in this case $n = 8$.

This method is the average fuzzy logic algorithm.

Fig. 8 shows a flowchart of adaptive fuzzy logic algorithm, and the following six steps are the algorithm in this paper.

Step 1: Defining the input and output variables for the temperature computing system

Each fuzzy rule of the system is an input variable and each fuzzy rule for test point temperature is an output variable.

Step 2: Defining the degree of distance between test points and reference points

Classifying the distances from test points to reference points as very close, close, medium, far, and very far.

Step 3: Choosing the optimal membership function with RMSE results

Gaussian, triangle, trapezoid and Sigmoid functions are the most common membership functions. The Gaussian function has good local approximation ability for the radial basis function (RBF) neural network. In the back-propagation network (BPN), the Sigmoid function has a better ability of finding the global optimum. In this study, choosing the membership functions for input variables based on the advantages of RBF and BPN. The Z-shaped (Very close), S-shaped (Very far) and Gaussian membership functions (Close, Medium, Far) are therefore used as variables to simplify the computations and to obtain an RMSE better than that of other membership functions in the fuzzy logical temperature computing system.

Step 4: Calculating correlation coefficients

The correlation coefficients were used to fix for fast and simple monitoring point temperature calculations instead of using a function for that. The fixed correlation coefficients in this system were calculated by averaging the correlation coefficients, which were assigned values of 0.1, 0.3, 0.5, 0.7, and 0.9 from the smallest to the largest, respectively and not arbitrary for this system.

Step 5: Establishing a system of fuzzy logic rules

According to the Steps 2 and 3, then the system of fuzzy logic rules have to be established.

Step 6: Omitting the fuzzy logic rules for the condition $||T_{Rj} - T_{\text{test}}|| \geq 1$

First, omitting the fuzzy logic rules for the condition $||T_{Rj} - T_{\text{test}}|| \geq 0.5$, $||T_{Rj} - T_{\text{test}}|| \geq 1$, $||T_{Rj} - T_{\text{test}}|| \geq 1.5$ and $||T_{Rj} - T_{\text{test}}|| \geq 2$. Comparison of above four conditions with RMSE results then show that the condition for $||T_{Rj} - T_{\text{test}}|| \geq 1$ is better than other conditions. Finally, computing the each fuzzy rule for test point temperature eliminates the fuzzy rules whose discrepancy with the output is greater than 1 and then computes the output again.

$$T_{\text{modify}} = \frac{\sum_{j=k}^{k} T_{R^k}}{k} \quad (25)$$

where k is the rest number of fuzzy rules.

Table 2
Eight fuzzy logic rules and temperatures for test points 1 and 2.

Rule number	Antecedent 1	Antecedent 2	Antecedent 3	Point 1 (°C)	Point 2 (°C)
1	Very Close	Close	Medium	24.54	26.93
2	Very Close	Close	Far	26.18	27.82
3	Very Close	Medium	Medium	24.91	24.77
4	Very Close	Medium	Far	26.34	27.58
5	Close	Close	Medium	29.53	26.59
6	Close	Close	Far	31.72	27.84
7	Close	Medium	Medium	28.8	24.87
8	Close	Medium	Far	30.84	27.63

5. Experimental results and discussion

Temperature was experimentally calculated for single or multiple (up to ten) points. Fig. 1 shows the experimental setup for a three-point temperature calculation. Firstly, the position of test point 1 is REF1 ($T_1 = 24\,^\circ$C, $d_1 = 6$ m), REF2 ($T_2 = 28\,^\circ$C, $d_2 = 13$ m) and REF3 ($T_3 = 33\,^\circ$C, $d_3 = 19$ m). The position of test point 2 is REF1 ($T_1 = 24\,^\circ$C, $d_1 = 8$ m), REF2 ($T_2 = 28\,^\circ$C, $d_2 = 10.6$ m) and REF3 ($T_3 = 33\,^\circ$C, $d_3 = 18.6$ m). The membership function of the input variables is assumed to be ($a = 5$ m, $b = 10$ m, $c = 15$ m, $d = 20$ m, $f = 25$ m) According to Fig. 4, the total number of fuzzy rules in this case is 8.

Table 2 shows the fuzzy logic rules for this case. The fuzzy rules given in (2) are used to compute temperature for each test point. According to (24) the temperature at test point 1 is 27.86 °C, and that at test point 2 is 26.75 °C. The respective values obtained by (25) are 27.57 °C and 27.05 °C.

In this case, the positions for test point 3 are changed to REF1 ($T_1 = 24\,^\circ$C, $d_1 = 9$ m), REF2 ($T_2 = 28\,^\circ$C, $d_2 = 15.6$ m) and REF3 ($T_3 = 33\,^\circ$C, $d_3 = 15.6$ m). Similarly, Fig. 4 shows that this case has 8 fuzzy rules. Table 3 shows the fuzzy logic rules for this case. Each fuzzy rule for measuring temperature at each test point is obtained by (2). Finally, according to (24), the temperature at test point 3 is 27.5 °C. Similarly, according to (25), the temperature at test point 3 is 27.87 °C.

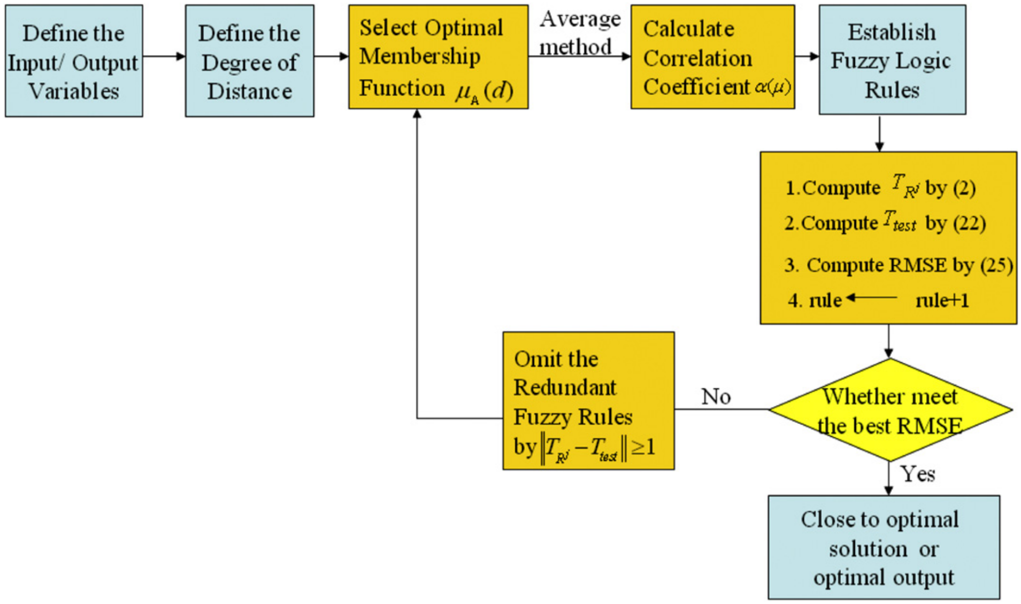


Fig. 8. Flowchart of the adaptive fuzzy logic algorithm.

Table 3
Eight-rule fuzzy logic system and test point 3 temperatures.

Rule number	Antecedent 1	Antecedent 2	Antecedent 3	Point 3 (°C)
1	Very Close	Medium	Medium	30.03
2	Very Close	Medium	Far	27.5
3	Very Close	Far	Medium	31.76
4	Very Close	Far	Far	24.66
5	Close	Medium	Medium	28.04
6	Close	Medium	Far	25.83
7	Close	Far	Medium	28.06
8	Close	Far	Far	24.09

Fig. 9 shows how average and adaptive fuzzy logic methods are used to compute temperature at each test point. The fuzzy rules used in the computing temperature system (rules 1–8) and the temperatures are given in the X-axis and Y-axis, respectively. The figure shows the temperature curves calculated by fuzzy rule at test points 1–3. The ninth point is the average of each fuzzy rule for the monitored area temperature, and the tenth point is the value calculated by adaptive method.

Fig. 10 shows that the temperature calculated for test point 1 using the actual measurement with different time. In Fig. 10, the X-axis is the estimated time (about 1200 h), and the Y-axis is the actual temperature measurement. Finally, the actual measurement is stable at 27.65 °C.

Fig. 11(a)–(c) shows the temperature errors for the average and adaptive fuzzy logic methods. In Fig. 9, the Y-axis is the error ratio between the average and adaptive method with actual measurement values. The X-axis is the total estimate time. In this study, the authors performed twenty measurements. Fig. 11(a) shows that average error ratios when using average and adaptive methods to calculate temperature at test point 1 ranged from 0.15 to 1.66 and from 0.01 to 1.91, respectively. The average error when using adaptive fuzzy logic method is lower than that when using average fuzzy logic method when excluding the thirteenth and eighteenth estimates as shown in Fig. 11(b). Similarly, Fig. 11(c) shows that the average error ratio value at test point 3 varies from 0.11 to 0.98 when using adaptive fuzzy logic method. When average fuzzy logic method is used, the values range from 0.36 to 2.14. The experiments confirm that adaptive fuzzy logic method is better than average fuzzy logic method.

The average error ratio in this system is estimated by

$$\frac{\sum_{k=1}^{n} ||T' - T_{\text{test}^k}||}{T'n} \tag{26}$$

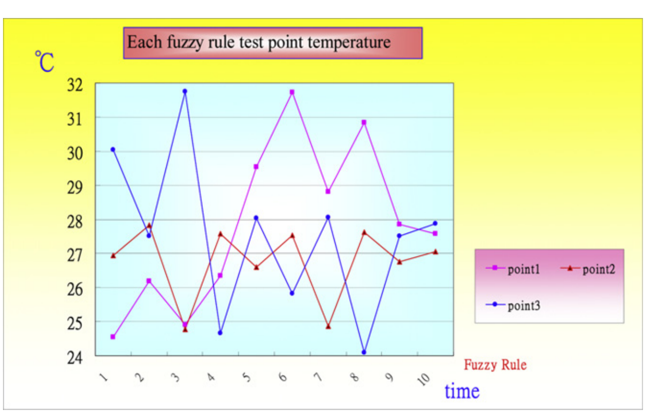


Fig. 9. Average and adaptive fuzzy logic methods for computing temperature at each test point.

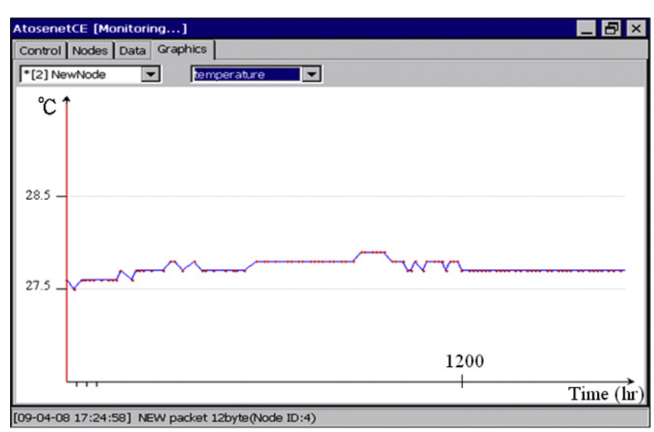
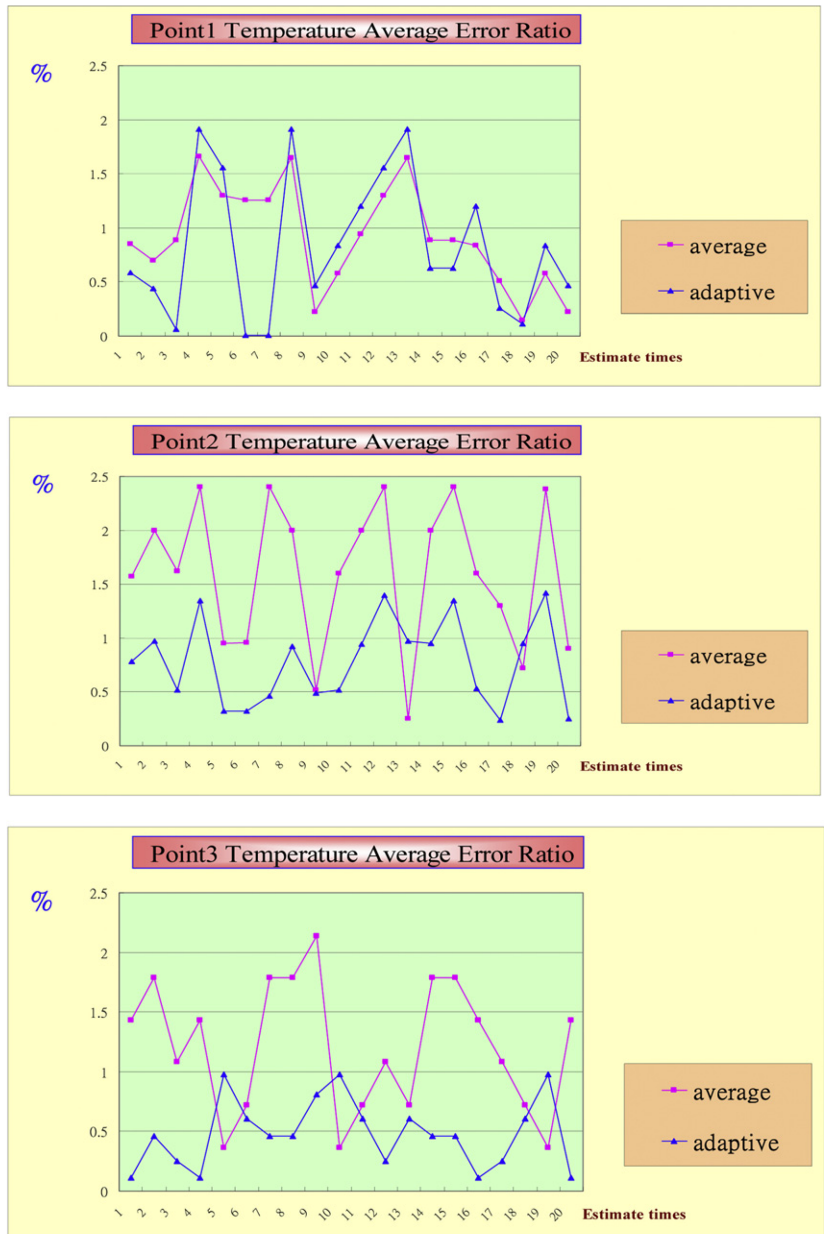


Fig. 10. Temperature at test point 1 calculated using actual measurement with different time.



(a) (b) (c)

Fig. 11. Comparision of values obtained by average and adaptive fuzzy logic methods at test points 1–3.

where $n = 20$, T': computed value (by average or adaptive method), and $T_{\text{test}k}$: kth measurement.

The equation used to calculate root mean square error (RMSE) by average and adaptive fuzzy logic algorithms methods is

$$\text{RMSE} = \sqrt{\frac{\sum_{k=1}^{n} ||T' - T_{\text{test}k}||^2}{n}} \tag{27}$$

The performance of the fuzzy logic model performance is evaluated by using RMSE as a statistical indicator to numerically represent computing accuracy. The RMSE for these test points is calculated using (25). Table 4 shows that the RMSE in temperature calculated for each test point by adaptive and average fuzzy logic methods are accurate and better than standard Mandani method. Then, Comparison of the two methods in terms of RMSE confirms that the adaptive fuzzy logic method is better than the average fuzzy logic method.

The RMSE values obtained by the average and modified methods confirm that both methods computed temperature very accurately. The relatively low RMSE values and the graphical analysis provided further confirmation. Next, the 3-point temperature calculation is changed to a 10-point calculation to account for ten points in the monitored area (red block in Fig. 1). Fig. 12 compares standard Mandani, average and adaptive fuzzy logic methods in terms of RMSE in values obtained for the ten points in the monitored area. Similarly, the figure shows that adaptive fuzzy logic method is better than the average and standard Mandani fuzzy logic method.

Table 4
The RMSE in temperature calculations for each test point.

Fuzzy logic algorithm	Point 1 (°C)	Point 2 (°C)	Point 3 (°C)
Standard Mandani method	1.224	1.215	1.107
Average method	0.485	0.484	0.475
Adaptive method	0.245	0.242	0.233

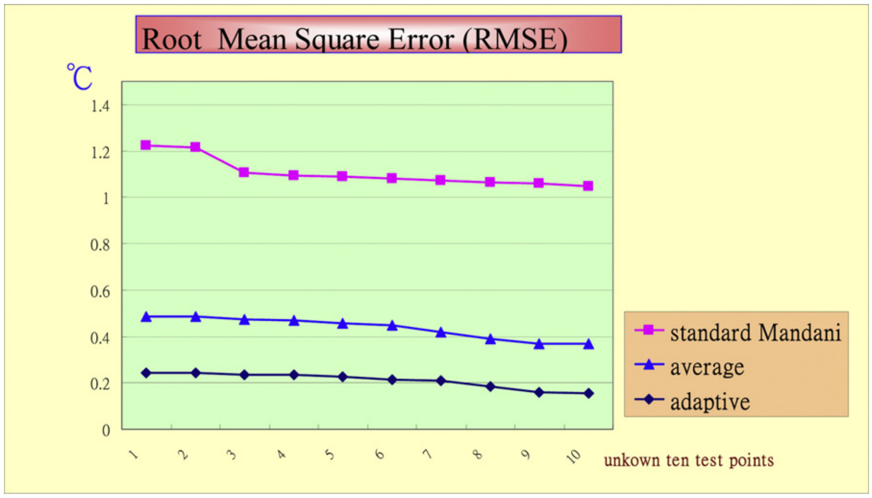


Fig. 12. Comparison of RMSE in 10-point calculation by standard Mandani, average and adaptive fuzzy logic methods.

6. Conclusions and future work

The experiments confirmed that the proposed fuzzy logic approach enables accurate temperature calculation in an area monitored by a wireless sensor network. The fuzzy inference system bridges the gap between numerical computing and readable linguistic elements. The fuzzy logic tool is also effective for using WSNs to compute temperature in a monitored area. The experimental results also confirm that adaptive fuzzy logic method outperforms average and standard Mandani fuzzy logic method. Clearly, the proposed method has a potentially important role in this research area. However, this cannot fully handle all the uncertainty present in real world problems. Type-2 fuzzy logic can handle uncertainty because it can model and reduce it to the minimum their effects and how to use the type-2 method in fuzzy logic system is our future work.

Although the fuzzy algorithm system adequately accounts for uncertainties, it cannot automatically adjust the weighting of fuzzy rules. One proposed solution is artificial neural networks, which account for uncertainties because of their superior learning capabilities. However, the weighting of a computing temperature fuzzy rule can be adjusted by using neural networks such as BPN, GRNN. The weighting values in this model clearly require training for different experimental environments. In addition to the fuzzy algorithm, future works will consider neural network technologies such as generalization. Future works may also further reduce RMSE by applying fuzzy inference systems, improving the learning capability of the neural network, simplifying fuzzy logic rules, or adjusting the membership function. The potential benefits of neuro-fuzzy systems include fast and accurate learning, good generalization capabilities, capability to accommodate both data and expert knowledge, and excellent explanation facilities in the form of semantically useful fuzzy rules.

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References

[1] G. Simon, M. Maroti, A. Ledeczi, G. Balogh, B. Kusy, A. Nadas, G. Pap, J. Sallai, K. Frampton, Sensor network-based counter sniper system, in: Proceedings of the Second International Conference on Embedded Networked Sensor Systems (Sensys), Baltimore, MD, 2004.

[2] J. Yick, B. Mukherjee, D. Ghosal, Analysis of a prediction-based mobility adaptive tracking algorithm, in: Proceedings of the IEEE Second International Conference on Broadband Networks (BROADNETS), Boston, 2005.

[3] M. Castillo-Effen, D.H. Quintela, R. Jordan, W. Westhoff, W. Moreno, Wireless sensor networks for flash-flood alerting, in: Proceedings of the Fifth IEEE International Caracas Conference on Devices, Circuits and Systems, Dominican Republic, 2004.

[4] T. Gao, D. Greenspan, M. Welsh, R.R. Juang, A. Alm, Vital signs monitoring and patient tracking over a wireless network, in: Proceedings of the 27th IEEE EMBS Annual International Conference, 2005.

[5] K. Lorincz, D. Malan, T.R.F. Fulford-Jones, A. Nawoj, A. Clavel, V. Shnayder, G. Mainland, M. Welsh, S. Moulton, Sensor networks for emergency response: challenges and opportunities, in: Pervasive Computing for First Response (Special Issue), IEEE Pervasive Computing, October–December 2004.

[6] G. Wener-Allen, K. Lorincz, M. Ruiz, O. Marcillo, J. Johnson, J. Lees, M. Walsh, Deploying a wireless sensor network on an active volcano, in: Data-Driven Applications in Sensor Networks (Special Issue), IEEE Internet Computing, March/April 2006.

[7] V.A. Kottapalli, A.S. Kiremidjian, J.P. Lynch, E. Carryer, T.W. Kenny, Two-tired wireless sensor network architecture for structural health monitoring, in: Proc. SPIE, San Diego, CA, March, 2003.

[8] M. Demirbas, Wireless sensor networks for monitoring of large public buildings, Department of large public buildings, Department of Buffalo, SUNY, Buffalo, NY, Tech. Rep., 2005.

[9] Y. Simon, A fuzzy logic approach to fire detection in aircraft dry bays and engine compartments, IEEE Transaction on Industrial Electronics 47 (October (5)) (2000) 1161–1171.

[10] Z.B. Li, H. Zhou, Research on the application of fuzzy data fusion to cable fire detecting system, in: Proceedings of the Third International Conference on Machine Learning and Cybernetics, vol. 4, Shanghai, August 2004, pp. 2083–2085.

[11] H. Bao, J. Li, X. Zeng, J. Zhang, A fire detection system based on intelligent data fusion technology, in: Proceedings of the Third International Conference on Machine Learning and Cybernetics, vol. 2, November 2003, pp. 1096–1101.

[12] D. Dubois, H. Prade, An introduction to fuzzy systems, Clinica Chimica Acta 270 (1998) 3–29.

[13] J.S.R. Jang, Self-learning fuzzy controllers based on temporal back propagation, IEEE Transactions on Neural Networks 3 (5) (1992) 714–723.

[14] D. Nauck, R. Kruse, Obtaining interpretable fuzzy classification rules from medical data, Artificial Intelligence in Medicine 16 (1999) 149–169.

[15] I. Virant-Klun, J. Virant, Fuzzy logic alternative for analysis in the biomedical sciences, Computers and Biomedical Research 32 (1999) 305–321.

[16] I. Guler, E.D. Ubeyli, Application of adaptive neuro-fuzzy inference system for detection of electrocardiographic changes in patients with partial epilepsy using feature extraction, Expert Systems with Applications 27 (3) (2004) 323–330.

[17] I. Guler, E.D. Ubeyli, A mixture of experts network structure for modeling Doppler ultrasound blood flow signals, Computers in Biology and Medicine 35 (2004) 565–582.

[18] J.S.R. Jang, C.T. Sun, Neuro-fuzzy modeling and control, Proceedings of the IEEE 83 (3) (1995) 378–406.

[19] F. Chiodo, A. Menditto, F. Ouane-Keita, S. Caroli, The management of information: storage and retrieval of data, Annali dell'Istituto Superiore di Sanita 30 (4) (1994) 433–437.

[20] J.A.W. McCall, A. Petrovski, A Decision Support System for Cancer Chemotherapy Using Genetic Algorithms. Computational Intelligence for Modelling, Control and Automation. Evolutionary Computation and Fuzzy Logic for

Intelligent Control Knowledge Acquisition and Information Retrieval, vol. 55, IOS Press, Amsterdam, 1999, pp. 65-70.
[21] K. Sadegh-Zadeh, Fundamentals of clinical methodology: nosology, Artificial Intelligence in Medicine 17 (1999) 87–108.
[22] K. Sadegh-Zadeh, Fuzzy health: illness, and disease, The Journal of Medicine and Philosophy 25 (5) (2000) 605–638.
[23] M. Sugeno, G.T. Kang, Structure identification of fuzzy models, Fuzzy Sets and Systems 28 (1988) 15–33.
[24] T. Takagi, M. Sugeno, Fuzzy identification of systems and its applications to modeling and control, IEEE Transactions on Systems Man and Cybernetics SMC-15 (1) (1985) 116–132.
[25] J.J. Jassbi, P.J.A. Serra, R.A. Ribeiro, A. Donati, A comparison of Mandai and Sugeno inference system for a space fault detection application, in: Automation Congress, WAC'06. World, July 2006, p. 2006.
[26] E.H. Mandani, Application of fuzzy algorithms for control of a simple dynamic process, Proceedings of the Institute of Electrical and Electronics Engineers 121 (1974) 1585–1588.
[27] X. Feng, Z. Gao, M. Yang, S. Xiong, Fuzzy distance measuring based on RSSI in wireless sensor network, in: Proceedings of 2008 3rd International Conference on Intelligent System and Knowledge Engineering, 2008.
[28] P. Manjunatha, A.K. Verma, A. Srividya, Multi-sensor data fusion in cluster based wireless sensor networks using fuzzy logic method, in: Proceedings of IEEE Region 10 Colloqium and the Third ICIIS, Kharagpur, India, December 8–12, 2008.
[29] X. Yang, Y. Li, One ZigBee personnel location system based on fuzzy logic, in: Wireless Communications, Networking and Mobile Computing. WiCOM'08. 4th International Conference, October 2008, p. 2008.
[30] H. Shu, Q. Liang, J. Gao, Wireless sensor network lifetime analysis using interval type-2 fuzzy logic systems, IEEE Transactions on Fuzzy Systems 16 (April (2)) (2008).
[31] Z. Bingul, Adaptive genetic algorithms applied to dynamic multiobjective problems, Applied Soft Computing 7 (2007) 791–799.
[32] P. Liu, H. Li, Efficient learning algorithms for three-layer regular feed forward fuzzy neural networks, IEEE Transactions on Neural Networks 15 (2004) 545–558.
[33] M.R. Mashinchi, A. Selamat, An improvement on genetic-based learning method for fuzzy article neural networks, Applied Soft Computing 9 (2009) 1208–1216.
[34] S. Sadi-Nezhad, K.K. Damghani, Application of a fuzzy TOPSIS method base on modified preference ratio and fuzzy distance measurement in assessment of traffic police centers performance, Applied Soft Computing 10 (2010) 1028–1039.
[35] M.L. Tseng, Using a hybrid MCDM model to evaluate firm environmental knowledge management in uncertainty, Applied Soft Computing 11 (2011) 1340–1352.
[36] M.L. Tseng, Importance-performance analysis on municipal solid waste management in uncertainty, Environmental Monitoring and Assessment 172 (1–4) (2011) 171–187.
[37] M.L. Tseng, L.W. Lan, R. Wang, A.S.F. Chiu, H.P. Cheng, Using hybrid model to evaluate the green performance in uncertainty, Environmental Monitoring and Assessment 175 (1) (2011) 367–385.