Indian Journal of Science and Technology, Vol 11(29), DOI: 10.17485/ijst/2018/v11i29/129061, August 2018 ISSN (Print) : 0974-6846
ISSN (Online) : 0974-5645

Comparative between Neuro–fuzzy and PI Controller Temperature of Condenser in Thermal Power Plant (160 MW)

Hosham Salim Anead, Khalid Faisal Sultan and Malak Moneeryounis

Department of Electrical and Electronic Engineering, University of Technology, Baghdad, Iraq;
Hoshams.2000@yahoo.com, ksultan61@yahoo.com, moneer.maroof@yahoo.com

Abstract

Objectives: The temperature in the condenser is one of the serious and necessary parameters that should be maintained to harness the fullest efficiency power plant (160 MW) operations. For this reason, the regulation can be achieved by Artificial Intelligence (AI) technology, containing (Hybrid) the neuro–fuzzy system. **Methods/Statistical Analysis:** ANFIS theory compares with the conventional PID method by using MATLAB/ Simulink program which tracks the temperature levels. **Findings:** The comparison was made using various parameters (settling time, overshoot, rise time, peak time) and used to excess the thermal efficiency of the condenser by tracking the temperature and to reach the degree of 80^0C in less time with accuracy, which also lead to maintain the condenser as shown in the results. **Application/Improvements:** Neuro–fuzzy was the more accurate, superiority and reach the steady state in the short time, while PI represented the being of an overshoot where it causes system malfunction, leading to the driving off operation.

Keywords: Condenser, Neuro–fuzzy Controller, PID, Temperature

1. Introduction

The critical control parameter in the boiler is the maintenance of water level by means of simulation model using MATLAB program. More than set step size was taken for example 2, 1 and 0.4. The results were compared to the unit step for water level for three Theories (Fuzzy–ANFIS–PID) with reference to Error deviation and Settlement time; where it was concluded that ANFIS is superior, faster and more accurate than other theories because it tracks the water level and controls it accurately. The artificial intelligence control ANFIS has the ability to self–learning by means of the linguistic expressions of the fuzzy logic, as well as the knowledge of the membership function and the rules fuzzy from existing data instead of the expert[1]. Three theories were used to control nonlinear systems in general (control of flow rate, disturbance and also noise). These theories are the control of the fuzzy, traditional control of PID and the control of ANFIS. The three theories were compared (overshoot, rise time, setting time) which shows that ANFIS controls better than other theories where it provides such as overshoot:zero with ANFIS, 0.04 with PID and 0.02 with fuzzy and also it shows the calculation and control of non-linear systems using ANFIS control where input and output are required[2]. Adaptive control uses the condenser model and the gas traction for power plants. Where a system was first designed to detect parameters using neural networks and the first two methods are detection Direct and second is reverse detection. The two methods of control are proposed using neural fuzzy networks. The first method uses non–control direct through the back–feed algorithm over time. The other method uses reverse control. Simulations performed on multiple input/output networks demonstrated that the proposed methods are strong against changes affecting the system[3]. This work shows the use

*Author for correspondence

of neuro–fuzzy in the modeling of non-linear dynamics of an unknown environment to give new researchers the ability of ANFIS to design nonlinear stations. ANFIS is an artificial intelligence system consisting of the integration of the fuzzy with the Neural "neuro–fuzzy".

Neural Network provides algorithms for learning, classifying and optimizing while the fuzzy handles higher–level thinking issues (linguistic) and therefore the two techniques are complemented by each other. Through the merger will achieve a low level of computational power and learning of (NNs) into (FL) systems. And the mechanics of the work of ANFIS where it integrates least square and gradient this is called the concept of Hybrid[4].

The aim of this article is to excess the thermal efficiency of the condenser by tracking the temperature and to reach the degree of 80°C in less time with accuracy, which also lead to maintain the condenser, using the theory of the neuro–fuzzy, which is best and superior than the conventional PI as shown in the results.

2. Fuzzy Logic Controllers

Fuzzy Logic Control is a dynamic behavior that describes rules based on expert knowledge. These rules are given in the following form: IF (antecedent) THEN (consequent). IF (x is A) and (y is B) THEN (z is C).

Where: A, B, C are linguistic terms of fuzzy set, such as (small, medium, large, fast ...).

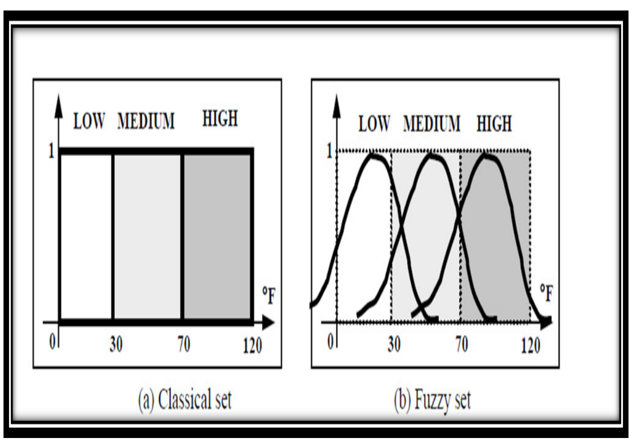

Figure 1. Sketch of classical and fuzzy sets[6].

X, y is variables that represent the input of the fuzzy controller while Z is represented by the output variable. It was found that the availability of the FLC is a convenient means of expression. In addition, there are multiple linguistic variables and thus the system will be known as multi-input or multi–output. The input has several variables and one output called MISO. While if more than one input and output are named MIMO. In addition, membership functions are distinguished by a curve which determines the method of assigning each point in the input area to a membership value between 0 and 1. There are many types of membership functions, where the ratio is chosen to the appropriate parameters and after the development in the study became various types of membership Used in the ANFIS model[5]. Figure 1 provides sketch of classical and fuzzy sets[6].

3. The Objective of using Fuzzy Inference Systems is Necessary

Fuzzy logic does not solve new problems but uses new methods to solve everyday problems. The mathematical concept is very simple. Fuzzy is flexible which can be modified either by adding a rule or removing it where there is no need to create a FLC from scratch. Fuzzy logic does not work with uncertainty but deals with elements in a fuzzy set (membership values). For example, the fuzzy logic work with 'He tall to the degree of 0.7' instead of 'He is 170 cm tall' depends on knowledge of experts who understand the system. It can mix fuzzy logic with other conventional control techniques.

4. Fuzzy Logic Systems Architecture

It has four main parts as shown:

4.1 Fuzzification

- Converts input which is crisp numbers into fuzzy logic sets to inference machine which leads to their easy use and application of the rules.
- Decision – making logic.
- The use of fuzzy implicit, which produces fuzzy controls, simulates the mechanism of inference system in humans. That is simulated decision-making in interpretation and application of the best results to control the plant.
- The knowledge base is composed of two parts, database and rule base.
- The database is used to characterize fuzzy control rules and processing of unclear data in fuzzy

logic. All this is done by personal experience and engineering judgment.

- Rule base, the fuzzy system is characterized by a set of linguistic expressions based on expert knowledge. The knowledge of the expert is formed in the form of "IF – THEN" rules which is executed through conditional statements in the fuzzy logic. The set of fuzzy control rules that are expressed as fuzzy conditional statements forms the rule base or the rule set for a Fuzzy Logic Controller.

4.2 Defuzzification

Fuzzy logic is converted to crisp values, which means converting the inference of the machine to the actual input for processes. Figure 2 indicates the components of a fuzzy inference system.

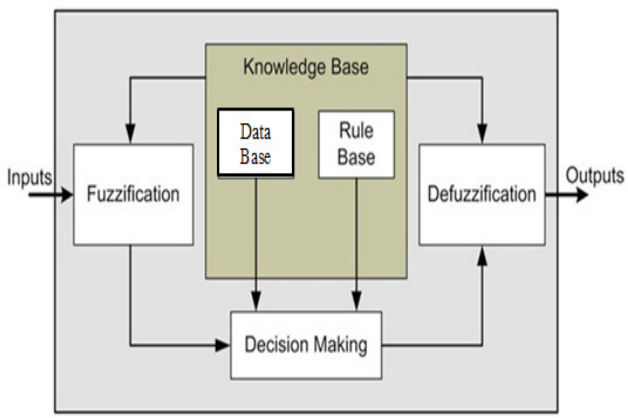

Figure 2. Components of a fuzzy inference system[7].

5. Architecture Neural Networks

The connection between neurons with other neurons can be a pattern of the layer. The ANN is usually made up of three completely different layers, where the basic layer is called the input layer that receives information or input from the external stimuli. The information is sent to the next layer, where there is no rule to determine the amount of neurons, but depends on the amount of input to be used in the network. The layer is called the hidden layer. The layer processes the data or electrical signals sent from the input layer by the activation functions. The number of hidden layers is based on the complexity of the situation at hand and then sent to the output layer which plays an important role in the validity of the information the output will be used as a determinant of the end result[7,8].

6. The Layers of a Neural Network

Neural Network structure layers can be divided into three main groups:

- Numbers of neurons are depended on inputs, all neurons inserted together form the input layer.
- All output neurons form the output layer.
- Hidden layer are one or more in neural network that is considered neurons in any intermediate layer.

7. Integration of Fuzzy Logic and Neural Networks

Neuro–fuzzy modeling is involved in the identification of numerical data samples that occupy the behavior of systems. This type of modeling has two advantages: To provide a model that allows controlling or possibly predicting an unknown method to prepare a model for better understanding of the system. The models are based on the rules of control and the use of the basic form of fuzzy logic, consisting of fuzzy set rules, for example, "If – Then". Much of this idea has been thoroughly reviewed and considered beginning with the beginning of the 1990s[9–16], remains the task of research. ANFIS is available in MATLAB[17]. Then ANFIS is in the form of a neural network based on Takagi–Sugeno fuzzy inference system which stores inputs through the input membership functions and Outputs are also stored through output membership functions.

Thus, the neuro–fuzzy theory is divided into two parts: Transition and permanent, where the accuracy is in the permanent part and the speed in the transition in case the system does not reach the steady state with the oscillations or changed pi work point, the point is returned to Ki due to integration modifies the accuracy while KP is controlled on speed. Table 1 indicates the comparison of fuzzy systems and Neural Networks.

8. Hybrid Learning Algorithm

Gradient method problems are slow and it is likely to be trapped in local minima. For this reason, ANFIS was used to train by the hybrid learning algorithm. Neuro-fuzzy uses two pathways, a front path and a backward path, by combining the two theories of the Gradient and Least square error. The front path, the information is determined and extracted from the Consequent parameter in the fourth layer using the theory of (LSE). As for the backward path, it is going backward, where premise parameter is modifying by means of the error derivative, thus determining the weight, indicating that the premise parameter is updated by the gradient descent. Table 2 briefly describes a hybrid learning method in ANFIS.

Table 1. Comparison of fuzzy systems and Neural Networks

Skills	FS	NN
Knowledge representation	✓	
Uncertainty tolerance	✓	✓
Imprecision tolerance	✓	✓
adaptability	✓	✓
Learning ability		✓
Explanation ability	✓	✓

Where: The terms used for grading are:
Bad [ ] Good [✓]

A distinction is made between two types of neural systems:

Hybrid neuro-fuzzy systems: In which the neural system and the fuzzy logic system cannot be disassociated as the network can be understood as artificial.

- Neural networks or at the same time as a fuzzy logic system.
- **Cooperative neuro-fuzzy systems**: Systems in which Artificial Neural Network is used to obtain the transactions of the system of fuzzy logic as a function of belonging and then the network is separated from it and the system of fuzzy logic works alone.

9. PID controller

A proportional–integral–derivative controller (PID controller) is a control loop feedback mechanism. As the name suggests, PID algorithm consists of three basic coefficients: proportional, integral and derivative which are varied to get optimal response[18] and Figure 3 shows of the control system PID.

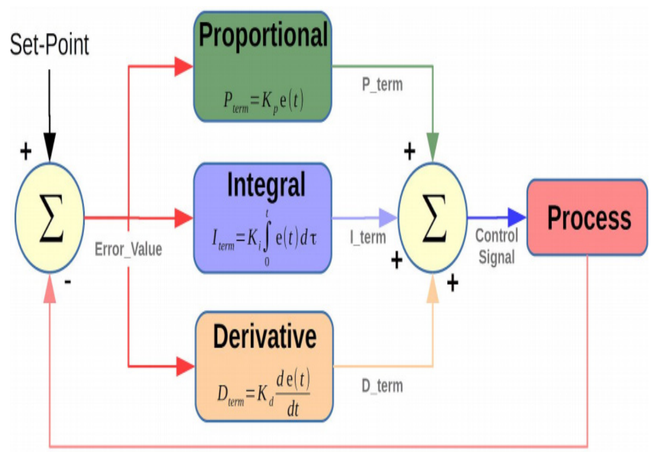

Figure 3. PID of the control system[18].

10. The Characteristics of Controllers

A proportional controller has the effect of reducing the rise time and reduces the steady error but will not be eliminated at all, while the integrated controller affects the removal of the error, which making the temporary response worse. Finally, the control of derivatives leads to increased stability of the system and improved transient response and limit overshoot. Here is a summary of the effect of each of the control units on the closed loop system but at the same time, these links may not be accurate exactly. One change of these controllers will affect the others and therefore uses the table as a reference only when determining the values of the K_p, K_i and K_d[19]. Table 3 indicates controller response.

11. Temperature of Condenser for Neuro-fuzzy and Conventional PID

Unit 6 for the condenser is installed for the thermal power plant AL–Dura, origin Germany. The temperature is 80°C. Figure 4 provides the picture of the condenser. The control monitor of the thermal station that controls the condenser part of the PID conventional theory of the self–control chambers of the power plant AL–Dura is represented as in Figure (4). The Figure 5 shows the monitoring condenser from self -control room.

Table 2. Hybrid learning process

Type	Path forwards	Path backwards
Premise parameter	Fixed	Gradient descent
Consequent parameter	rise	Fixed
single	Node output	Error rate

Table 3. Controller response

Controller response	Rise time	overshoot	Settling time	S.S error
ki	decrease	Increase	Increase	Remove
kd	Little change	Decrease	Decrease	Little change
kp	Decrease	Increase	Little change	Decrease

Table 4. Temperature classical PI controller

Operating point	80^0C
Kp	0.47
Ki	1.604

Table 5. Training error of temperature

Type mf	N. layer	N. Iteration	AverageError	
			Constant	
Triangular	6	50	0.012	
Trapezoidal	6	50	0.273	
Bell shapped	6	50	0.006	
Symmetric Gaussian function	6	50	0.0055	
			Linear	
Triangular	6	50	0.013	
Trapezoidal	6	50	0.015	
Bell shapped	6	50	0.003	
Symmetric Gaussian function	6	50	0.0015	Best

Table 6. Comparison parameters between ANFIS and PI for temperature of steam condenser

Parameters	Rise Time (Sec)	Settling Time (Sec)	Overshoot	Peak	Peak Time (Sec)
Temperature					
ANFIS	1.7738	3.9522	0	80	20
PI	1.3105	4.344	11.248	88.998	2.7

Figure 4. The picture of the condenser at AL–Dura power plant.

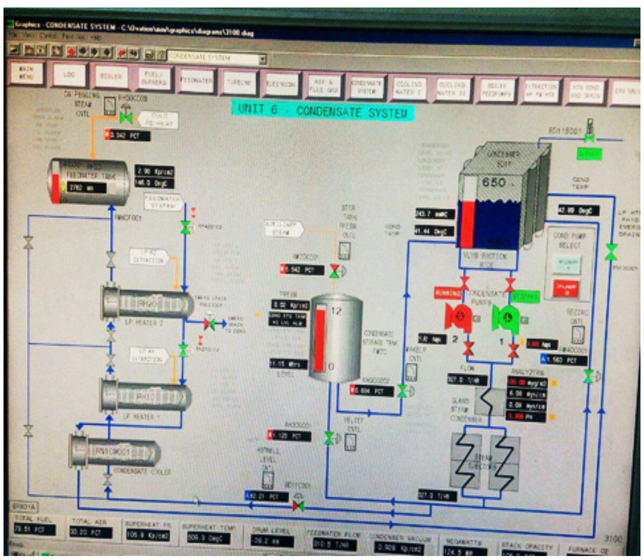

Figure 5. Monitoring condenser from self–control room.

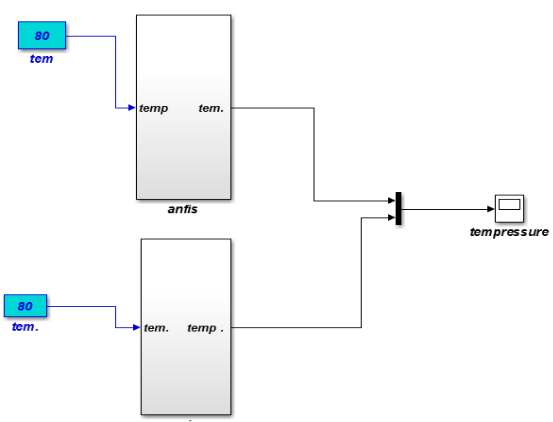

Figure 6. General simulation ANFIS and PI conventional of the boiler of the AL–Dura thermal station.

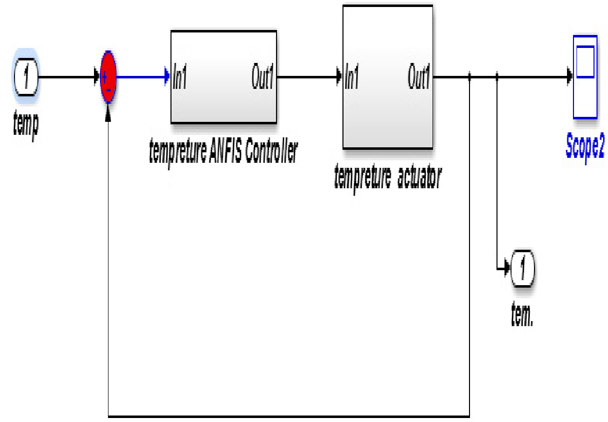

Figure 7. Simulation ANFIS of the boiler of the AL–Dura thermal station.

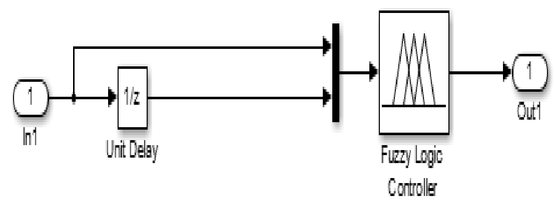

Figure 8. Block ANFIS of thermal station.

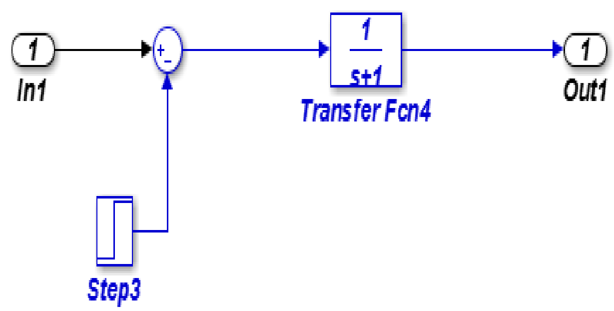

Figure 9. Block actuator of thermal station.

In this work, temperature parameter was controlled, which is input. Enter this input on the ANFIS control system then to the actuator and back through the feedback in order to be the rules of control methods. As well as a simulation design for PI Conventional and also enter parameter to model as shown in Figures 6 and 7.

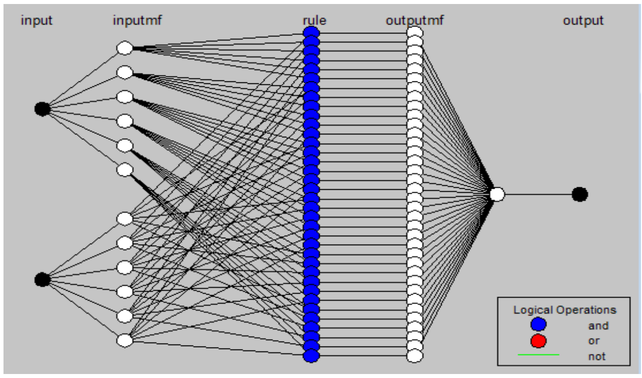

Figure 10. Tuning of classical PID at temperature control.

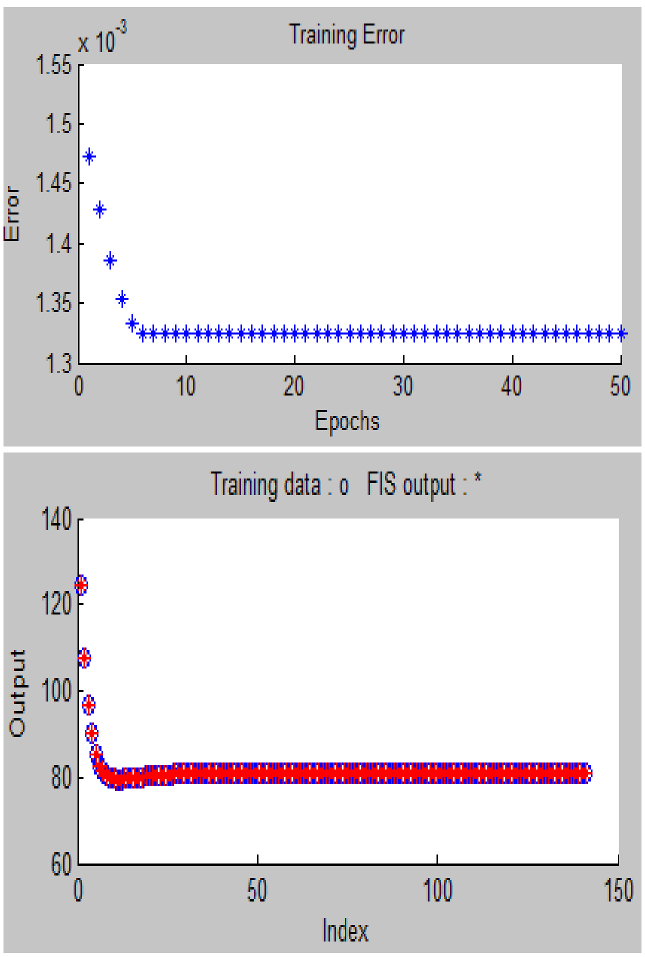

Figure 11. Training error and training data with FIS output.

While the component of block ANFIS is generally formed as in Figure 8.

The component of the actuator block is as follows in the Figure 9.

The temperature classical PI controller is indicated in the Table 4.

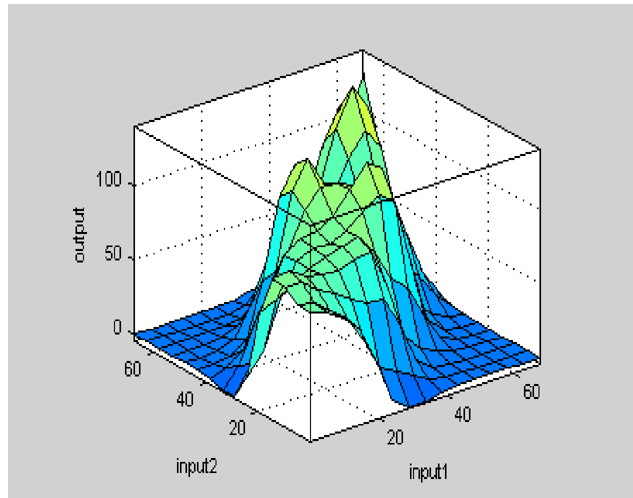

Figure 12. Fuzzy surfaces.

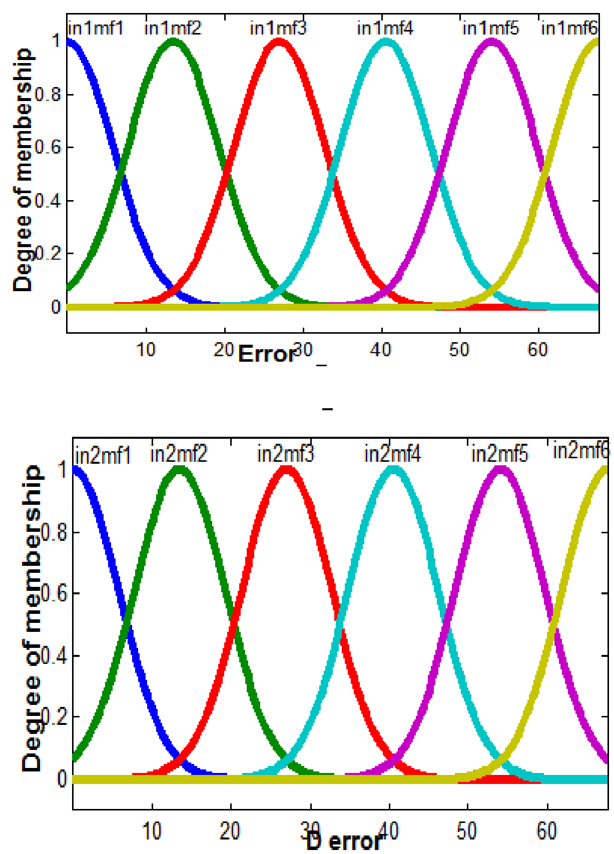

Figure 13. Membership function plot.

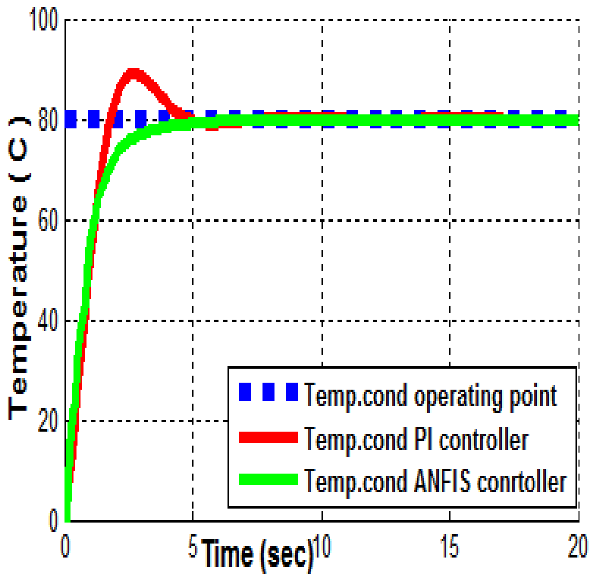

Figure 14. State response temperature.

When training data exists types of membership function (triangular, trapezoidal, bell shaped, Gaussian) a lower error rate would be the best type. Temperature operating point is max and min respectively (75–80)°C is the best type mf Gaussian, average error = **0.0015** (Table 5).

12. Analysis and Discussion of the Simulation

This paper is tackled controller on the temperature entered to the condenser by using the ANFIS simulation model of the MATLAB (2014a) program and obtained the following results as showed in the Figures 10 to 14.

- Temperature ANFIS controller

Finally, discussion of the present controller point of temperature in the condenser. The temperature regulation by neuro–fuzzy controller shows the accurate performance of the proposed controller in tracking the temperature thus good. This regulation, compared with PI controller and it shows that the performance of the PI controller is having large overshoot and long time at peak time, as shown in Table 6. The confirmed for operating point controller at 80°C. The performance diagrams are presented in Figure 10. The ANFIS controller tracked temperature accurately and within less period of time.

13. Conclusion

The temperature of the condenser was regulated at the thermal power plant by adaptive neuro–fuzzy Inference System control. This work used 201 data and the best Gaussian function was used after training and testing, when the membership function was represented: 6 and the epochs: 50. In conclusion, ANFIS got better and extra accurate in tracking and controlling the temperature pass than the PI conventional and this is shown in analysis and discussion of the simulation where the ratio of the overshoot is 0% and peak time is the least time period than PI.

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