Temperature Control System Using Artificial Neural Network

1C Ranjit Kumar 2A Harsha Vardhan 3A Sai Bharadwaj
1&2Department of Electronics &Control Engineering,
3Department of Electronics and Instrumentation Engineering
Sree Vidyanikethan Engineering College, Tirupati.

Abstract –

Artificial Intelligence (ANN) based controller for temperature control of a water bath system. The generation of membership function is a changeling problem for fuzzy systems and the rejoinder of fuzzy systems depends mainly on the membership functions. Artificial Neural Network based input and output used to tune the membership functions in fuzzy system. Two input and single output artificial intelligence is designed to control the temperature system .Further the tuning of controller parameters is difficult in PID because the overshoot and also time constant is large. Fuzzy controller does not require a priori model of process for implementation but the membership values are found by trial and error. A five layer neural network is used to adjust input and output parameters of membership function in a fuzzy logic controller. The hybrid learning algorithm is used for training this network .When compared with other controllers (PID and fuzzy controller), neural network shows a better performance achieved with its tuning. Finally, validity of this approach can be illustrated by practical implementation using LabVIEW.

Keywords - PID Controller, Fuzzy controller, Neural

Network Controller, temperature control, hybrid learning.

I. INTRODUCTION

Process control systems are often nonlinear and difficult to control accurately. Their dynamic models are more difficult to derive. The conventional PID controllers, in various combinations have been widely used for industrial processes due to their simplicity and effectiveness for linear systems, especially for first and second order systems. It has been well known that Proportional Integral Derivative (PID) controllers can be effectively used for linear systems, but usually cannot be used for higher order and nonlinear systems [1].

Fuzzy control is becoming one of the brightness and most rapidly ascending stars in the galaxy of intelligent control. This is because it offers a simpler, quicker and more reliable solution that is clear advantages over conventional technique. One of its main advantages is that no mathematical modeling is required since the controller rules are especially based on the knowledge of system behavior and experience of the control engineer [2].

The inaccuracy of mathematical modeling of the plants usually degrades the performance of the controller, especially for nonlinear and complex control problems. System mainly includes three parts: normalized fuzzy quantization module, intelligent integration module, and the control algorithm module. They shows that in the case of the same response time, the performances of the fuzzy controller with intelligent integration in a stable time, overshoot, robustness and several areas are better than conventional PID controller [3]. A five layer neural network is used to adjust input and output parameters of membership function in a fuzzy logic controller. The hybrid learning algorithm is used for training this network [4]. Back propagation neural network is trained to learn the inverse dynamic model of a temperature control system and then it's configured as a direct controller to the process. The back propagation neural network based on the generalized delta learning rule, a gradient descent search technique, has been widely used.

The back propagation algorithm has several disadvantages, among which is lack of guaranteed convergence, but it's simple yet powerful mathematical algorithm has made it the mainstay of neuro-computing. Before the neural network can be used as a controller, it first must learn the model of the plant. There are several learning architectures proposed where by the neural network may be trained [5].This paper gives an example where a multilayered back propagation neural network is trained offline to perform as a controller for a temperature control system with no a priori knowledge regarding its dynamics.

The inverse dynamics model is developed (general learning) by applying a variety of inputs vectors to the neural network [5]. Neural networks can thus serve as black-box models of nonlinear, multivariable static and dynamic systems and can be trained by using input– output data observed on the system. The most common ANNs consist of several layers of simple processing elements called neurons, interconnections among them and weights assigned to these interconnections. More layers can give a better fit, but the training takes longer. Choosing the right number of neurons in the hidden layer is essential for a good result. Too few neurons give a poor fit; while too many neurons result in over-training of the net (poor generalization to unseen data).A compromise is usually sought by trial and error methods [6].Based on the observation neural network gives better performances when compared to other two controllers.

II. DESCRIBTION OF TEMPERATURE CONTROL WATER BATH SYSTEM

The water bath process consist of several things mainly water tank, sensor, data acquisition system and (Artificial Intelligence), labVIEW controller and heater. Here thermocouple is used as the sensor .DAQ is used for inter connection between sensor and controller as well as controller and driver circuit. The thermocouple output is in terms of mille volt range so we use a amplifier circuit for increasing the voltage range. The working of the system is described as, when the temperature is measured by the thermocouple is converted into the voltage, which is going to the controller through DAQ. The difference between set point and actual value is applied to the controller, nothing but error .The PWM signal is produced corresponding to the 10 output voltage of the sensor. ANFIS is used here to control the temperature of the water bath process, it's tuned automatically and correcting the error in the process its shown figure 1.

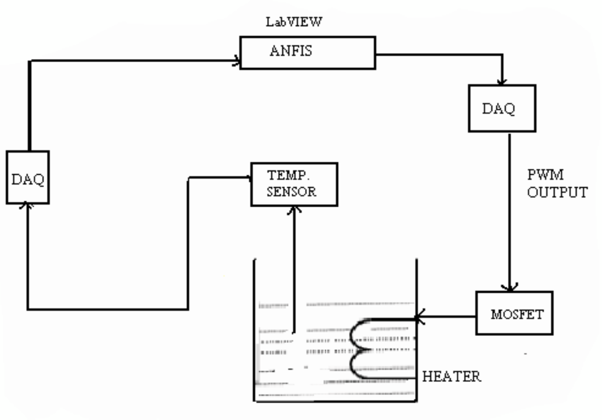

Fig.1 Schematic Diagram for the Water Bath Temperature Control System

K_i

III. SYSTEM IDENTIFICATION

A. Steps for Performing System Identification

1. Give a noticeable change in step input.
2. Observe the change in process variable and note down the steady state.
3. Find out the total change in PV (Process variable) that is going to occurs.
4. Compute the value of 63.2% of PV

5. Note down the time (t1) when it pass through the value

6. Substrate this from the time (t2) When the PV starts to build up, when input change is given
7. Time constant (t) =t2-t1
8. KP= change in steady state Change in input
9. Time delay time td is the time taken to getting the output from the system, when we applying the input.
10. The general form of the first order transfer function is given by

$$\frac{Y(S)}{X(S)} = \frac{K_p e^{-\theta s}}{\tau s+1}$$

According to the open loop test, the readings are listed above. The transfer function obtained from this reading is given by

$$\frac{Y(S)}{X(S)} = \frac{0.5662e^{-0.3s}}{7.5s+1}$$

IV. DESIGN & CALCULATIONS

A. PID Controller

Zeigler Nichols open loop tuning formula,
Steady state value=7.5
28.3% of the steady state value t 1 = 2.5424 sec.

63.2% of the steady state value t 2 = 6.0515sec.
Time constant (T) = (t2 - t1) × 1.5
= (6.0515 -2.5424) × 1.5

= 5.2636sec.

Time delay (td) = (t2 -T) = (6.0515 – 5.2636)
= 0.7879sec. Transfer function of the given Process,

$$\frac{Y(S)}{X(S)} = \frac{0.5662e^{-0.3s}}{7.5s+1}$$

Proportional gain,

$$= \frac{T}{t_d K_p} = \frac{5.2636}{0.7879\times0.566} = 11.8030\text{sec}$$

Integral gain, $= \frac{K_c}{T_i}$

Here $T_i = 3.33t_d$ = (3.33×0.7879)

= 2.623sec

$$K_i = \frac{11.8030}{2.623} = 4.499\ \text{sec}^{-1}$$

Derivative gain, $K_d = K_c\ T_d$

$T_d = 0.5\, t_d = 0.5 \times 0.7879 = 0.39395$ sec

$K_d = 14.1636 \times 0.39395 = 5.5797$ sec.

V. CONTROLLER DESIGN

A. PID Controller:

A proportional integral derivative controller (PID controller) is a generic control loop feedback mechanism (controller) widely used in industrial control systems .PID is the most commonly used feedback controller. A PID controller calculates an "error" value as the difference between a measured process variable and a desired set point. The controller attempts to minimize the error by adjusting the process control inputs. A PID controller will be called a PI, PD, P or I controller in the absence of the respective control actions.

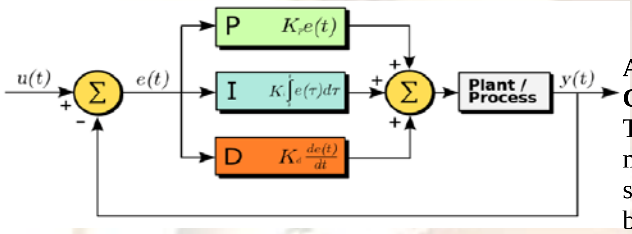

Fig.2 Block Diagram of a PID Controller

The PID control scheme is named after its three correcting terms, whose sum constitutes the manipulated variable (MV). The proportional, integral, and derivative terms are summed to calculate the output of PID controller. Defining U(t) as the controller output, final form of PID algorithm

$$u(t) = k_p e(t) + k_i \int e(t)dt + k_d \frac{d}{dt} e(t)$$

Where,

k_p: Proportional gain, a tuning parameter

k_i : Integral gain, a tuning parameter k_d: Derivative gain, a tuning parameter e: Error = SP – MV
t: Time or instantaneous time (the present)

The Values of Kp, Ki and Kd values of PID Controller is shown in below table 1 are obtained by using the Ziegler Nichols method.

Table 1 Values of PID parameter

Controller	Kp	K_I	K_D
PID	14.16	8.98	5.57

B. Neural Controller

The neural network controller is created directly based on the neural network identifier. The neural network identifier is used as means to back propagate the performance error to get the equivalent error at the output of the neural network controller .The accuracy of the plant model is critical in ensuring that the controller is accurate as well. The error between the plant output and the identifier output is also checked for the accuracy level of the identifier. This error is used to back propagate and adjust the weights of the identifier to provide the most accurate representation of the plant. The neural network for controller is also designed as a three-layer neural network. It has an input layer, a hidden layer and an output layer.

VI. RESULT AND DISCUSSION

A. Ziegler Nichols Closed Loop Response for PID Controller

The transfer function obtained through empirical method of modeling is used as the system for studying the performance of P, PI & PID Controllers by Ziegler Nichols closed loop response for PID controller as shown in figure above for the temperature control system for water bath system is shown in figure 4

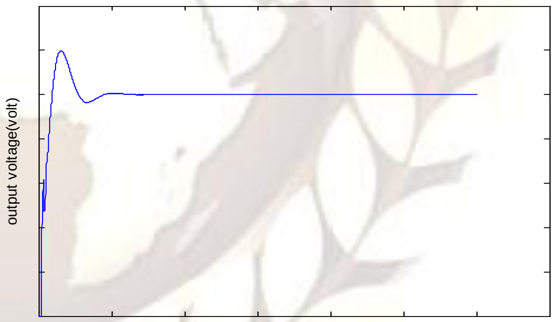

Fig.3 Simulation Responses of PID Controller

B. Comparison of PID controller and Neural Network Controller

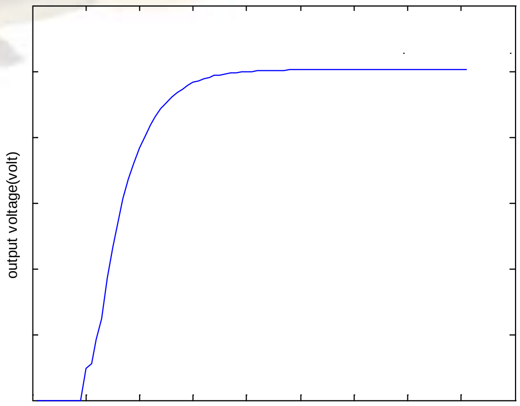

Fig.4 Response of Neural Network Controller

The control characteristics of a temperature control with pid controller and neural network controller compared and tabulated below.

Table 2 Controller Parameters

CONTROLLER	RISE TIME(sec)	SETTLING TIME(sec)
PID CONTROLLER	35	43
NEURAL NETWORK	29	34

When compared with PID controller and neural network controller, the neural network controller gives better performance for the temperature control system.

VII. CONCLUSION

In this study the temperature process and the control strategy adopted is Artificial Intelligence. The temperature controller was identified using the process reaction curve method. By using the transfer function model, simulation of Proportional Integral Derivative controller and neural network controller was implemented. Artificial neural network based Neuro fuzzy is suitable for adaptive temperature control of a water bath system. Artificial neural network, where the rules should be decided in advance before performance learning is performed, there are no rules initially in the neural network. Comparison with other controller PID and the neural network give better performance it's verified. Simulation result shows that the neural networks produce the stable control signal than the PID controller and has a perfect temperature tracking capability.

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