IMPLEMENTATION OF INTELLIGENT CONTROLLER FOR A NON-LINEAR PROCESS

E. Nandhini[1] , M.Balaji[2]

[1]*Department of Electrical & Electronics Engg. ,Dr. MCET, T.N (India)*

[2]*Department of Electronics & Instrumentation Engg., Dr.MCET, T.N (India)*

ABSTRACT

This paper presents the real-time implementation of a neural network based controller for a non-linear process. The control structure is demonstrated on a conical tank system (CTS).The control of liquid level in a conical tank is non-linear due to variation in the area of cross-section of the tank system. So designing a controller for conical tank presents a challenging problem.PID controller is the classical control algorithm in the field of process control. Major limitation of PID is that it shows poor performance with non-linear and interacting processes. This can be overcome by soft-computing techniques like neural network, fuzzy logic, etc. From the results it is observed that neural network based controller shows faster settling time and minimum overshoot.

Keywords: Artificial Neural Networks, Internal Model Control (IMC), Non-linear process, PID controller.

I INTRODUCTION

In real-world applications, most of the industrial processes are non-linear in nature. The control of such non-linear process is a difficult task. There are different types of controllers applied to process to maintain the desired level. The optimum setting for PID tuning is proposed by [1]. The design of PID controllers for unstable FOPTD model was described by [2]. Although PID controllers have advantages on linear systems, these controllers are not suitable for systems with time-delay, high-ordered, nonlinear systems. This gained the researchers attention towards intelligent control schemes. A two-level, optimization based method for deriving tuning parameters for PID was proposed by Mhaskar [3]. It is demonstrated on a non-linear Continuous Stirred-Tank Reactor (CSTR) which has the response similar to the non-linear controller. Artificial Neural Networks (ANN), in recent years has become an attractive tool to construct complex non-linear process models [5]. Chen [8] described an improved conventional PID control structure using linearization through neural network for a non-linear process. It has several advantages. One of which is the linear control scheme applied to the non-linear control design has less computation compared to non-linear counterpart based on non-linear neural network model. Shu [7] proposed a PID Neural Network for time-delay systems which resulted in short convergence time and quick learning speed and can be applied to practical processes. IMC based Neural Network to adjust the control parameters for roll motions of the container ship were described by Fust Alarcin [6]. A robust neural network based intelligent controller for a Continuous stirred-Tank Heater (CSTH) was developed by Gaurav [4]. The result shows that the proposed ANN controller well tracks the set-point variations and also rejects the unwanted load disturbance.

In this paper, implementation of neural network based controller for controlling liquid level in a conical tank is presented. The issue of analysing the dynamic behaviour of process represented by non-linear models is the main concern in this work; this is motivated by the fact that situations do arise when it is undesirable to neglect the inherent nonlinearities of a process.The conical tank system which exhibits the non-linearity is taken as system for the research.It is highly nonlinear due to the variation in area of cross section of the level system with height. The performances are compared with conventional IMC-PID controller and the results are tabulated.

II TEST SYSTEM

The conical tank system (CTS) that is available in the institution is taken as the test system. The schematic of the CTS is shown in figure.1. The real time system has a conical tank, reservoir and water pump, current to pressure convertor, compressor, Differential Pressure Transmitter (DPT), DAQ chord and a Personal Computer which acts as the controller and forms a closed loop. The inflow rate to the conical tank is regulated by changing the stem position of the pneumatic valve by passing the control signal from computer to I/P converter through digital to analog converter (DAC). The operating current for regulating the valve position is 4-20 mA, which is converted to 3-15 psi of compressed air pressure. The water level inside the tank is measured using DPT and converted to an output current range of 4-20 mA. This output current is given to the controller through analog to digital converter (ADC). The DAQ card is used for interfacing the personal computer with the conical tank system thus forming a closed loop.

Fig.1 Conical Tank Trainer

III SYSTEM IDENTIFICATION

System identification is normally done using step response methods. The process dynamics is analysed from open loop response with varying input percentages. The percentage of opening of control valve which is a manipulated variable is chosen as 32%, 35%, 38%, 40%, 42%, 45%. The open loop response of the system is shown in Fig.2. The system is found to be first order plus dead time process (FOPDT). Therefore the transfer function for FOPDT process is given by the equation,

$$G(s) = \frac{ke^{-tds}}{Ts+1}$$

From the open loop response, transfer function for all control valve position is found from the TABLE.I given below.

TABLE.I Transfer function

Input(%)	System gain (k)	Delay time (T_d)	Time constant (τ)
32	1.12	14	22.02
35	1.09	8	35.55
38	1.09	7	31.17
40	1.08	12	30.31
42	1.03	17	49.77
45	1.11	15	43.63

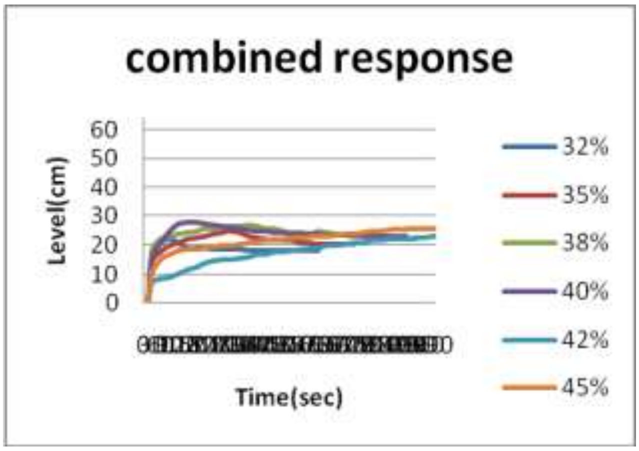


Fig.2 Open loop response

IV CONTROL STRATEGIES

4.1. IMC Tuning Technique

The IMC technique is one of the recent traditional tuning techniques that yield better values among the techniques available for conventional methods. The controller has to be designed for maintaining the optimal set point of the system after deriving the transfer function model. This can be achieved by properly selecting the tuning parameters k_p, K_i, $k_d$for a PID controller. The tuning parameters for First Order Plus Delay Time (FOPDT) is given below,

$$\mathbf{K_p} = 2T + C/2k(\lambda + \tau)$$

$$\mathbf{K_i} = 1/\tau_i \, ; \qquad \boldsymbol{\tau_i} = T + (\tau/2)$$

$$\mathbf{K_d} = T\,\tau/(2T + \tau)$$

Where $\lambda = 0.25\,\tau$

4.2. Perceptron Network

The perceptron is an algorithm for supervisedclassification of an input into one of several possible non-binary outputs. It is a type of linear classifier, i.e. a classification algorithm that makes its predictions based on a linear predictor functioncombining a set of weights with the feature vector. The algorithm allows for online learning, in that it processes elements in the training set one at a time.

ALGORITHM:

The following steps have to be followed while training the network.

Step 1: Initialize weights and bias.

i.e, $w_1, w_2, \ldots w_n = b = 0$ and

learning rate $\alpha = 0$ to 1.

Step 2: Activate the inputs.

$X_i = S_i$

Step 3: Calculate the net input to the output unit

$$Yin = \sum_i xi.wi$$

Step 4: Calculate Y.

$$Y = f(Yin) = 1 \ ; Yin > \theta$$

$$0 \ ; -\theta < Yin < \theta$$

$$-1; Yin < -\theta$$

Step 5: Match with target.

If $Y = t$, $w_i(new) = w_i(old)$

$b(new) = b(old)$

if $Y \neq t$, $w_i(new) = w_i(old) + \alpha.t.x_i$

$b(new) = b(old) + \alpha.t$

Step 6: Stop the iteration once all targets are reached.

V SIMULATION

5.1. IMC Tuning Technique

The Simulink model and closed loop response using IMC tuning technique is obtained for 40% with k_p=0.59, k_i=0.023, k_d=10.10 is shown in fig.6.1 and 6.2 respectively.

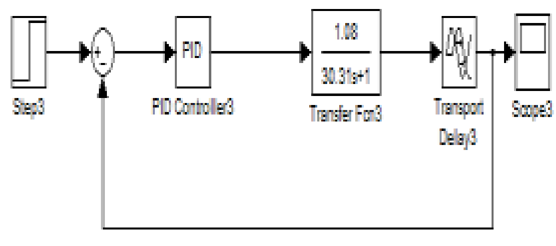


Fig.6.1. Simulink model for IMC

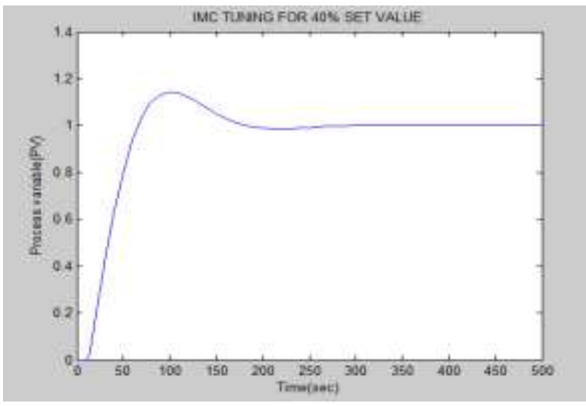
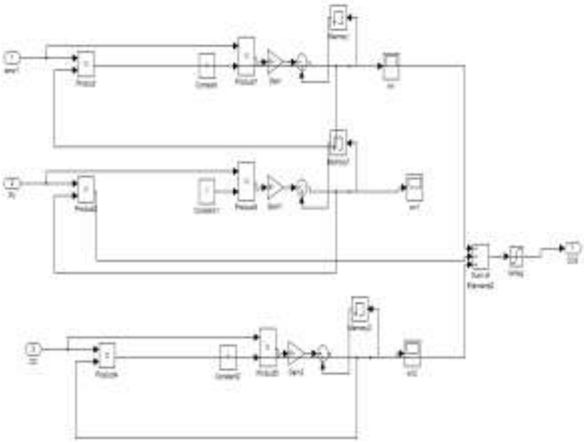


Fig. 6.2. Response of IMC

5.2. Neural Controller

The MATLAB Simulink model for neural controller trained using perceptron network and its response is shown in fig.6.3 and 6.4 respectively. Here the inputs used to perform control action are error signal which is the difference between process variable and set point, process variable (PV), controller output (CO).



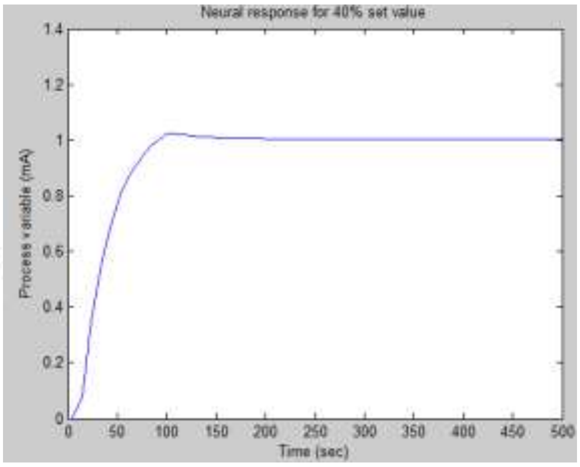


Fig.6.3. Simulink model of perceptron controller Fig.6.4.Response of perceptron controller

VI CONCLUSION

From the simulation results obtained for different setpoint values, neural network controller shows better performance compared to conventional IMC tuning technique. The perceptron neural network controller has fast settling time and minimum overshoot. Thus neural network controller can be applied to nonlinear varying processes.Table.2 shown below shows the comparison between the performances of IMC tuned controller and neural controller.

TABLE.II Comparison between IMC and Neural controller

Inputs %	Settling time (sec)		Peak overshoot	
	IMC	Neural controller	IMC	Neural controller
32	180	150	1.1	1.05
35	280	150	1.2	1.02
38	330	150	1.2	1.015
40	280	200	1.15	1.025
42	430	300	1.16	1.028
45	400	250	1.16	1.032

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