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Intelligent Controllers for Conical Tank Process

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***Abstract*—Level control is an important control objective in process industries. Determining the optimal controller is vital, as it result in precise control of liquid level in the conical tank. The conventional PID controllers are used which will not provide a satisfactory control for various operating conditions. To overcome these difficulties, an intelligent controller is to be proposed. The objective of this project is to implement an intelligent controller for conical tank process. A Fuzzy Logic, Fuzzy PI and Neural Network controllers are implemented. Each controller is constructed based on the data collected from the process. The optimal control is identified as the Neural Network controller based on the performance indices such as settling time and overshoot.**

***Keywords*—PID Controller; Neural Network; Fuzzy Logic.**

I. INTRODUCTION

The control of liquid level in tanks and flow between the tanks is a basic problem in process industries. The process industries require the liquids to be pumped or stored in tanks and then transfer to another tanks. Many times the liquid will be processed by chemical or mixing treatment in tanks, but always the level of the liquid in the tank must be controlled. Conical tanks find wide application in process industries. They are widely used in hydrometallurgical industries, food processing industries and as a part of waste water treatment plants. So control of conical tank presents a challenging problem and also due to its non-linearity and constantly changing cross section. The majority of the control theory deals with the design of linear controllers for linear systems. PID controller proved to be a perfect controller for simple and linear processes. When it comes to the control of nonlinear and multi variable processes, the controller parameters have to be continuously adjusted. The artificial neural networks have ability to estimate every nonlinear function with at least one hidden layer with sufficient neurons. Here Levenberg-Marquardt [4] algorithm is to be used to train the neural network. It uses its intelligence to control the level inside the tank. So it will give more accurate compared to the other intelligent controllers like Fuzzy Logic controller and Fuzzy PI controller.

II. SYSTEM DESCRIPTION

A. Conical Tank System

The conical tank level process is a highly nonlinear process because of its varying cross section from bottom to top. The experimental setup is shown in Fig. 1. The parameters vary with respect to the process variable is considered. At a fixed outlet flow rate the system is controlled and maintained at the desired level. The tank level process to be simulated is single input single output (SISO) tank system [1]. The desired level 'h' is maintained by manipulating the inlet flow rate 'Qin' to the system. Here 'h' is the controlled variable and 'Qin' is the manipulated variable.

Fig. 1. Experimental setup of conical tank level process.

B. Block Diagram

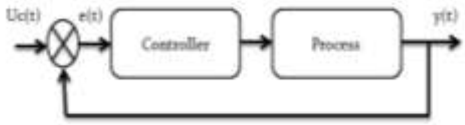


Fig. 2. Block diagram of proposed method.

The Fig. 2 shows the simplified block diagram of the process. Multiple controllers are implemented and tested for the same process. PID, Fuzzy logic controller, Fuzzy PI controller and neural network controller are implemented for conical tank system.

C. Process Model

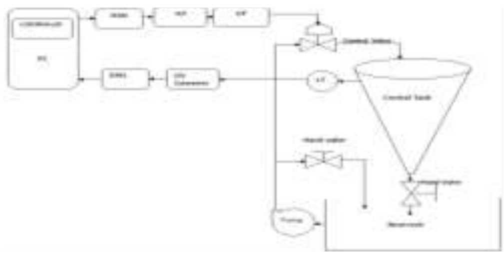


Fig. 3. Process model of proposed system

The Fig. 3 shows the process model of proposed system, where;

LT : Level transmitter.
I/V : Current to voltage converter.
V/I : Voltage to current converter.
I/P : Current to pressure converter.
DAQ : Data acquisition card.

III. Mathematical Modelling

The conical tank level process considered here is shown in Fig. 4.

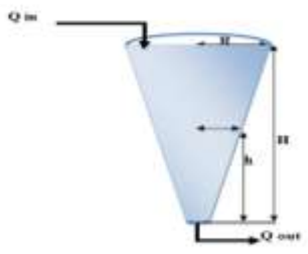


Fig. 4. Conical tank.

ρ : Density of liquid in the tank Kg/lt
$\rho 1$: Density of liquid in the inlet stream Kg/lt
$\rho 2$: Density of liquid in the outlet stream Kg/lt
V : Total volume of the conical tank cm^3
q :Volumetric flow rate of inlet stream LPH
q_o : Volumetric flow rate of outlet stream LPH
R : Maximum radius of the cone cm
r : Radius of the cone at steady state cm
H : Maximum height of the cone cm
h : Height of the cone at steady state cm

Using the low of conservation of mass,

Rate of accumulation of mass in the tank= Rate of mass flow in- Rate of mass flow out

$$\frac{\begin{bmatrix}\text{Accumulation}\\ \text{of total mass}\end{bmatrix}}{\text{time}} = \frac{\begin{bmatrix}\text{Input of}\\ \text{total mass}\end{bmatrix}}{\text{time}} - \frac{\begin{bmatrix}\text{Output of}\\ \text{total mass}\end{bmatrix}}{\text{time}}$$

$$\frac{d(\rho v)}{dt} = \rho_1 q - \rho_2 q_o$$

Since the liquid which we are using is water, the density is same thought, $\rho=\rho 1=\rho 2$.

The volume of cone $V = \frac{1}{3}\pi r^2 h$

Where, $r = \frac{R}{H}h$

$$\frac{H(s)}{Q(s)} = \frac{Rt}{(\tau s+1)}$$

Where, time constant $\tau = Rt \propto hs^2$ and process gain $Rt = \frac{2\sqrt{h}}{c}$

Specifications of conical tank:

Height	: 80 cm
Volume	: 33.5 litres
Bottom Diameter	: 7.62 cm
Top Diameter	: 36.62 cm
Angle	: 10 deg
Material	: Stainless Steel

The transfer function of the conical tank system obtained is

$$\frac{H(s)}{Q(s)} = \frac{2.516}{(112.03s+1)}$$

IV. Conventional Controller Implementation

The conventional controller discussed here is the PID controller. It is the most widely used controller because of its simplicity and will provide good performance for most of the systems.

A. *PID Controller*

A PID controller is a generic control loop feedback mechanism widely used in industrial control systems and the most commonly used feedback controller. A PID[3] 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 inputs. If there is the absence of the knowledge about the underlying process; the PID controller is the best choice. Zeigler Nichol's open loop tuning method is used for finding the tuning parameters. The tuning parameter used here is kp=2.516, ki=1.0015 and kd=25.035. The MATLAB Simulink diagram for PID controller is shown in Fig. 5.

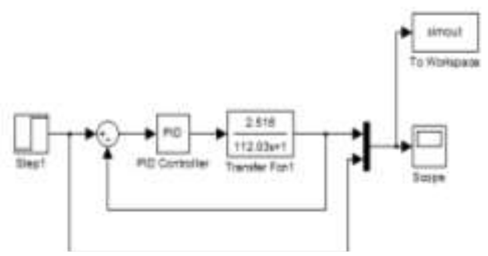


Fig. 5. Simulation of PID controller.

V. INTELLIGENT CONTROLLER IMPLEMENTATION

The intelligent controllers discussed here are Fuzzy Logic controller, Fuzzy PI controller and Neural Network controller. These are called intelligent controllers because it uses its intelligence that is its knowledge about the process to obtain optimum control over the entire operating range.

A. *Fuzzy Logic Controller*

In compare with the conventional controllers, fuzzy controllers have a high ability to control nonlinear, time in-variant, time delayed and complex processes. Fuzzy control is based on fuzzy logic, a logical system much closer to human thinking and neural language. Fuzzy logic [3] deals with reasoning that is approximate. FLC is an attractive choice when precise mathematical formulations are not possible. Four main components compromises fuzzy methodology are fuzzification, rule base, fuzzy inference and defuzzification.

Here the mamdani method is to be used. A triangular membership functions is used here for error, for derivative error and for the output.

TABLE I. FUZZY RULES FOR FUZZY LOGIC CONTROLLER

		Error(e)				
Change in error(de/dt)		VL	L	Z	H	VH
	VL	NB	NB	NB	N	M
	L	NB	NB	N	M	P
	Z	NB	N	M	P	PB
	H	N	M	P	PB	PB
	VH	M	P	PB	PB	PB

The Table I shows the fuzzy rules for Fuzzy Logic controller. The linguistic variables for error are VL, L, Z, H and VH. The linguistic variables for change in error are VL, L, Z, H and VH. The linguistic variables for output are NB, N, M, P and PB.

Fig. 6. Membership functions for error, change in error and output.

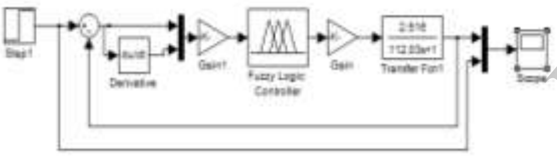


Fig. 7. Simulation of Fuzzy Logic controller

Fig. 6 shows the membership functions for the inputs error, derivative error and for the controller output. The MATLAB Simulink diagram for the simulation is shown in Fig. 7.

B. Fuzzy PI Controller

The Fuzzy PI controller uses the fuzzy rules for selecting the gain. The gain for the PI controller is given as a range of values. Based on the inputs, error and change in error the appropriate gains are to be selected. A fuzzy PI controller gives a performance comparably better than an ordinary fuzzy logic controller. The Table II shows the rules for the fuzzy PI controller.

TABLE II. FUZZY RULES FOR FUZZY PI CONTROLLER

			Error(e)				
Change in error(de/dt)			NB	NS	Z	PS	PB
	K_p	NB	ZERO	MIN	MIN	MED	MAX
	K_i		MIN	MIN	MIN	ZERO	ZERO
	K_p	NS	ZERO	MIN	MED	MED	MAX
	K_i		MED	MED	MIN	MIN	MIN
	K_p	Z	ZERO	MIN	MED	MED	MAX
	k_i		MIN	MIN	MIN	MAX	MED
	K_p	PS	MIN	MIN	MIN	MIN	MAX
	k_i		MED	ZERO	ZERO	MED	MED
	K_p	PB	MED	MED	MED	MAX	MAX
	K_i		MED	MED	MIN	MIN	MAX

The membership functions are for the inputs error and change in error and for the outputs kp and Ki. The membership functions are shown in Fig. 8.

Fig. 8. Membership functions for error, change in error, Kp and Ki.

The linguistic variables used for error are NB, NS, Z, PS and PB. The linguistic variables for change in error are NB, NS, Z, PS and PB. For the outputs Kp and Ki, the linguistic variables used are Zero, Min, Med and Max. The Fig. 9 shows the MATLAB Simulink diagram of Fuzzy PI controller.

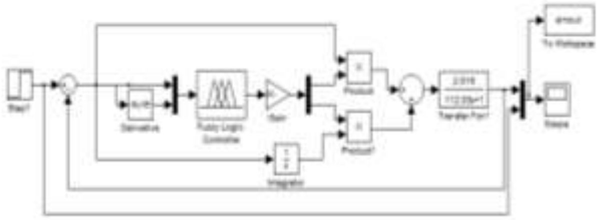


Fig. 9. Simulation of Fuzzy PI controller.

C. Neural Network Controller

The neural network [6] is created directly based on the neural network identifier. Its design is fully incorporated the learning strategy into the trained identifier. The weights of the neural network identifier are constantly verified against the actual plant output. This ensures that the weights allow the neural network identifier to properly predict the actual plant output. Neural network identifier is used as means to back propagate the performance error to get the same error at the output of the neural network controller. To generate and train the neural network the MATLAB codes are to be used. Here we use the Levenberg-Marquardt (LM) algorithm [4] for training the neural network. It provides numerical solution for the problem of minimizing a nonlinear function. It is fast and has a stable convergence. So it is suitable for training small and medium sized problems. The LM algorithm is a combination of steepest descent algorithm and Gauss Newton algorithm. The steepest descent is widely used today but it is inefficient due to slow convergence. The reason is the curvature of the error surface may not be same in all directions. It can be greatly improved by gauss Newton algorithm. It can find proper step size for each direction and converges very fast. The LM has the speed advantages of the gauss Newton algorithm and the stability of steepest descent method. It can converge well even if the error surface is much more complex than the quadratic solution. The MATLAB Simulink diagram of the neural network controller is shown in Fig. 10.

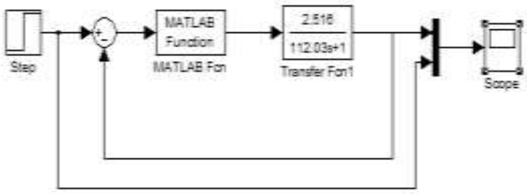
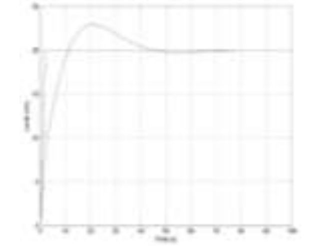
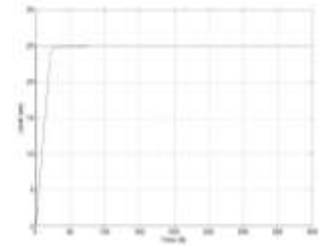


Fig. 10. Simulation of Neural Network controller

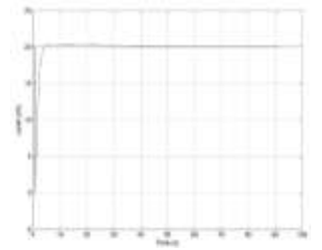
VI. RESULTS AND DISCUSSION



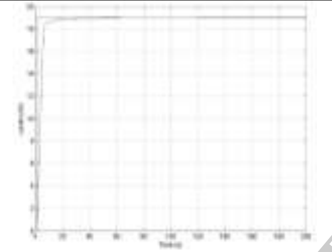
Simulation response of PID controller



Simulation response of Fuzzy Logic controller



Simulation response of Fuzzy PI controller



Simulation response of Neural network controller

Fig. 11. Simulation responces

The simulation response is shown in Fig. 11. The PID controller is designed using Zeigler Nichol's tuning method [6]. Even though PID controller is a robust controller, its response has an overshoot and oscillations. The intelligent controllers implemented are Fuzzy Logic controller, Fuzzy PI controller and Neural Network controller. The Fuzzy Logic and Neural Network controller doesn't have overshoots. But Fuzzy PI exhibits an overshoot. The Neural Network controller has lowest settling time as compared to the other intelligent controllers.

A. *Comparison*

The comparison of various performance measures are shown in Table III

TABLE III. COMPARISON OF PERFORMANCE MEASURES

Controller	**Settling time(Sec)**	**Peak overshoot**
PID Controller	80	1.25
Fuzzy Controller	50	Nil
Neural Network	40	Nil
Fuzzy PI Controller	45	20.5

VII. CONCLUSION AND FUTURE WORK

Intelligent controllers were used to control the liquid level in the conical tank process. Different controllers which include conventional PID controller, Fuzzy Logic controller, Fuzzy PI controller and Neural network controllers were implemented and their performance was analyzed. By comparing their main performance indices such as settling time and peak overshoot it is found that neural network controller exhibits better performance. Future work is the real time implementation by using Lab VIEW.

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