

Design of Sugeno fuzzy logic controller for Resistance furnace

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Abstract— In this paper, we demonstrated the application of Sugeno type fuzzy model to develop FLC-sugeno controllers for resistance furnace. We designed and simulated the operation of the system with PI-classical and FCL-sugeno controllers on Matlab/Simulink. The simulation results have been compared, evaluated through control quality according to quality criteria such as Rise time, Overshoot, Settling time, ISE (Integrated Square of Error). This shows that FLC-sugeno outperforms PI-classical as giving better quality control in terms of every indicator.

Keywords—fuzzy logic, fuzzy control, sugeno model, resistance furnace.

I. INTRODUCTION

When the rules of systems are expressed by linguistic rule set, linguistic words only contain qualitative information. However, human beings are still capable of reasoning based on that information effectively. It is these rules that are knowledge based on human experience in the process of working and understanding the system. Under the linguistic information gained from the system, people can make sound decisions about the system that is the approximate reasoning.

L.A Zadeh gave a mathematical model for expressing a linguistic value with a “fuzzy set” and using a “membership function” to determine how much a piece belongs to a set. Along with the mathematical operations on the fuzzy sets extended from the classical ones, L.A. Zadeh proposed the basis of mathematical theory in 1965 for the first time [1]. It is a mathematical model that allows representation and calculation on linguistic values and process of approximate reasoning processes. In the set of approximate reasoning problems, there is an application in the field of cybernetics, the fuzzy control problem [2].

The advantage of fuzzy control is that the designer does not need to know the mathematical representation of the object (transfer function or state-space equation), the fuzzy model is given by the rule set which presents a nonlinear input/output relationship so it can be said

that the controller is adaptive to the input values, so it is effective for nonlinear objects [3].

It cannot be denied that fuzzy control has confirmed the important position in modern control engineering so far. Fuzzy control gives remarkable accuracy and performance because of its simplicity in the structure of the system. Widespread applications of fuzzy control in areas such as automation and control systems in industry, military, control in the transportation sector, structural control in the field of construction , ... [4] - [8].

In the next section, we will design PI-classical and FLC-sugeno controllers for resistor heat exchanger and simulate system performance in Matlab/simulink environment. Simulation results are used to compare and evaluate the control quality through the parameters between PI-classical and FLC-sugeno controllers. Thereby, the FLC-sugeno controller is superior to the PI-classical controller.

II. CONTROLLER BASED SUGENO FUZZY MODEL

A. Sugeno fuzzy model

The Sugeno fuzzy model, also known as the TSK fuzzy model, was introduced in 1985 [9], [10]. In the general Sugeno model, there are m input components x_1, x_2, \dots, x_m and one output component y . Each input element x_i consists of n fuzzy sets. The output element y consists of p functions. This model with its rule set form is given as follows:

$$\begin{aligned} \text{If } x_1 = A_{11} \text{ and } x_2 = A_{21} \dots x_m = A_{m1} \text{ then } y_1 &= f_1(x_1, x_2) \\ \text{If } x_1 = A_{12} \text{ and } x_2 = A_{22} \dots x_m = A_{m2} \text{ then } y_2 &= f_2(x_1, x_2) \quad (1) \\ &\dots \\ \text{If } x_1 = A_{1n} \text{ and } x_2 = A_{2n} \dots x_m = A_{mn} \text{ then } y_p &= f_p(x_1, x_2) \end{aligned}$$

For each rule, the output is determined by a particular function. Normally, the function $f_i(x_1, x_2)$ is a polynomial of the inputs x_1, x_2 but it can also be any function, depending on the output description of the system. When $f_i(x_1, x_2)$ is a constant, it is called a zero-order Sugeno fuzzy model, which is also a special form of the Mamdani model when the output fuzzy sets are in the form of a singleton. Zero-order Sugeno fuzzy model is quite simple in both design and installation.

Given a zero-order Sugeno fuzzy model with the following rule set:

$$\begin{aligned} &\text{If } x_1 = A_{11} \text{ and } x_2 = A_{21} \dots x_m = A_{m1} \text{ then } y_1 = c_1 \\ &\text{If } x_1 = A_{12} \text{ and } x_2 = A_{22} \dots x_m = A_{m2} \text{ then } y_2 = c_2 \quad (2) \\ &\dots \\ &\text{If } x_1 = A_{1n} \text{ and } x_2 = A_{2n} \dots x_m = A_{mn} \text{ then } y_p = c_p \end{aligned}$$

Where c_1, c_2, \dots are constants.

Suppose that the rule set has the numbers of input variables $m = 2$, we have a fuzzy model with the following rules:

$$\begin{aligned} &\text{If } x_1 = A_{11} \text{ and } x_2 = A_{21} \text{ then } y_1 = c_1 \\ &\text{If } x_1 = A_{11} \text{ and } x_2 = A_{22} \text{ then } y_2 = c_2 \\ &\text{If } x_1 = A_{12} \text{ and } x_2 = A_{21} \text{ then } y_2 = c_3 \quad (3) \\ &\text{If } x_1 = A_{12} \text{ and } x_2 = A_{22} \text{ then } y_2 = 4 \\ &\dots \\ &\text{If } x_1 = A_{1n} \text{ and } x_2 = A_{2n} \text{ then } y_p = c_p \end{aligned}$$

With the input value vector $input = (x_{01}, x_{02})$, there are maximum of four rules which can be "burned", then we calculate the weights w_1, w_2, w_3, w_4 as shown in Figure 1.

Output value y_0 is computed based on (4):

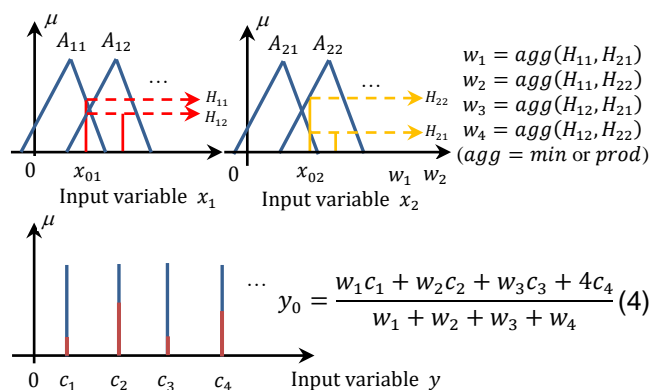


Figure 1. Sugeno fuzzy model with the output is a constant

When $f_i(x_1, x_2)$ is the first-order function (polynomial) based on x_1 or x_2 , it is called the first-order Sugeno fuzzy model. The output value is computed by weighted input method with change of linear of y_1, y_2, \dots based on x_1 or x_2 .

Output value y_0 is computed based on:

$$y_0 = \frac{w_1 y_1 + w_2 y_2 + \dots}{w_1 + w_2 + \dots} \quad (5)$$

There may also be systems that describe the output of the rule by nonlinear functions. In this case, the output membership function will be of type S, such as bell-shape, gauss, sigmoid, S-shape, etc.

The Sugeno fuzzy model is also capable of describing a system in fuzzy state space. According to

Takagi-Sugeno, a fuzzy region LA^k is described by the rule:

$$R_{sk}: \text{If } x = LA^k \text{ then } \dot{x} = A(x^k)x + B(x^k)u \quad (6)$$

This rule is interpreted that if the state vector x lies in the fuzzy domain LA^k then the system is described by the localized differential equation of the set $\dot{x} = A(x^k)x + B(x^k)u$. If all state of the system can be described in the wide area. The state matrix $A(x^k)$, $B(x^k)$ in (6) is the constant matrix of the system at the center of the fuzzy domain LA^k and is determined through identification. Hence, we have:

$$\dot{x} = \sum w_k (A(x^k)x + B(x^k)u), \text{ where } w_k(x) = \mu_{LA^k}(x) \quad (7)$$

At this time, the control rule will be:

$$R_{ck}: \text{If } x = LA^k \text{ then } u = K(x^k)x \quad (8)$$

Control rule for the entire state space has the following form:

$$u = \sum_{k=1}^n w_k K(x^k)x \quad (9)$$

Depending on the specific system, the designer can use a suitable fuzzy model to describe the input/output rule of the system. In the following part, we used the zero-order Sugeno fuzzy model to design the FLC-sugeno controller for the thermistor furnace.

B. Design and construction of the fuzzy controllers

The diagram of the fuzzy controller is typically consists of the components as in Figure 2.

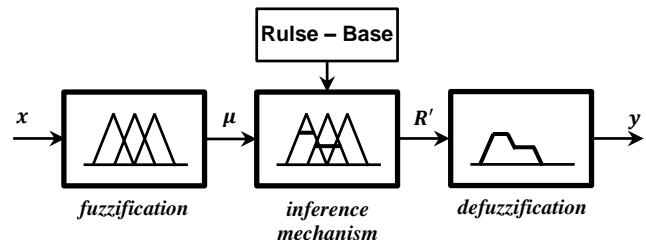


Figure 2. Structural diagram of fuzzy controller

- **Fuzzification:** Through the explicit input value $[x_{0i}]^T$ of the controller, the fuzzy part will compute the degree of satisfaction so that the dependent vector $[\mu_i^*]^T$ has the number of elements equal to the number of fuzzy sets of input variables. The input signal usually consists of justification error signal between the reference value and the feedback value from the output, the status signal of the system, etc.

- **Rule – base:** The knowledge base consists of the rules that have the structures of "If ... then ..." where linguistic clauses describe the relationship between I / O variables.

- **Inference mechanism:** The mechanism of reasoning based on the rule set is carried on in accordance with the rules of some composition. That is the implementation of the rule R which is based on the controller rule set.

- **Defuzzification:** The part of defuzzification. Through the output fuzzy set R' , the defuzzed fraction computes the clear value y_0 as the output value (control value) for each of the explicit values $[[x_{0i}]^T$ to control the object.

Principle of fuzzy controller synthesis is completely based on the experience of the designer. These design experiences are presented in many tasks such as defining input/ output linguistic variables, defining linguistic values (linguistic labels), defining control rules, shapes of fuzzy sets that present the linguistic labels, t-norm calculations, t-conorm operations, defuzzification methods, etc. The model of the controller is correct or not, the quality of control is good or not depends on the experience which is dominant in design steps.

Generally, the process of designing a fuzzy controller is performed with the following steps:

Step 1: Defining input/output linguistic variables: Through surveys, we define the input and output linguistic variables of the controller and their defined domain. At the same time, the linguistic values for each linguistic variable is also determined.

Step 2: Defining fuzzy sets for linguistic variables: In this step, we need to determine the shape and position of the membership function of fuzzy set for each linguistic label.

Step 3: Building control rule set: Collecting the knowledge of control rule set from a variety of sources. This plays an important part in deciding the correctness of the control rules and the operation of the controller. Normally, the rules are based on the knowledge of the variable relationship between the output and the input or experience of the system operator.

Step 4: Choose composite rules: We can choose any composite rule. In fact, the Max-Min and Max-Prod rules are often chosen for their simplicity and efficiency. There is, however, no constraint on this choice. Choosing Min or Prod allows **and** depend on the specific lesson, so it can be said that the choice depends on the experience of the designer

Step 5: Select the defuzzification principle: In many applications, for the Mamdani fuzzy model, defuzzification methods are usually preferred. This is because the defuzzification value is compiled from every element in the resulting fuzzy set. However, focus-based computations of defuzzification are quite complex and costly in terms of the number of the calculations. For simplicity, the designer can choose the defuzzification as the maximum principle. With this principle, it is also possible to derive the defuzzification value as the left-right or right-angled value or the mean value of the domain with the maximum dependent degree of the resultant fuzzy set. For the Sugeno fuzzy model, defuzzification calculations are performed according to a weighted average calculation such as (4) or (5), depending on the order of the model. The choice of defuzzification method also depends on the designer's experience.

Step 6: Optimization: During the process of simulation or testing, based on the observation and evaluation, the designer can screen the rules and calibrate the parameters of the controller according to different criteria for controllers to aim at optimization. Regulatory and parametric corrections can be made at every choice in the design steps described above.

III. DESIGN OF CONTROLLERS

A. Resistance furnace

Resistance furnace is a heating device which temperature needs to be adjusted, mainly the temperature in the furnace. Controlling or controlling the furnace temperature is usually done by controlling the furnace power by controlling the supply power [11] - [15].

Consider a resistance furnace with a power $P = 1 \text{ KW}$. SiC, with temperature range of $[25 - 250^\circ\text{C}]$. The furnace has an approximate transfer function (received through the process of object recognition), which is the first-order inertial step (time delay):

$$W(s) = K \frac{e^{-\tau s}}{1+Ts} \quad (9)$$

Where:

$K = 10^\circ\text{C}$ – Amplification coefficient.

$T = 1300 \text{ s}$ – Time constant (second).

$\tau = 30 \text{ s}$ – Time delay (second).

$$W(s) = \frac{10e^{-30s}}{1+1300s} \quad (10)$$

B. The controller of PI-classical

The component $u(t)$ of the PI - classical controller is described by:

$$u(t) = K_p \left(e(t) + \frac{1}{T_I} \int_0^t e(t) dt \right) \quad (11)$$

Where K_p is the scale factor, $K_I = \frac{K_p}{T_I}$ is integration factor and $e(t)$ is the control error. Through (11), when it is transferred to discrete domain, we have:

$$u(k) = K_p e(k) + K_I \sum_{j=1}^k e(j) \quad (12)$$

Parameters are calculated by the method Ziegler & Nichols: $K_p = 1.19, K_I = 0.01$.

C. The controller of FLC-sugeno

Step 1: Identify input/output variables and their background sets.

The controller has 2 input/output variables e (error) is the control error, variable in the domain $[-4.0, 4.0]$ and ce (change error) is the linguistic state variable show the changeable speed of e , variable in the range $[-50, 50]$. The output of the controller is u , in order to control the object, it is variable is the range of $[-4.0, 4.0]$.

The linguistic labels for the input/output linguistic variables are defined as:

$$e, ce = \{VN < LN < ZE < LP < VP\}$$

$$u = \{VN < N < LN < ZE < LP < P < LP\}$$

Where:

$VN = \text{Very Negative}$, $LN = \text{Little Negative}$, $ZE = \text{Zero}$, $LP = \text{Little Positive}$, $VP = \text{Very Positive}$

Step 2: Define fuzzy sets for linguistic labels to input/output variables

Membership function of the trimf fuzzy set of input variables e is shown in Figure 3 and ce as in Figure 4. The fuzzy set of the variable u type singleton with the values: $NB = -3.32$, $NM = -2.14$, $NS = -0.96$, $ZE = 0.22$, $PS = 1.29$, $PM = 2.36$, $PB = 3.43$.

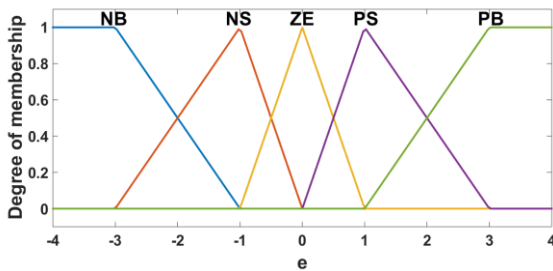


Figure 3. The fuzzy set of linguistic label of variable e

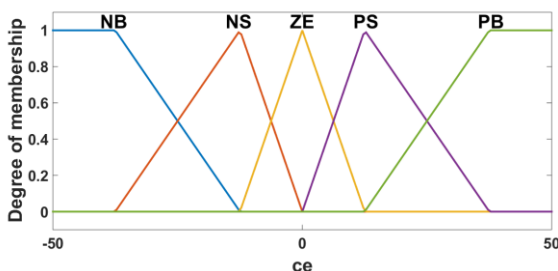


Figure 4. The fuzzy set of linguistic label of variable ce

Step 3: Construct the control rule set

The control rule set of the fuzzy controller is given as in TABLE I.

TABLE I. THE RULE BASE SYSTEM

$ce \backslash e$	NB	NS	ZE	PS	PB
NB	NB	NB	NM	NS	ZE
NS	NB	NM	NS	ZE	PS
ZE	NM	NS	ZE	PS	PM
PS	NS	ZE	PS	PM	PB
PB	ZE	PS	PM	PB	PB

The rules in the table can be understood as following:

- If $e = VN$ and $ce = VN$ then $u = VN$,
- If $e = VN$ and $ce = LN$ then $u = VN$,
- If $e = VN$ and $ce = ZE$ then $u = N$,
- If $e = VN$ and $ce = LP$ then $u = ZE$, ...

The corresponding input/output is shown in the Figure 5.

Step 4: Choose composite rule: The composite rule is chosen as sum-prod.

Step 5: Select the defuzzification principle: the output value u of FLC-sugeno is computed by the weighted average (4).

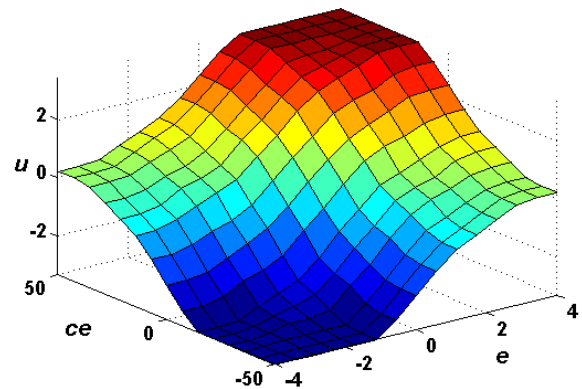


Figure 5. Input-output relationship surface of FLC-sugeno

The model simulates the system with PI-classical and FLC-sugeno controllers when there is no interference as shown in Figure 6 and when there is output interference as in Figure 7.

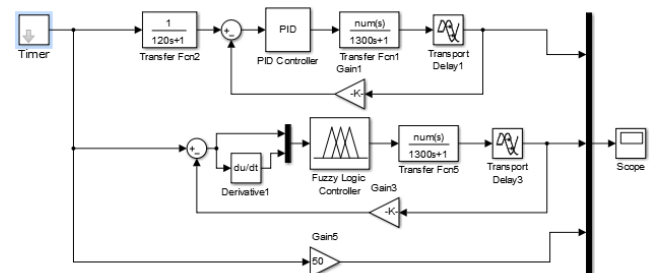


Figure 6. Simulation model with no interference

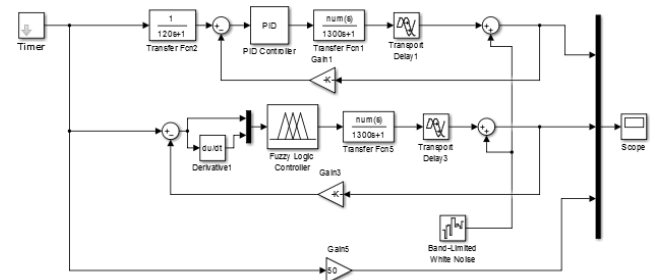


Figure 7. Simulation model with interference

IV. SIMULATION RESULT

Simulation model based on the model in Figure 6 and Figure 7 where $time = 1000 s$, the reference value is $t_{ref} = 200^{\circ}C$, both with load interference and no load interference at the output (interference amplitude $N = 5\%$ reference value) bring us the result as in Figure 8 and Figure 9.

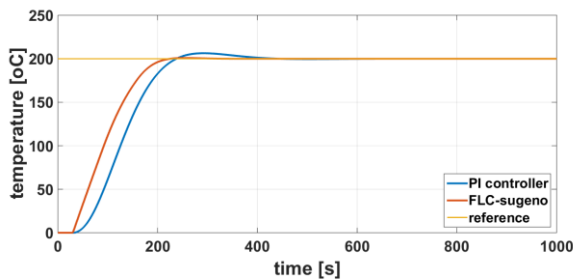


Figure 8. Response if there is no output interference

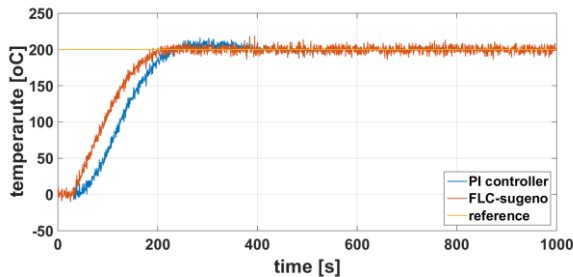


Figure 9. Response if there is output interference ($N = 5\%ref$)

Some numerical simulations of control quality indicators are synthesized in TABLE II.

V. DISCUSSION

In Figure 8 and Figure 9, the curve “reference” corresponds to the set value $t_{ref} = 200^{\circ}C$, the curve “PI controller” is the response of the system to the PI-classical controller, the curve “FLC-sugeno” is the response of the system to the FLC-sugeno controller. Observing the responses on the graph we can see that even if there is no interference or no disturbance at the output of the system, the FLC-sugeno controller always responds better than the PI-classical controller. After the time of delay of $\tau = 30 s$, the response of the FLC-sugeno controller has very small Rise time and Settling time, especially the amount of Overshoot is negligible

The numerical results (TABLE II.) also show that the FLC-sugeno controller has control indicators far less than PI-classical controller. ISE which responses to FLC-sugeno is reduced to about 71.23% compared to PI-classical

TABLE II. RESULT SIMULATION

	PI-classical		FLC-sugeno	
	Without Noise	Noise	Without Noise	Noise
Rise time [s]	211.9	205.5	181.8	180
Overshoot [%]	3.17	8	0.435	5
Settling time [%]	211.9	205.5	181.8	180
ISE	8,171,900	8,223,500	5,825,700	5,861,200

The simulation results show that the FLC-sugeno controller promotes its control advantages with its nonlinearity (shown in Figure 5). It is also the adaptability of the controller when giving the control value u to the ranges where the deviation values e and ce are at different values. Thus, the stronger the

nonlinear control object is, the more FLC fuzzy controller will promote its superiority.

VI. CONCLUSION

In this paper, we have designed and simulated the FLC-sugeno controller. In order to present the efficiency of the approach using the fuzzy controller, we have compared the system response to the PI-classical controller through quality control assessed through a number of indicators. Hence, it can be seen that FLC-sugeno is quite simple, even in design and implementation. Sugeno's defuzification does not take much calculation so the response rate of the controller is very good. In particular, the nonlinearity of FLC-sugeno provided a better response than PI-classical.

REFERENCES

- [1] Zadeh L. A., “Fuzzy sets”, Inform. and Control, 8, pp. 338-353, 1965.
- [2] Kevin M. Passino, Stephen Yurkovich, “Fuzzy Control”, An Imprint of Addison-Wesley Longman, Inc, 1998.
- [3] Ho Nguyen Cat, Lan Vu Nhu, Duy Nguyen Tien, “Hedge-Algebra-Based Voltage Controller for a Self-Excited Induction Generator”, The 7th National Conference on Fundamental and Applied IT Research, Thai Nguyen, 2014.
- [4] R.M. Hilloowala, A.M. Sharaf (1996), “A rule-based fuzzy logic controller for a PWM inverter in a stand alone wind energy conversion scheme”, IEEE Transactions on Industry Applications, 32(1), pp. 57-65.
- [5] Wu Wang (2009), “Adaptive Fuzzy Sliding Mode Control for Inverted Pendulum”, Proceedings of the Second Symposium International Computer Science and Computational Technology (ISCST'09) Huangshan, P. R. China, pp. 231-234.
- [6] YE Hong-tao, LI Zhen-qiang, LUO Wen-guang (2013), “Dissolved Oxygen Control of the Activated Sludge Wastewater Treatment Process Using Adaptive Fuzzy PID Control”, Proceedings of the 32nd Chinese Control Conferenc, Xi'an, China.
- [7] C. A. C. Belchior, R. A. M. Araújo, J. A. C. Landeckb (2012), “Dissolved Oxygen control of the activated sludge wastewater treatment process using stable adaptive fuzzy control”, Computers and Chemical Engineering, 37, pp. 152-162.
- [8] Mohamad Reza Dastranj, Mahbubeh Moghaddas, Younes Ghezi, and Modjtaba Rouhani (2012), “Robust Control of Inverted Pendulum Using Fuzzy Sliding Mode Control and Genetic Algorithm”, International Journal of Information and Electronics Engineering, 2(5), pp. 773-776.
- [9] T. Takagi, M. Sugeno, “Fuzzy Identification of Systems and Its Applications to Modelling and Control”, IEEE Transactions on Systems, Man, and Cybernetics, vol. 15, no. 1, pp. 116-132, 1985.

[10] M. Sugeno, G. Kang, "Structure Identification of Fuzzy Model", Fuzzy Sets and Systems, vol. 28, pp. 15-33, 1988.

[11] Seyed Kamaledin Mousavi Mashhadi, Mehdi Zahiri Savzevar, Jamal Ghobadi Dizaj Yekan (2013), "Simulation of Temperature Controller for an Injection Mould Machine using Fuzzy Logic", Journal of mathematics and computer Science, Vol. 7, pp. 33 – 42.

[12] Isizoh A. N., Okide S. O, Anazia A.E., Ogu C.D, Temperature Control System Using Fuzzy Logic Technique, International Journal of Advanced Research in Artificial Intelligence (IJARAI), Vol. 1, No. 3, pp. 27-31, 2012.

[13] P. Singhala, D. N. Shah, B. Patel, "Temperature Control using Fuzzy Logic", International Journal of Instrumentation and Control Systems (IJICS) Vol.4, No.1, pp. -10, January 2014.

[14] Olejár M., Cviklovič V., Hrubý D., Tóth L., "Fuzzy control of temperature and humidity microclimate in closed areas for poultry breeding", Res. Agr. Eng., 60 (Special Issue): S31–36, 2014.

[15] Tarun Kumar Das, Yudhajit Das, "Design of A Room Temperature And Humidity Controller Using Fuzzy Logic", American Journal of Engineering Research (AJER) e-ISSN : 2320-0847 p-ISSN : 2320-0936, Volume-02, Issue-11, pp-86-97, 2013.