# Intelligent Temperature Controller for Water-Bath System

Om Prakash Verma, Rajesh Singla, Rajesh Kumar

*Abstract*—Conventional controller's usually required a prior knowledge of mathematical modelling of the process. The inaccuracy of mathematical modelling degrades the performance of the process, especially for non-linear and complex control problem. The process used is Water-Bath system, which is most widely used and nonlinear to some extent. For Water-Bath system, it is necessary to attain desired temperature within a specified period of time to avoid the overshoot and absolute error, with better temperature tracking capability, else the process is disturbed.

To overcome above difficulties intelligent controllers, Fuzzy Logic (FL) and Adaptive Neuro-Fuzzy Inference System (ANFIS), are proposed in this paper. The Fuzzy controller is designed to work with knowledge in the form of linguistic control rules. But the translation of these linguistic rules into the framework of fuzzy set theory depends on the choice of certain parameters, for which no formal method is known. To design ANFIS, Fuzzy-Inference-System is combined with learning capability of Neural-Network.

It is analyzed that ANFIS is best suitable for adaptive temperature control of above system. As compared to PID and FLC, ANFIS produces a stable control signal. It has much better temperature tracking capability with almost zero overshoot and minimum absolute error.

*Keywords*—PID Controller, FLC, ANFIS, Non-Linear Control System, Water-Bath System, MATLAB-7.

## I. INTRODUCTION

TEMPERATURE control is an important factor in many process control system. Water-Bath temperature control [1] is one of the most important and widely used applications of non-linear control system [2] in process control industry and its application, in the production of a variety of drinks products such as chocolate drink, strawberry milk products etc. The process industries which use Water-Bath temperature control are Nestle, Yeoh Hiop Seng, F&N, etc. If the temperature is out of the given range, the final product is badly affected.

Therefore, it is necessary to reach at desired temperature points quickly within specified time period and to avoid large overshoot [3]. Since the process-control systems are often non-linear and tend to change in an unpredictable way, they are not easy to control accurately. Temperature is basic

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physical quantity, when is measured and controlled. The temperature control system traditionally uses PI [4] and PID conventional controller [5] to control the required level of temperature. A PID controller is the classical control algorithms in the field of process control. The predominance of conventional controller in the process control remains satisfactory for many years due to its robustness and effectiveness, for a wide range of operating conditions and partly to its functional simplicity but the major drawback of conventional controllers are they are very prone to change in system parameters, delays, nonlinearities and applied to obtain zero overshoot. It is also very difficult to design the mathematical model that raises unnecessary rigorosity, preciseness and accuracy for conventional controllers. The inaccuracy of mathematical modeling of the plants usually degrades the performance of the controller, especially for nonlinear and complex control problems.

In order to overcome these difficulties, another alternative technique may be employed which is based on unconventional control technique. The idea of unconventional controller is basically based on this paper is artificial intelligence (AI) technique which may have been employed to improve the controller performance for a wide range of plants. AI technique includes Neural Network (NN) [6], Fuzzy Inference System (FIS) [7] and Adaptive Neuro Fuzzy Inference system (ANFIS) [8] which have been widely applied to proper tuning of PID controller parameters. The fast improvements in the processing power of modern digital control technology make Fuzzy Logic Control (FLC) and Neuro Fuzzy System (NFS) viable and appealing in many industry sectors. In this paper, the comparison study is made on the basis of performance index of conventional controller PID and Intelligent Controller (FLC's & ANFIS) in terms of Absolute Error (AES) [9], overshoot, delay, and tracking capability [10].

## II. EXPERIMENTAL SETUP

The process considered here is one of most widely used processes in the process industry, a Water-Bath Temperature Control System. The schematic diagram of Water-Bath System is shown in Fig. 1.

The Water-Bath System consists of water tank in which cold water is entering the tank from one side and hot water is leaving from the other side. The aim is to obtain the output water at the desired temperature.

The assumptions made for the system are as follows:
1) The volume of water tank is constant.
2) The inlet flow rate is equal to the outlet flow rate.
3) There is no change of state.
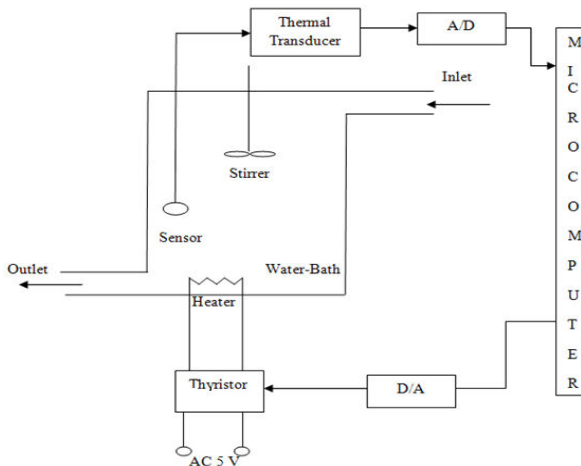
4) Uniform temperature is maintained in tank.



Fig. 1 Water-Bath System

The dynamics of the Water-Bath system is as follows:

$$\frac{dT}{dt} = \frac{F}{V}(T_i - T) + \frac{Q}{VC_p\rho} \qquad (1)$$

where, T is the tank temperature, F is the flow rate, Ti is the inlet temperature, V is the volume of the tank, Q is the heat input, Cp is the specific gravity and ρ is the density of water.

The equivalent electrical model dynamics equation of Water-Bath continuous time temperature control system is given by:

$$\frac{dy(t)}{dt} = \frac{F(t)}{C} + \frac{y_0 - y(t)}{RC} \qquad (2)$$

where t denotes time, y(t) is output temperature in °C, F(t) is the heat flowing inward the system, $y_0$ is the room temperature (constant, for simplicity), C denotes the system thermal capacity and R is the thermal resistance between the system borders and surroundings.

Assuming that R and C are essentially constant, obtaining the pulse transfer function for the system in (1) by the step response criterion results in the discrete-time system:

$$y(k + 1) = a(T_s)y(k) + b(T_s)u(k) \qquad (3)$$

where k is the discrete time-index, u(k) and y(k) denotes the system input and output, respectively, and Ts is the sampling period. Denoting by α and β some constants values depending on R and C, the remaining parameter can be expressed by:

$$a(T_s) = e^{-\alpha(T_s)} \qquad (4)$$

and,

$$b(T_s) = \frac{\beta}{\alpha}(1 - e^{-\alpha(T_s)}) \qquad (5)$$

The system described in (1) to (3) was modified to include a saturating non-linearity so that output temperature cannot exceed some limitations.

The discrete-time control plant equation described by:

$$y(k + 1) = a(T_s)y(k) + \frac{b(T_s)}{1 + e^{(-0.5y(k) - \gamma)}} u(k) + (1 - a(T_s))y_0 \quad (6)$$

where $a(T_s)$ and $b(T_s)$ are given by (3) and (4).

The Parameters are: $\alpha = 1.00151E - 4$, $\beta = 8.67973E - 3$, $\gamma = 40.0$ and $y_0 = 25.0°C$. They were obtained from a real Water-Bath plant.

Linearize [11] the equation obtained (6), the final simulate discrete-time linear equation for control plant is

$$y(k + 1) = 0.988\,y(k) + 0.222u(k) \qquad (7)$$

The plant input u(k) was limited between -5 and 5, and it is also assumed that the sampling period is limited by Ts ≥ 30 sec.

## III. PROPOSED CONTROLLER

### A. Fuzzy Logic Controller (FLC)

Fuzzy logic is more effective in feedback control system and easier to implement. Since Water-Bath temperature control system shows highly non linearity to some extent, hence fuzzy inference system is highly efficient method for proposed problem. Fuzzy control system divides into the single variable fuzzy control system and the multi-variables [12] fuzzy control system. The Water-Bath temperature controller uses the two-dimensional fuzzy controller model shown in Fig. 2.
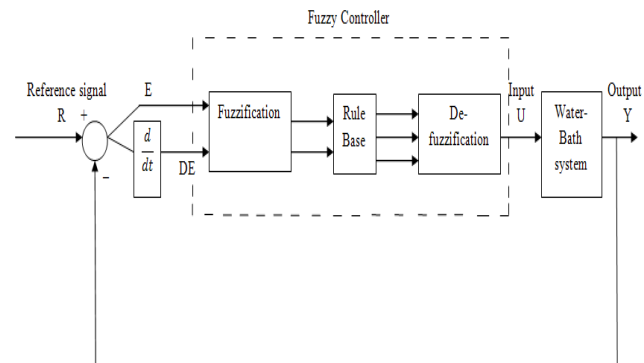


Fig. 2 Fuzzy Control Model for Water-Bath system

The system used two input variables error (E) change of error (DE) and one output variable(U). The computational structure of fuzzy logic control scheme is composed of fuzzification [13], inference engine [14] and defuzzification [15]. The input to the fuzzy controller is error E(k) and the change in error DE(k) is computed from the reference output U(k) based on error and change in error as shown in Fig. 3 using FIS Editor.
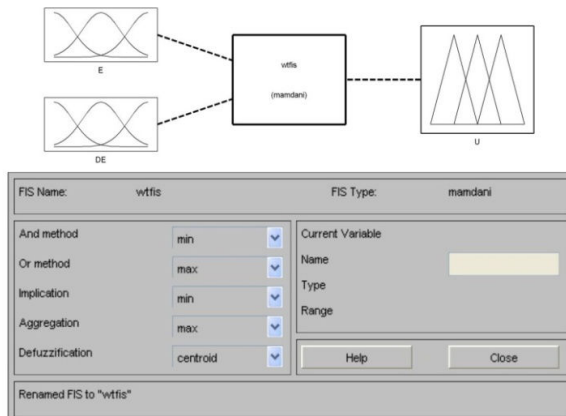
Fig. 3 FIS Editor of Fuzzy Control Model for Water-Bath system

The fuzzy control rules have the form:

R1: if X is $A_1$ and Y is B1 then Z is C1
R2: if X is $A_2$ and Y is B2 then Z is C2
. . . . .
. . . . .
$R_n$: if X is $A_n$ and Y is $B_n$ then Z is $C_n$

where X, Y and Z are linguistic variables represents two process state variables and one control variable respectively; $A_i$, $B_i$ and $C_i$ are linguistic value of the linguistic variable X, Y and Z in the universe of discourse U, V and W respectively with $i = 1, 2, ...., n$; here AND operator and MAMDANI type FIS is used. 49 Rule base is shown in Table I, Rule Viewer and Surface Viewer is shown in Figs. 4 and 5 respectively.

TABLE I
RULE BASE

| DEE | NB | NM | NS | ZR | PS | PM | PB |
|-----|----|----|----|----|----|----|----|
| NB | NB | NB | NB | NB | NM | NS | ZR |
| NM | NB | NB | NB | NM | NS | ZR | PS |
| NS | NB | NB | NM | NS | ZR | PS | PM |
| ZR | NB | NM | NS | ZR | PS | PM | PB |
| PS | NM | NS | ZR | PS | PM | PB | PB |
| PM | NS | ZR | PS | PM | PB | PB | PB |
| PB | ZR | PS | PS | PB | PB | PM | PB |

where, NB: Negative Big, NM: Negative Medium, NS: Negative Small, ZR: Zero, PS: Positive Small, PM: Positive Medium, PB: Positive Big
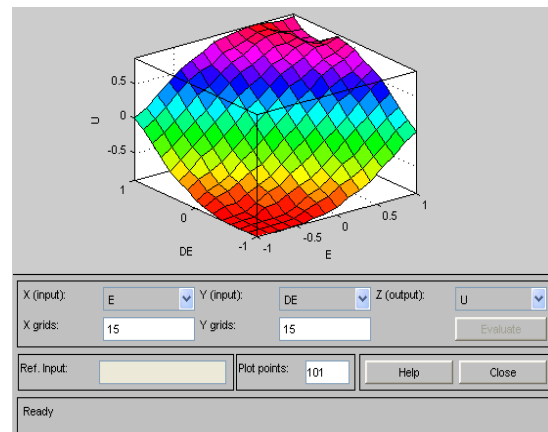


Fig. 4 Surface Viewer of Fuzzy Control Model for Water-Bath system

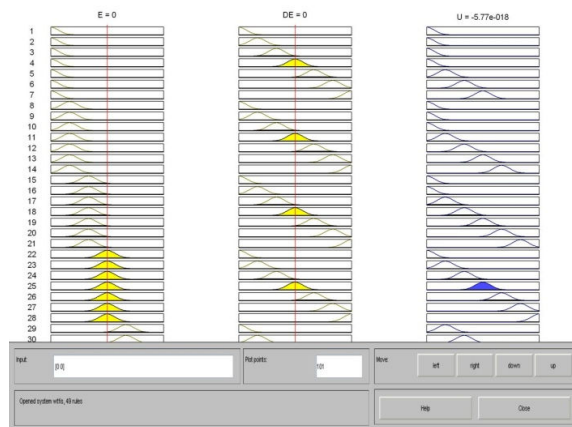For controlling the inferred fuzzy control action to real value, centroid method is used.



Fig. 5 Rule Viewer of Fuzzy Control Model for Water-Bath system

### B. Adaptive Neuro Fuzzy Inference System (ANFIS)

In conventional fuzzy approach the models are designed according to a priori knowledge about membership functions and the consequent models. If this set is not available but a set of input–output data is observed from the process, the components of a fuzzy system (membership and consequent models) can be represented in a parametric form and neural networks tune the parameters. In that case the fuzzy systems turn into neuro fuzzy system. A fuzzy system can explain the knowledge it encodes but can't learn or adapt its knowledge from training examples, while a neural network can learn from training examples but can't explain what it has learned. Fuzzy systems and neural networks have complementary strengths and weaknesses. As a result, combination of neural networks and fuzzy logic offers the possibility of solving tuning problems and design difficulties of fuzzy logic. The resulting network will be more transparent and can be easily recognized in the form of fuzzy logic control rules or semantics. The novelty of these schemes is that the fuzzy controller in the resulting control value can be distributed back among the

control rules, instead of the integrating neural networks in certain parts of the controller, acting as black boxes to optimize the weights.

A neuro fuzzy system is a combination of neural network and fuzzy systems in such a way that neural network or neural network algorithms are used to determine the parameters of the fuzzy system. This means that the main intention of neuro fuzzy approach is to create or improve a fuzzy system automatically by means of neural network methods. An even more important aspect is that the system should always be interpretable in terms of fuzzy if-then rules, because it is based on a fuzzy system reflecting vague knowledge. The idea of a neuro fuzzy system is to find the parameters of a fuzzy system by the means of learning methods obtained from neural network. A common way to apply a learning algorithm to a fuzzy system is to represent it in a special neural network- like architecture. Then a learning algorithm such as back propagation is used to train the system. However, neural network learning algorithms are usually gradient descent methods. This cannot be applied directly to a fuzzy system, because the functions used to realize the inference process are usually not differentiable. In order to realize the system, we need to replace the functions used in the fuzzy system (like min and max) by differentiable functions or do not use a gradient-based neural learning algorithm but a better-suited procedure.

Modern neuro-fuzzy systems are often represented as multilayer feed forward neural network. A neuro-fuzzy system is a fuzzy system that is trained by a learning algorithm (usually) derived from neural network theory. The (heuristic) learning procedure operates on local information, and causes only local modifications in the underlying fuzzy system. The learning process is not knowledge-based, but data driven. Besides, a neural-fuzzy system can always be interpreted as a system of fuzzy rules. It is possible both to create the system out of training data from scratch, and to initialize it from prior knowledge in the form of fuzzy-rules.

The learning procedure of a neural-fuzzy system takes the semantical properties of the underlying fuzzy system into account. This results in constraints on the possible modification of the system's parameters. It also approximates an $n$ dimensional (unknown) function that is partially given by the training data. The fuzzy rules encoded within the system represent vague samples, and can be viewed as vague prototypes of the training data.

Generally, a neuro-fuzzy system should not be seen as a kind of (fuzzy) expert system, and it has nothing to do with fuzzy logic in the narrow sense. It can be viewed as a special kind of feed forward neural network. The units in this network use $t-$norms or $t-$conorms instead of the activation functions normally used in neural networks. Fuzzy sets are encoded as (fuzzy) connection weights. Neuro-fuzzy controller is the fuzzy based paradigm that grasps the learning abilities of ANN to enhance the intelligent system's performance using a priori knowledge.

Using a given input-output data set, ANFIS constructs a fuzzy inference system (FIS) whose membership function

parameter are tuned using either a backpropagation algorithms [16] alone, or in combination with a least square type of method. This helps fuzzy system to learn, adapt and optimize membership functions. This gives the best fit membership functions in fuzzy system.

ANFIS is created through the concepts of fuzzy sets and the Sugeno fuzzy inference system [17] which imitates the human decision making. The advantage of ANFIS is to immediately calculate output. It is not necessary to create the complex mathematical model. ANFIS can learn from the sample data such as the input output sets from the system and can adapt parameters inside its network.

ANFIS largely removes the requirement for manual optimization of the fuzzy system parameters. A neural network is used to automatically tune the system parameters, for example the membership functions bounds, leading to improved performance without operator invention.

The neuro fuzzy system with the learning capability of neural network and with the advantages of the rule-base fuzzy system can improve the performance significantly and can provide a mechanism to incorporate past observations into the classification process. In neural network the training essentially builds the system. However, using a neuro fuzzy scheme, the system is built by fuzzy logic definitions and is then refined using neural network training algorithms.

Some advantages of ANFIS are:
1) Refines fuzzy if-then rules to describe the behaviour of a complex system.
2) Does not require prior human expertise.
3) Greater choice of membership functions to use.
4) Very fast convergence time.

### C. Anfis Architecture

For simplicity, we assume that the fuzzy inference system under consideration has two inputs x and y and one output z. For a first-order Sugeno fuzzy model, a common rule set with two fuzzy rules is the following:

RULE 1: If x is $A_1$ and y is $B_1$, then $f_1 = p_1x + q_1y + r_1$,
RULE 2: If x is $A_2$ and y is $B_2$, then $f_2 = p_2x + q_2y + r_2$,

$$f = \frac{w_1 f_1 + w_2 f_2}{w_1 + w_2} = \bar{w}_1 f_1 + \bar{w}_2 f_2 \qquad (8)$$

Fig. 6 shows the reasoning mechanism for this sugeno model with the corresponding equivalent ANFIS architecture, where nodes of the same layer have similar functions. Here we denote the output of the $i^{th}$ node in layer l as $O_{l,i}$. The output of the ANFIS is calculated by employing the consequent parameters found in the forward pass. Table II summarizes the activities in each pass. The output error is used to adapt the premise parameters by means of a standard backpropagation algorithm. It has been proven that this hybrid algorithm is highly efficient in training the ANFIS.

Hybrid learning algorithm combines the gradient descent method and the Least Square Estimator (LSE) method is used to refine these parameters.
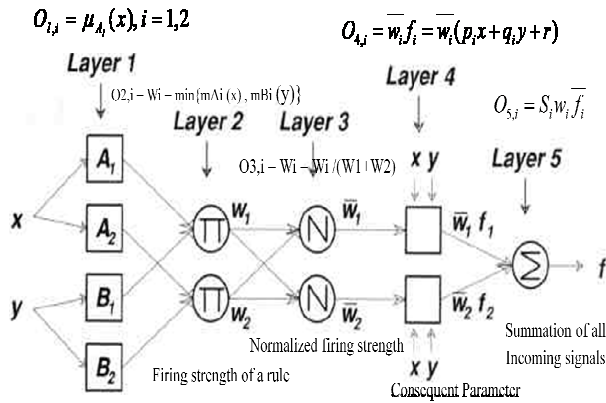
$$O_{1,i} = \mu_{A_i}(x), i = 1,2$$

$$O_{4,i} = \overline{w_i}f_i = \overline{w_i}(p_i x + q_i y + r)$$

Layer 1

Layer 4

$\{O2,i - Wi - \min\{mAi(x), mBi(y)\}\}$

Layer 2  Layer 3

$$O_{5,i} = S_i \overline{w_i f_i}$$

O3,i – Wi – Wi /(W1 + W2)

x y

Layer 5

Firing strength of a rule

Normalized firing strength

Consequent Parameter

Summation of all
Incoming signals

Fig. 6 Equivalent ANFIS architecture

TABLE II
TWO PASSES IN THE HYBRID LEARNING PROCEDURE FOR ANFIS

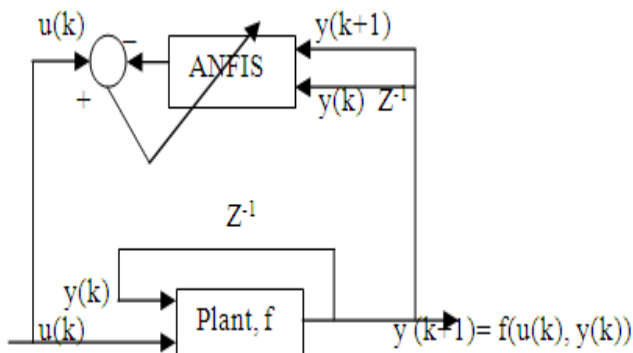|  | Forward Pass | Backward pass |
|---|---|---|
| Premise Parameters | Fixed | Gradient descent |
| Consequent Parameters | Least-square estimator | Fixed |
| Signals | Node outputs | Error signals |

### D. ANFIS Controller

Fig. 7 Learning of ANFIS Controller

One of the uses of ANFIS in control system is to learn the inverse of the plant, so that it can be used as a controller after training phase. Fig. 7 has shown the learning phase of ANFIS. Water-Bath temperature system is example of above in which the target plant is to be controlled. Notice that the learning of ANFIS is based on error back propagation. After the learning phase is finished, the trained ANFIS is then to be used as a controller for the plant. Based on these mechanisms, FIS editor (Sugeno type), Rule Base, membership function, surface viewer and Rule viewer are tested which are as shown below:
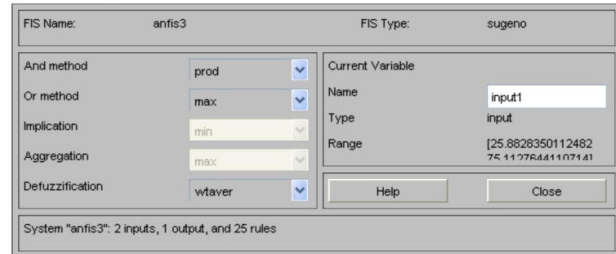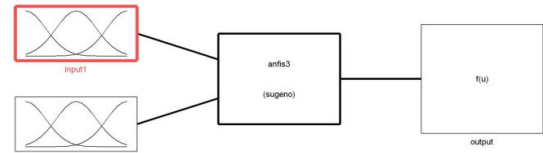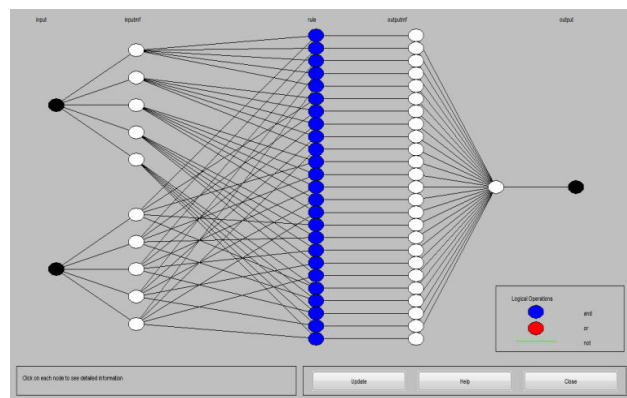
Fig. 8 ANFIS Editor of water bath system

Fig. 9 ANFIS Structure of Water bath system

Fig. 10 ANFIS Rule base of Water bath system

## IV. RESULTS AND DISCUSSIONS

This section includes the output response of Conventional controller PID, Fuzzy Logic Controller (FLC) and Adaptive-neuro-Fuzzy-Controller (ANFC) and their performances are investigated and compared with PID. The goal is to design a Controller that will control the water temperature to follow a reference profile;

TABLE III
DESIRED REFERENCE TEMPERATURE VS. SPECIFIED TIME PERIOD

| Desired Reference Temperature °C | Specified Time Period(sec) |
|---|---|
| 35 | $0 \leq t \leq 30$ |
| 45 | $30 < t \leq 60$ |
| 55 | $60 < t \leq 90$ |
| 65 | $90 < t \leq 120$ |
| 75 | $120 < t \leq 150$ |
| 65 | $150 < t \leq 180$ |
| 55 | $180 < t \leq 210$ |
| 65 | $210 < t \leq 240$ |
| 75 | $240 < t \leq 260$ |

With sampling time $(T_s)$ = 25sec.

### A. PID Controller Response

The value of $K_p$, $K_I$ and $K_D$ are found with PID tuner, $K_P = 0.0119555871127301$, $K_I = 0.00186883091998847$ and $K_D = 120.94044888255$. The response of PID Controller is as shown in Fig. 11.
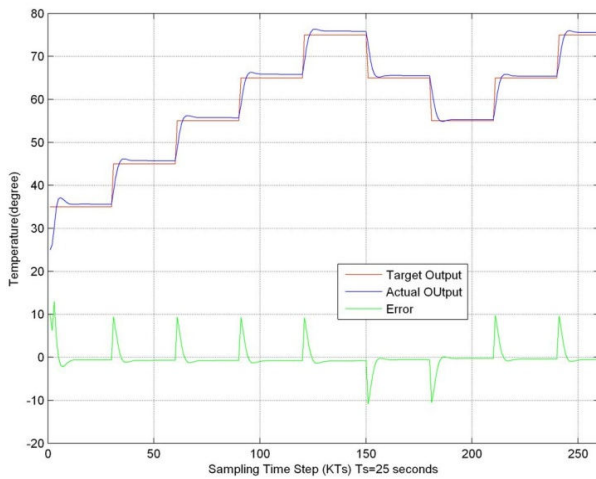


Fig. 11 Output response of PID controller

### B. FLC Controller Response

Fuzzy controller has some scaling parameters; they are GE, GCE, and GU, corresponding to the process error, the change in error, and the controller's output, respectively. These parameters are taken manually tuning: $GE = 0.018$, $GCE = 0.0015$, $GU = 150$.
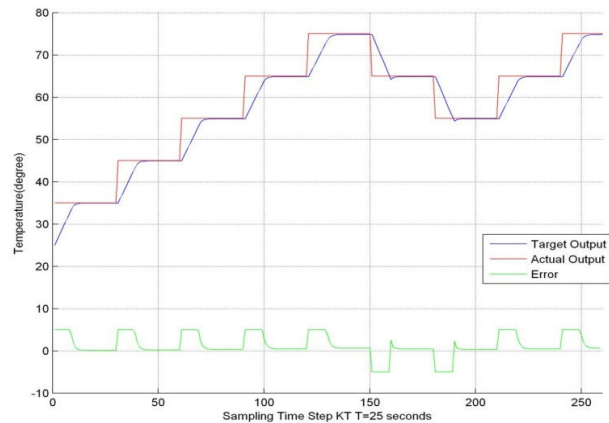
The response is shown in Fig. 12.



Fig. 12 Output response of FLC controller

### C. ANFIS Controller Response

In implementing the training scheme, a sequence of random input signals $u_{rd}(k)$ limited between -5 and 5 are injected directly to the Water-Bath system. And input-output characteristic of the system is obtained as shown in Fig. 13. Table IV shows the comparison of parameters indices between PID-Controller and Intelligent Controller (FLC and ANFIS).
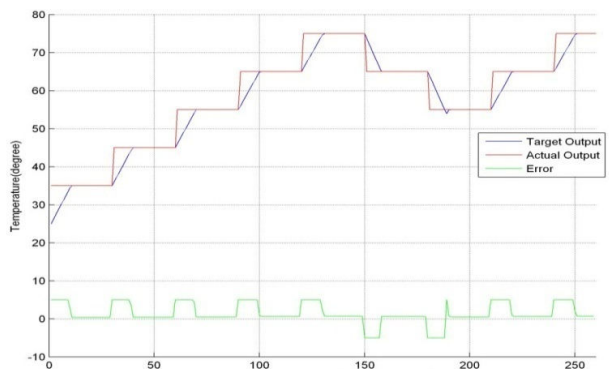


Fig. 13 Output response of ANFIS controller

### V. CONCLUSION

The comparison clearly shows that ANFIS based controller gives optimized performance index in terms of less settling time with minimum overshoot i.e. zero overshoot, least absolute error and better temperature tracking capability.

TABLE IV
COMPARISONS OF DIFFERENT CONTROL PARAMETERS

| S. No. | Control Parameter | PID | FLC | ANFIS |
|---|---|---|---|---|
| 1 | Rise Time tr (sec) | 4.073 | 8.609 | 7.5 |
| 2 | Peak Time tp (sec) | 6 | 14 | 11 |
| 3 | % Peak Overshoot Mp | 6.1 | $\approx 0$ | $\approx 0$ |
| 4 | Absolute Error | 602.8965 | 510.0784 | 395.4782 |
| 5 | Settling Time ts (sec) (2% tolerance band) | 10.463 | 9.924 | 9.84 |

Results show that the ANFIS and Fuzzy logic Controller method results in a quicker response with no overshoot than the conventional PID Controller. It also improves the settling

time of the process. Moreover, it has strong temperature tracking capability and the absolute error (ASE) performance criteria also shows that ANFIS has better performance.

The ANFIS is inherently a modified TSK (Takagi-Sugeno-Kang)-type fuzzy rule-based model possessing neural network's learning ability. In contrast to the general Adaptive Neuro-Fuzzy-Inference Systems, where the rules should be decided in advance before parameter learning is performed, there are no rules initially in the ANFIS.

It is concluded that ANFIS not only overcomes the problem of PID and Fuzzy Controller but also better control capability in Water-Bath temperature control system. In critical system, ANFIS Controller can become a better solution as compared to conventional PID Controller.

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