

Estimation of Air-Cooling Devices Run Time Via Fuzzy Logic and Adaptive Neuro-Fuzzy Inference System

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Abstract - In this paper, fuzzy logic controller and adaptive neuro-fuzzy inference system (ANFIS) methods were applied to develop a run time control system for air-cooling devices. The system uses the current temperature and door state of the room as input variables and predicts the optimum run time for the device. For the fuzzy logic controller, three different membership functions were assessed and their performance was evaluated. The triangular membership function displayed superior performance for the current case. The ANFIS model was developed and validated via various validation parameters to ensure it has the ability to estimate the run time accurately. The obtained ANFIS model showed significant validation parameters for both the training and test set. Also, the ANFIS model was superior to the fuzzy logic controller in terms of determining the optimum run time. Thus, the ANFIS modeling approach can be used as an efficient and accurate method to develop systems for controlling the run time of air cooling devices.

Key Words: Fuzzy logic, ANFIS, Embedded system, Microcontroller, Fuzzy controller.

1. INTRODUCTION

For many years, the fuzzy logic controller has been an important and popular method [1]. Due to the imprecise nature of computer-assisted control issue solutions, the fuzzy logic controller was created. Fuzzy logic controller deals with data and processes it in a manner similar to human thinking [2]. The fuzzy logic implies human-like reasoning for determining the optimum solution. Unlike classic logic systems where the values are considered only exact (i.e. true or false), fuzzy systems allow vague representation via fuzzy sets of the input values [3]. The inference in fuzzy systems uses a set of pre-defined IF-THEN rules to decide the output value from the inputs. An example of a fuzzy rule would be; IF the Temperature is COLD THEN Run Time is SHORT [4]. The output of a fuzzy system is defuzzified to a crisp value that can be used in real-world applications. The main advantage of using fuzzy systems is that their structure is relatively simple and intuitive for humans. Also, the system can be easily adjusted and modified as required [5, 6]. The Adaptive neuro-fuzzy inference system (ANFIS) is a hybrid learning system that combines the fuzzy logic systems and neural network

characteristics [7]. The ANFIS modeling uses training data combined with a set of fuzzy logic rules to produce a machine learning model that can be used for making predictions of the output variable from the values of the input variables [8]. Due to the ability of neural networks to adjust and learn the data, the ANFIS approach can provide more powerful predictions compared to mere fuzzy logic systems [9].

Various studies have been reported in the literature that involves using ANFIS and fuzzy logic systems in air-cooling devices-related applications. For instance, Soyguder et al. [10] developed an expert system that includes ANFIS and fuzzy logic optimization to control heating, ventilation and air-cooling (HVAC) systems. Their system mainly focused on controlling the humidity and the temperature of the HVAC. The obtained ANFIS models were validated and showed low error in terms of estimating the required parameters for controlling the system.

In another study, Al-Jarrah et al. [11] developed an algorithm via ANFIS modeling that focused on controlling air-cooling systems at different pressure values. The built ANFIS model was evaluated and assessed using experimental test data. The predictions of the model were compared to the real values and the computed error parameters indicated a reliable and predictive model for managing the performance of air-conditioners at different pressure values.

In this study, we use the fuzzy logic system and ANFIS modeling methods to develop a system that can predict the optimum run time for air-conditioners using the current room temperature and the door state of the chamber as the input variables. The current temperature of the room is a common factor to consider when determining the optimum running time. Also, considering that rooms with opened door require a longer period of air cooling due to the faster heat transfer, the door state was added as another factor for determining the run time.

2. METHOD

Two different approaches were used to build a run time prediction system for air-cooling devices, namely the fuzzy logic system and the ANFIS. The dataset used composed of 100 records of temperature and door state as input variables and the optimum run time of air conditioner as the output variable. The implementation of the software was carried out via the Python programming language, using mainly the NumPy package for array-based and numerical operations [12]. Also, the Matlab package was used for generating the plots of the results [13]. In the upcoming sections, a brief description of each method will be provided alongside the procedures used in developing the systems.

2.1 Fuzzy Logic:

The fuzzy logic systems work-flow can be broadly divided into three distinct steps, namely, the fuzzification of the input, the application of the IF-THEN set of rules and the defuzzification step [3]. The steps of the fuzzy system are illustrated in Figure 1. In the upcoming sections, a brief description of each step is provided alongside the procedure applied for the current case.

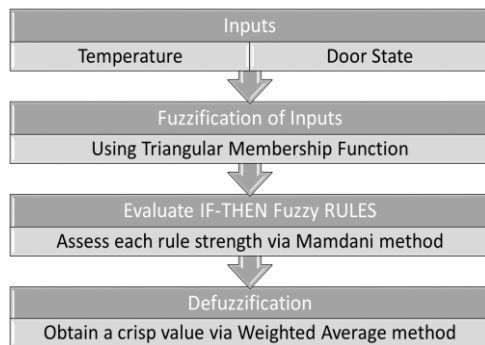


Fig -1: Work-flow diagram of the fuzzy logic system.

2.1.1 Input Fuzzification

Initially, a set of linguistic variables is defined based on the current application, those linguistic variables are used in the IF-THEN rules evaluation [14]. For example, for the temperature input variable, five different linguistic variables are defined; Very Cold, Cold, Warm, Hot and Very Hot. Based on the numerical value of the input temperature, each of those linguistic variables will be assigned a fuzzy value (ranging from 0 to 1) [15]. For this purpose, a membership function is used. There are various types of membership functions with different shapes such as triangular and trapezoidal membership functions [16]. The membership function converts the input value to a fuzzy value via a specific mathematical equation, for example, the equation of the triangular membership function is depicted in (1) and (2). Three values representing the upper, lower and medium values of each linguistic variable are also taken into

consideration [17, 18]. Table 1 shows the linguistic variables of the temperature input variable as well as the a, b and c values required by the triangular membership function equation for computing the fuzzy value.

$$\mu_F(x; a, b, c) = \begin{cases} 0; & x \leq a \\ \frac{x-a}{b-a}; & a < x \leq b \\ \frac{c-x}{c-b}; & b < x < c \\ 0; & x \geq c \end{cases} \quad (1)$$

$$\mu_F(x; a, b, c) = \max\left(\min\left(\frac{x-a}{b-a}, \frac{c-x}{c-b}\right), 0\right) \quad (2)$$

Table-1: The values of the input temperature linguistic variables. The a, b, and c values are used in the triangular membership function as shown in Figure 3.

Linguistic Variable	a	b	c
Very Cold	5	10	15
Cold	10	15	20
Warm	15	20	25
Hot	20	25	30
Very Hot	25	30	35

In this study, three different membership functions were used and tested on the data, namely, the triangular, trapezoidal and Gaussian membership functions, which are widely used in different fuzzy logic applications [19-21]. The shape of each membership function is shown in Figure 2. Each membership function was assessed by making predictions of the output variable (the run time) and compared with the experimental optimum value. The mean absolute error (MAE) parameter was computed for each one and compared with one another. The lower the value of the MAE parameter the more accurate and reliable the membership function is considered to be [22].

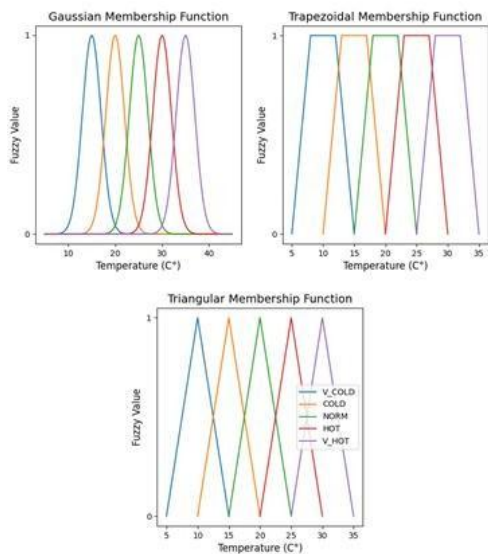


Fig -2: The shapes of the three membership functions used in this study.

2.1.2. IF-THEN rules

After the input fuzzification stage which determines the degree of membership of each input linguistic variable, the next stage involves the evaluation of rules using IF-THEN statements [5]. For example, IF Temperature is COLD AND Door State is OPEN THEN Run Time is LONG. To assess the strength of these rules, the degree of membership obtained from the input fuzzification is used. The set of rules used in the current fuzzy system is shown in Table 2.

Table-2: The set of rules implemented in the fuzzy logic system

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Temp/Door State	Open	Half Open	Closed
Very Cold	Very Long	Very Long	Long
Cold	Very Long	Long	Long
Warm	Long	Medium	Medium
Hot	Medium	short	Very Short
Very Hot	Very Short	Very Short	Very Short

There are different methods to compute the strength of each rule. The method applied in the current system is the Mamdani method [23]. This method simply takes the minimum strength of the rules in the inference system. For example, in the rule IF Temperature is VERY COLD AND Door State is OPEN THEN Run Time is VERY LONG. If the VERY

COLD and OPEN fuzzy values are 0.7 and 0.4, the VERY LONG is assigned the minimum value which is 0.4. The output of this stage is a strength value of each rule, which is used in the next stage which involves defuzzification to obtain the crisp output value [3, 24].

2.1.3. Output defuzzification

Following the evaluation of the rules using the IF-THEN statements, the output is a strength of each linguistic output variable, which is a fuzzy value. The last step is the defuzzification of the obtained values to get a crisp output value [25]. There are various methods for performing defuzzification. In the current system, the weighted average method is adopted, which is simple and effective. The equation used for computing the crisp value using this method is shown in (3) [26].

$$x^* = \frac{\sum_{i=1}^n u_{Ci}(X_i) \cdot (X_i)}{\sum_{i=1}^n u_{Ci}(X_i)} \tag{3}$$

Where $u_{Ci}(X_i)$ is the strength of each rule and X_i is the maximum value used in the triangular membership function. This method yields results that are similar to the commonly used center of area methods, however, it demands less computations and is easier to implement [25, 26].

2.2. Adaptive Neuro-Fuzzy Inference System (ANFIS)

The ANFIS method combines the fuzzy logic system and the neural network approaches to provide a more efficient prediction system [8]. In particular, it uses the characteristics of the fuzzy logic including the input fuzzification via a membership function and the IF-THEN rules evaluation as well as the learning abilities of neural networks. This makes the system more accurate and robust with higher efficiency in terms of learning the data and making better predictions [27].

2.2.1. Structure and layers

Considering that ANFIS is a neural network, it is composed of layers and nodes connected by edges that represent weights. The input variables are transferred and modified as they pass through the layers of the network to produce the output value. The weights are updated during the training process of the network to adjust the data [28]. The general structure of the ANFIS network is shown in Figure 3.

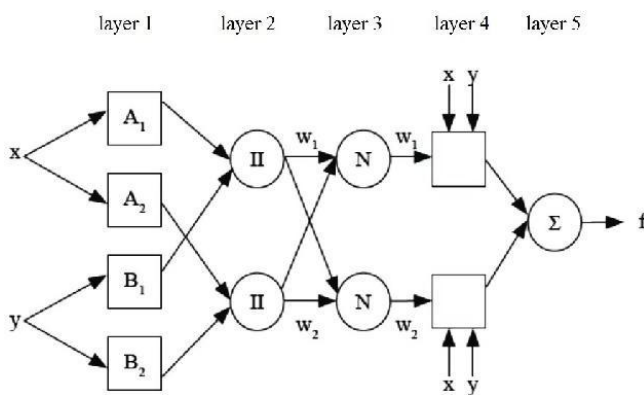


Fig -3: The structure of the ANFIS network.

The ANFIS structure consists of 5 different layers. The first layer is the membership function layer, in which the input variables are fuzzified via the membership function equation to produce the membership degree value. The second layer uses the output of the first layer (the membership degree values) to compute the firing strength of each linguistic variable in the second layer, which will be required for the rules evaluation by the subsequent layers of the network [29]. The third layer is the normalization layer, in which the weights are normalized, this makes the value of each weight in the range [0, 1]. The fourth layer carries out the rules evaluation to determine the strength of each rule to the overall output. The fifth layer uses a summation method for the values obtained from the previous layer to determine the final output value [30].

2.2.2. Model training and validation

To train and validate the ANFIS model, the overall data was divided into two different sets, namely, the training set which was used for training and the model and the test set which was used for evaluation of the model performance [31]. The training process of the ANFIS involves a running of the network for several epochs (cycles), during each epoch, the error of the network prediction is computed via a cost function and the weights of the network are updated to minimize the error [32]. The root means squared error (RMSE) was used as the cost function [33]. To determine the optimum number of epochs, the networks were allowed to run for 1000 epochs and the error was computed after each epoch. The number of epochs that corresponds to the lowest error is considered to be the optimum epoch number for training the network.

After training the model, the test set was used to assess the ability of the model to make predictions. The model was applied to predict the run time of the test set, and the error between the model's prediction and the real value was measured. The coefficient of determination (R2), the MAE and the RMSE were calculated, which are commonly used validation parameters to assess the performance of machine learning models [22, 33, 34].

3.2 Hardware implementation

Considering that the purpose of the developed software is to control air cooling devices, the developed ANFIS model was installed and tested on a Field-Programmable Gate Array (FPGA) embedded system [35]. The hardware part of the system is composed of Zynq-7020 FPGA processor with the AXI BRAM memory and AXI GPIO, these components are available in the Vivado integrated development environment (IDE), the hardware structure is shown in Figure 4.

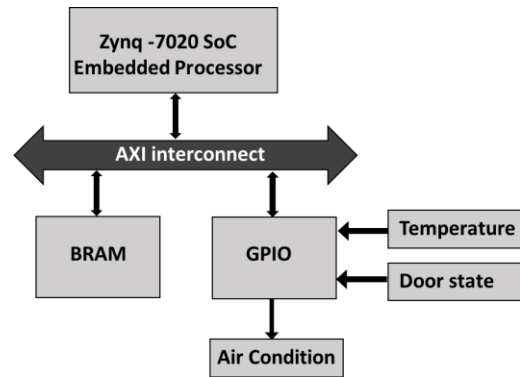


Fig-4 The structure of the designed hardware.

The hardware architecture includes two ports, a memory block RAM with 64 KB size and BRAM Controller. BRAM data is accessed within single cycle latency. Advanced Xilinx Interconnects (AXI) is introduced to the system hardware to act as bus system. The general purpose input/output (GPIO) unit provides a hardware interface between the processor system AXI and the sensors (temperature and door state sensors) [35, 36].

For implementing the software part of the system, the software development kit (SDK) tools were used, which are available in the Vivado IDE [37].

3. RESULTS AND DISCUSSION

3.1. Fuzzy logic system

The three built fuzzy logic systems were evaluated by predicting the output variable (run time) using the temperature and door state as input variables. The output of each system was compared to the optimum run time and the error of prediction was measured. The error plot of the three systems is depicted in Figure 5. As can be seen, the triangular membership function showed the lowest MAE value (4.766), which indicates a lower prediction error compared to the other two membership functions. The trapezoidal and Gaussian membership functions had higher MAE values (4.812 and 5.025, respectively) which reflects lower prediction accuracy compared to the triangular membership function.

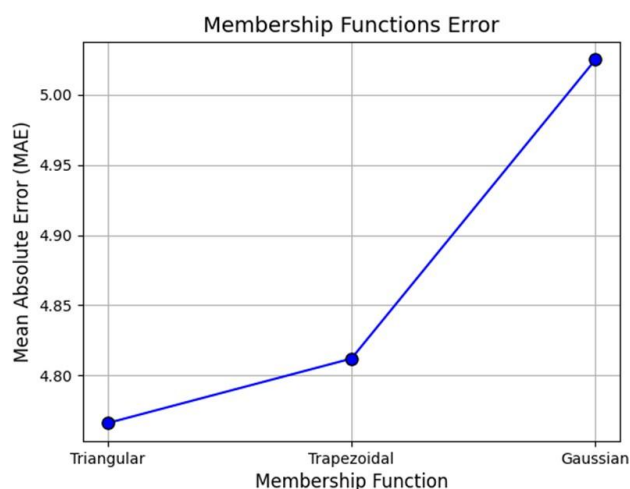


Chart -1: membership function (MAE)

Considering that the triangular and trapezoidal membership functions have similar shapes as well as input parameters compared to the Gaussian membership function [18, 19], it can be seen that they are more suitable for this type of application, as they both showed lower and similar error rate. The triangular membership function was further used as the membership function in the ANFIS model development as it displayed better prediction ability in comparison to the other two membership functions.

3.2. ANFIS model

The ANFIS model was built using the triangular membership function and the set of rules previously described. The optimum number of epochs was determined to be 300 epochs based on the RMSE values. Figure 6 shows the change in the RMSE values as the number of epochs progresses. As can be seen, initially the RMSE value drops fairly quickly as the model is learning the data, then at around epoch 200 the RMSE value becomes more stable and drops more slowly. At around epoch 300 the optimum number of epochs is reached as the RMSE value begins to increase after this epoch, which indicates the occurrence of over-fitting of the model due to large number of epochs. The RMSE value continues to increase afterward which is expected due to over-training of the network.

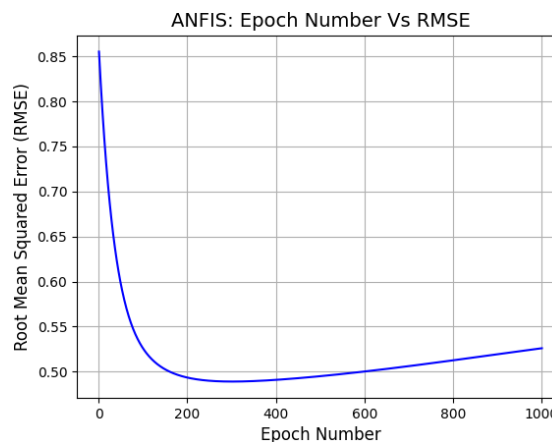


Chart -2: The RMSE values were plotted against the epoch number during the training of the ANFIS model.

The model obtained at 300 epochs was validated by assessing its ability to predict the output variable (run time) of the test set compounds. The validation parameters were computed for the training and the test set compounds. However, the training set validation parameters cannot be considered reliable as the model was fit and trained using this set. On the other hand, the validation parameters of the test set are considered reliable as the data was not involved in the training of the model, and reflects the model's ability to make predictions on unseen data. Table 3 shows the validation parameters and their corresponding values. The R2 value for both the training and test set was close to the optimum value of 1, which shows that the model can explain the variance in the output variable using the input variables. The MAE values for the training and test set were 0.338 and 0.413, respectively, which are both low and indicate the model can make accurate predictions. As expected the training set MAE value was slightly lower because the model was fit using the training set data and hence the lower error is expected [34]. The RMSE values showed a similar trend to the MAE values. Figure 7 shows the predicted output by the model against the actual value for both the training and test set.

Table-3: The validation parameters of the obtained ANFIS model.

Parameter	Value
R2	0.993
MAE	0.338
RMSE	0.424
R2(test)	0.992
MEA(test)	0.413
RMSE	0.529

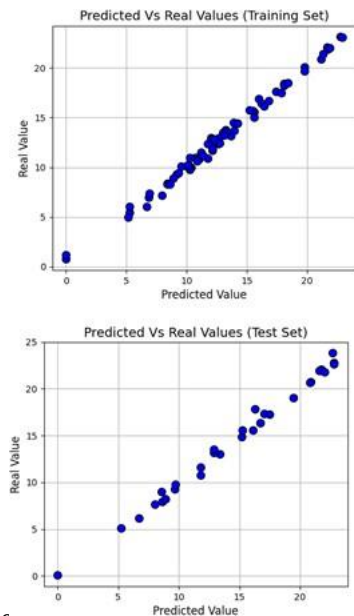


Chart -3: The predicted output values by the ANFIS model are plotted against the real values.

Comparing the ANFIS model performance with the fuzzy logic system shows that the ANFIS model is significantly superior in terms of accurate prediction. For instance, the MAE values of the ANFIS model and the best obtained fuzzy logic system (the triangular membership function system) are 0.338 and 4.766, respectively, which reflects the higher accuracy of the ANFIS model. This can be attributed to the fact that the ANFIS model can learn the data and adjust to it to make better predictions due to its neural networks paradigm, which is more flexible compared to the mere fuzzy logic systems that use only a set of fixed rules evaluation to estimate the output value [8, 10, 27].

4. CONCLUSION

The fuzzy logic system and ANFIS approaches were conducted to develop fuzzy logic systems and an ANFIS model to predict the optimum run time of air conditioners using the current temperature and door state as input variables. Three different membership functions were examined and their performance was assessed. The triangular membership function displayed better results compared to the trapezoidal and Gaussian membership functions. The obtained ANFIS model showed superiority

over the fuzzy logic systems in terms of prediction accuracy as demonstrated by the lower error rates. Overall, the ANFIS model proved to be highly efficient and accurate for application in run-time control of air-conditioning systems.

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