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Fuzzy Mamdani performance water chiller control optimization using fuzzy adaptive neuro fuzzy inference system assisted

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ABSTRACT

Fuzzy Mamdani knows as one of the modern control systems. It was known to have a better performance result when compared to conventional methods. However, because the input of this modern control system sometimes is based on human experience, therefore its performance is sometimes below the conventional one. We propose using the adaptive neuro fuzzy inference system assisted (ANFIS) approach to optimize the fuzzy Mamdani membership function input to overcome this problem. We have tested our hypotheses in water chiller applications based on microcontrollers. Even though it is still behind conventional methods to cool 200 ml water, which is 6 minutes, using fuzzy ANFIS methods, we manage to improve the speed performance in cooling water from 20 minutes to 17 minutes, which is from room temperature to just 24 ^{o}C.

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1. INTRODUCTION

In modern times like this, a control system is a must in every device used by humans. This modern control system is used in many applications, ranging from washing machines [1], [2], refrigerators, power plants operation [3], optimum solar panel tracking [4], traffic lights [5], and many others [6]. Even cars right now already had an automatic control based on their computers. In the past, the control system used was a conventional one that did not require special algorithms to control the system. However, the modern control system has used a special algorithm to produce better performance system control [7]. It can be said that without a modern control system, human work will be inefficient. Many modern control systems exist and have been applied by humans to electronic equipment, and fuzzy is one of those algorithms.

Zadeh was well known for proposing a fuzzy system in 1965 [8]. This system was developed using approximate reasoning to find its solution, neither very imprecise nor very precise [9], [10]. Zadeh's approach was using fuzzy logic that develops boolean logic into a degree of truth for every membership set and not just 0 or 1 or false or truth. Because of this approach, we can easily implement it in real-world situations, where many things cannot be approached with just normal Boolean logic. Fuzzy also can be combined with other methods or algorithms such as PID [11]–[13], B-Spline [14], particle swarm [15], and many others. Even though fuzzy is usually used for control [16]–[18], however recently, a lot of new fuzzy methods has been developed not only for control but also for other real-world problems, such as the multi-criteria decision-making (MCDM) problem [19]–[21], forecasting [22]–[24], clustering [25] and many others.

One of the new fuzzy methods would be fuzzy Mamdani. Fuzzy Mamdani was developed in 1974 by Mamdani [26] for control application. This method is a machine learning algorithm [27] that quantifies human experience and uses it as an input for its control system [28]. It can imitate humans in solving control systems that cannot be solved using conventional methods. Thus, it has better control performance than conventional control [29].

However, sometimes input based on human experience its results are less satisfying. It happens when the input is wrong, or human is less experience with the problem, or not enough data. Hence, its performance can drop below conventional control (simple on-off control). Therefore in this paper, we propose to improve the fuzzy membership function input (based on human experience) using adaptive neuro fuzzy inference system (ANFIS) methods to provide better performance in control. To validate the results, we try to builds a water chiller and controls it using a microcontroller. We will compare its performances in controlling water chiller using conventional control (on-off control), fuzzy Mamdani control (based on human experience), and optimize fuzzy Mamdani control (ANFIS Optimize).

2. RESEARCH METHOD

In this subsection we would like to explain to full detail of ANFIS (sometimes called fuzzy ANFIS) method. After we explain with full detail of ANFIS method, then we would like to proceed with detail explanation for the hardware that we are going to use. This hardware was designed for control and data acquisition in this paper.

2.1. Adaptive neuro fuzzy inference system (ANFIS) method

To improve fuzzy membership function input, we are employing the ANFIS method. This method will learn to improve fuzzy membership function input using conventional control result measurement data in water chiller applications. After learning its data, ANFIS will improve the fuzzy membership function inputs. ANFIS was one of the fuzzy methods that were developed in 1993. It was developed based on fuzzy if-then rules from Takagi and Sugeno by Jang [30]. With the ANFIS method, the fuzzy system can adapt naturally based on its data training [31]. Figure 1 shows ANFIS architecture based on Jang paper. The ANFIS consists of 5 layers. The layer with box type is adaptive, and the layer with circle type is fixed. Fuzzy ANFIS is based on fuzzy if-then rules from Takagi and Sugeno [32].

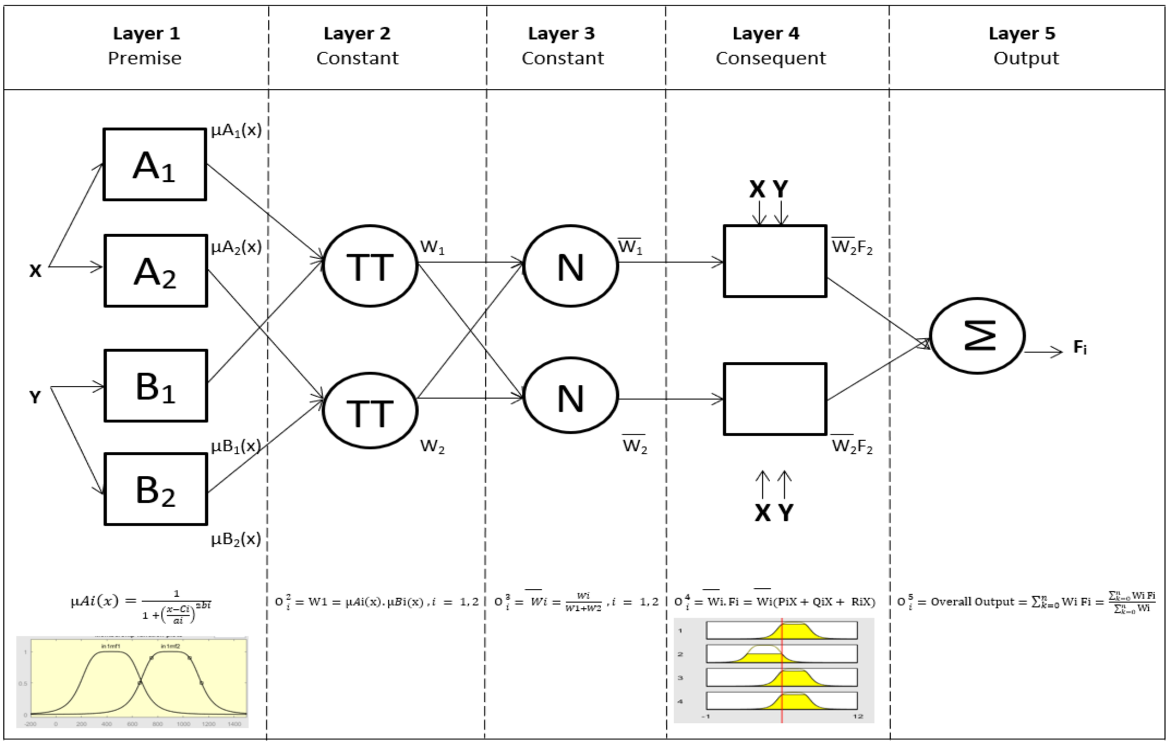


Figure 1. ANFIS architectures [33]

For layer 1 each layer output is symbolized by O_i^1. This serves to raise the degree of membership.

$$O_i^1 = \mu Ai(x)\ and\ O_i^1 = \mu Bi(x), i = 1, 2 \quad (1)$$

We can use trapezoidal or triangular-shaped membership functions, but in Jang paper, they are using bell-shaped membership function because it can give a maximum equal to 1 and minimum equal to 0. Therefore,

$$\mu Ai(x) = \frac{1}{1+[\left(\frac{x-Ci}{ai}\right)^2]bi} \quad (2)$$

For layer 2 multiply the incoming signals, where each node represents the firing strength of a rule.

$$O_I^2 = \mu Ai(x)x\ \mu Bi(x),\ i = 1, 2 \quad (3)$$

For layer 3 normalized firing strengths were applied.

$$O_i^3 = \overline{Wi} = \frac{Wi}{W1+W2},\ i = 1, 2 \quad (4)$$

For layer 4 calculating the output based on the parameters of the rule consequent.

$$O_1^4 = \overline{Wi}\,.Fi = \overline{Wi}\ (Pix + Qix + Rix\ ),\ i = 1, 2 \quad (5)$$

For layer 5 computes the overall output as the summation of all incoming signals.

$$O_i^5 = Overal\ Output = \sum_{k=0}^{n} \overline{Wi}\,.Fi = \frac{\sum_{k=0}^{n} WiFi}{\sum_{k=0}^{n} Wi} \quad (6)$$

While ANFIS networks learn from gradient descent and chain rule, the error rate needs to be known for data training for each node output. Assuming i-th position node outputs as O_i and training data set has P entries, we can get error measure as:

$$Ep = \sum_{M=1}^{\#L} (Tmp - O_{mp}^L)^2 \quad (7)$$

where T_{mp} is m component from P target output vector, and O_{mp}^L is m component from actual output vector that has been produced by P input vector. Therefore error rate can be calculated as:

$$\frac{\partial Ep}{\partial O_{i\,p}^k} = \sum_{m=1}^{\#k+1} \frac{\partial Ep}{\partial O_{m\,p}^{k+1}} \frac{\partial O_{m\,p}^{k+1}}{\partial O_{i\,p}^k} \quad (8)$$

where $1 \le k \le L - 1$ is an error rate of an internal node, it is expressed as the linear combination error rate of the nodes in the next layer. For all $1 \le k \le L$ and$1 \le i$, we can find $\frac{\partial Ep}{\partial O_{i\,p}^k}$ using (7) and (8). We have α as a parameter of the adaptive network.

$$\frac{\partial E}{\partial \alpha} = \sum_{O*\epsilon S} \frac{\partial Ep}{\partial O*} \frac{\partial O*}{\partial \alpha} \quad (9)$$

Where S is the set of nodes whose output depends on α. Derivative for overall error measure E in respect to α is:

$$\frac{\partial E}{\partial \alpha} = \sum_{p=1}^{p} \frac{\partial Ep}{\partial \alpha} \quad (10)$$

the update formula for generic parameter α is:

$$\Delta\alpha = n\frac{\partial E}{\partial \alpha} \quad (11)$$

where η is a learning rate that can be written:

$$n = \frac{k}{\sqrt{\sum_{\alpha}\left(\frac{\partial E}{\partial \alpha}\right)^2}} \tag{12}$$

where k is the number of step size, the length of each gradient transition in the parametric space.

2.1. Hardware design

To validate our result, we propose to build hardware for water chiller application, so we can do a real-time measurement. In our proposed hardware, we plan to cool 200 ml water from 30 ºC to 24 ºC. The hardware consists 5 blocks which is power supply, microcontroller wemos, temperature sensor using DS18B20, transistor driver using TIP 122 Darlington power transistor, and cooling element using Peltier. Figure 2 show hardware block device for water chiller application. Figure 3 show hardware schematic for water chiller application. In Figure 3(a) show hardware schematic microcontroller and temperature sensor schematics, while in Figure 3(b) show hardware schematic for transistor driver and Peltier.

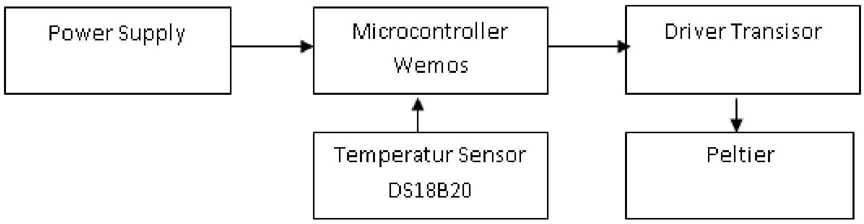
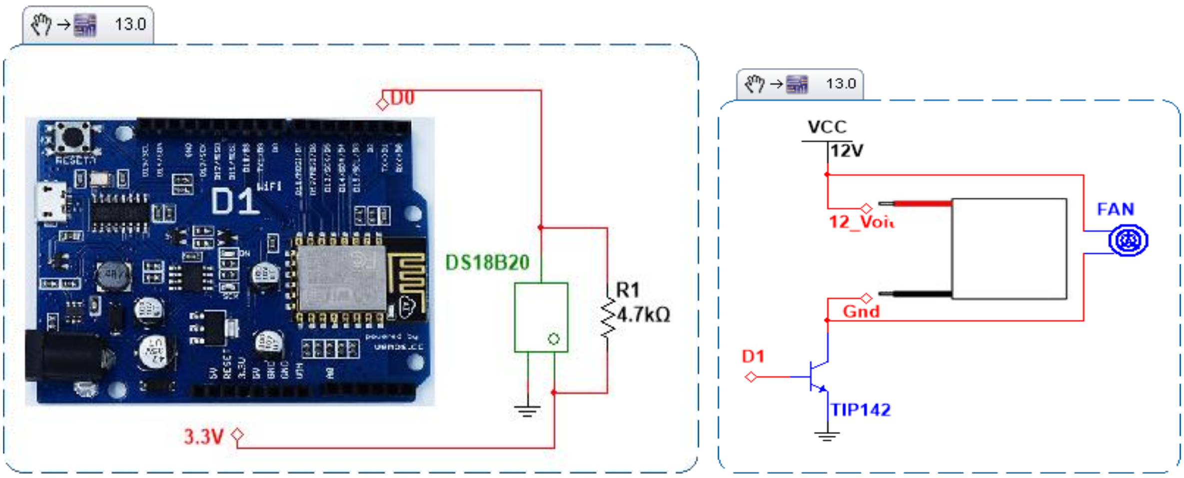


Figure 2. Hardware block diagram



(a) (b)

Figure 3. Hardware schematic for water chiller application (a) microcontroller and temperature sensor schematics and (b) driver transistor and Peltier schematics

3. RESULTS AND ANALYSIS

For the first measurement, we input the fuzzy membership function based on our experience. Figure 4 shows a fuzzy membership function based on the human experience. After measurement using the fuzzy Mamdani method was finished and data was collected, we do a second measurement. In this second measurement, we use conventional control data and input it into the ANFIS system. Using 1000 epoch in the ANFIS system, we have new fuzzy membership function input. Figure 5 showa a fuzzy membership function based on ANFIS. Table 1 shows a comparison before and after using the ANFIS method in fuzzy membership function.

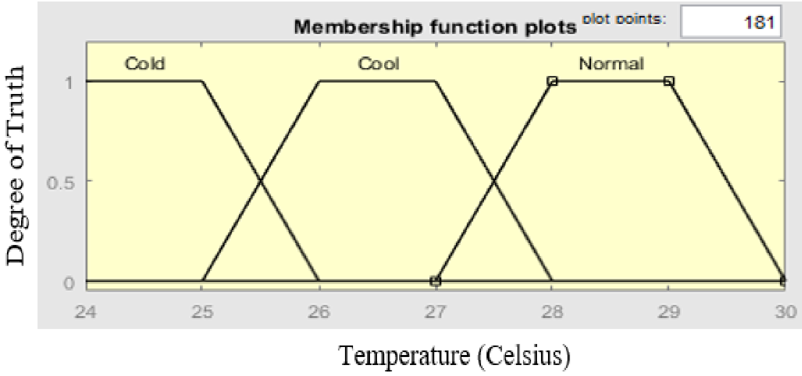


Figure 4. Fuzzy membership function input based on human experience

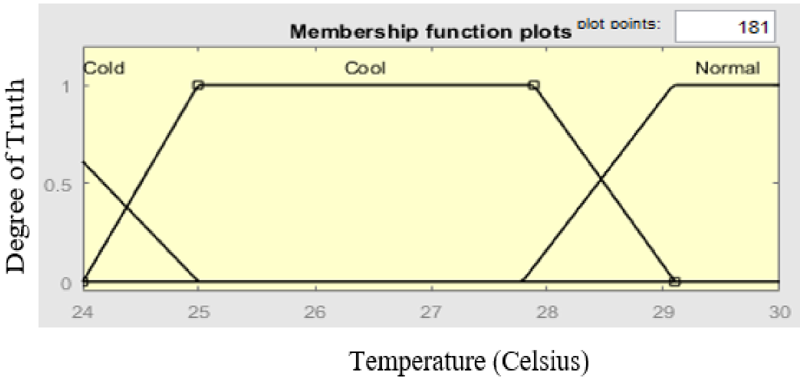


Figure 5. Fuzzy membership function input optimization using ANFIS

The ANFIS mathematic model would be:

$$\frac{\left(\left(\begin{cases} 0; x \le 21.9 \text{ or } x \ge 25 \\ \frac{x-21.9}{24-21.9}; 21.9 \le x \le 24 \\ \frac{25-x}{25-23.37}; 23.37 \le x \le 25 \\ 1; 23.1 \le x \le 23.37 \end{cases}\right) A\right) + \left(\left(\begin{cases} 0; x \le 24 \text{ or } x \ge 29.1 \\ \frac{x-24}{24.99-24}; 25 \le x \le 26 \\ \frac{29.1-x}{29.1-27.88}; 27.88 \le x \le 29.1 \\ 1; 24.99 \le x \le 27.88 \end{cases}\right) B\right) + \left(\left(\begin{cases} 0; x \le 27.78 \text{ or } x \ge 32.1 \\ \frac{x-27.78}{29.08-27.78}; 27.78 \le x \le 29.08 \\ \frac{32.1-x}{32.1-30.9}; 30.9 \le x \le 32.1 \\ 1; 29.08 \le x \le 30.9 \end{cases}\right) C\right)}{\begin{cases} 0; x \le 21.9 \text{ or } x \ge 25 \\ \frac{x-21.9}{24-21.9}; 21.9 \le x \le 24 \\ \frac{25-x}{25-23.37}; 23.37 \le x \le 25 \\ 1; 23.1 \le x \le 23.37 \end{cases} + \begin{cases} 0; x \le 24 \text{ or } x \ge 29. \\ \frac{x-24}{24.99-24}; 25 \le x \le 26 \\ \frac{29.1-x}{29.1-27.88}; 27.88 \le x \le 29.1 \\ 1; 24.99 \le x \le 27.88 \end{cases} + \begin{cases} 0; x \le 27.78 \text{ or } x \ge 32.1 \\ \frac{x-27.78}{29.08-27.78}; 27.78 \le x \le 29.08 \\ \frac{32.1-x}{32.1-30.9}; 30.9 \le x \le 32.1 \\ 1; 29.08 \le x \le 30.9 \end{cases}}$$

where:
A: constant set Cold which is 0
B: constant set Cool which is 255
C: constant set Normal which is 255

In this research ANFIS was used to optimize the fuzzy Mamdani membership function. To make easier to understand, we present before and after optimization. In Table 1 left we present the old Mamdani membership function (based on human experience), and in Table 1 right we present what ANFIS has been optimizing, the new fuzzy Mamdani membership function.

Using ANFIS, we successfully improved the fuzzy membership function input for the control system. We also managed to improve the performance fuzzy Mamdani system compared with the conventional control system. Table 2 and Figure 6 show performance comparisons before and after using ANFIS and also with the conventional control system.

Table 1. Fuzzy Mamdani membership function comparison before and after using ANFIS

Human experience fuzzy Mamdani control		Fuzzy Mamdani control with ANFIS	
For Cold		For Cold	
0	$x \leq 23$ or $x \geq 26$	0	$x \leq 21.9$ or $x \geq 25$
$\frac{X - 23}{24 - 23}$	$23 \leq x \leq 24$	$\frac{X - 21.9}{24 - 21.9}$	$21.9 \leq x \leq 24$
1	$24 \leq x \leq 25$	1	$23.1 \leq x \leq 23.37$
$\frac{26 - x}{26 - 25}$	$25 \leq x \leq 26$	$\frac{25 - x}{25 - 23.37}$	$23.37 \leq x \leq 25$
For Cool		For Cool	
0	$x \leq 25$ or $x \geq 28$	0	$x \leq 24$ or $x \geq 29.1$
$\frac{X - 25}{26 - 25}$	$25 \leq x \leq 26$	$\frac{X - 24}{24.99 - 24}$	$25 \leq x \leq 26$
1	$26 \leq x \leq 27$	1	$24.99 \leq x \leq 27.88$
$\frac{28 - x}{28 - 27}$	$27 \leq x \leq 28$	$\frac{29.1 - x}{29.1 - 27.88}$	$27.88 \leq x \leq 29.1$
For Normal		For Normal	
0	$x \leq 27$ or $x \geq 35$	0	$x \leq 27.78$ or $x \geq 32.1$
$\frac{X - 27}{28 - 27}$	$27 \leq x \leq 28$	$\frac{X - 27.78}{29.08 - 27.78}$	$27.78 \leq x \leq 29.08$
1	$28 \leq x \leq 29$	1	$29.08 \leq x \leq 30.9$
$\frac{35 - x}{35 - 29}$	$29 \leq x \leq 35$	$\frac{32.1 - x}{32.1 - 30.9}$	$30.9 \leq x \leq 32.1$

Table 2. Fuzzy Mamdani performance with and without ANFIS, versus conventional control method

Minutes	Conventional control (Temperature in Celsius)	Fuzzy Mamdani control without ANFIS (Temperature)	Fuzzy Mamdani control with ANFIS (Temperature)
0	28.5	28.81	29.12
1	25.5	26.19	26.25
2	24.69	25.5	25.87
3	24.37	25.44	25.56
4	24.19	25.25	25.37
5	24.06	25	25.19
6	24	24.81	25.00
7	24	24.81	24.87
8	24	24.75	24.75
9	24	24.62	24.69
10	24	24.62	24.69
11	24	24.62	24.50
12	24	24.62	24.37
13	24	24.31	24.31
14	24	24.31	24.25
15	24	24.31	24.12
16	24	24.31	24.06
17	24	24.25	24
18	24	24.12	24
19	24	24.12	24
20	24	24.12	24

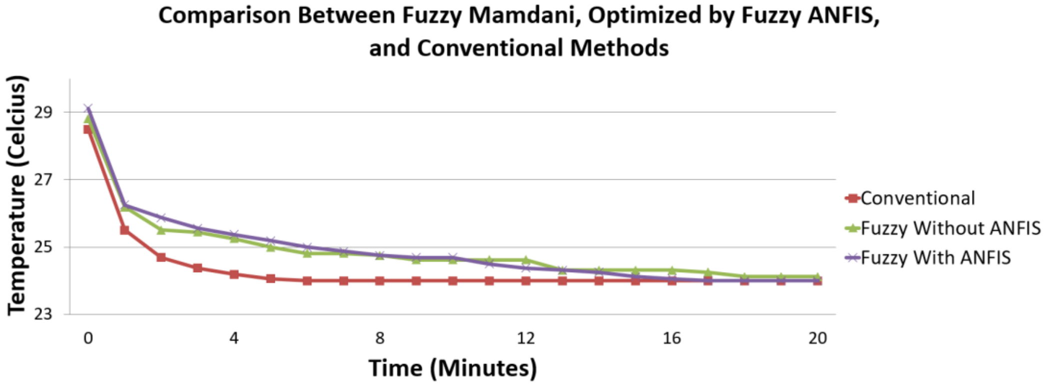


Figure 6. ANFIS performance comparisons conventional control, fuzzy control before and after using ANFIS in water chiller application

4. CONCLUSION

In this paper we propose ANFIS algorithm to optimize the fuzzy Mamdani membership function input. Fuzzy Mamdani method was used to cool 200 ml drinking water in water chiller applications. Unfortunately, its speed performance to cool 200ml drinking water was still falls behind against conventional methods (On-Off). However, using ANFIS we manage to improve the speed performance to cool 200 ml drinking water from 20 minutes to become 17 minutes, which is from room temperature to just 24 ^oC. Hence, we conclude that ANFIS can optimize fuzzy Mamdani in water chiller application.

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