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Design Of Neural Based PID Controller For Nonlinear Process

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Abstract

In this paper, a neural network (NN) based internal model control (IMC) - PID controller is proposed for a non-linear process. The controller structure has been outlined and its performance is demonstrated on a conical tank process. The control of liquid level in a conical tank is nonlinear due to the variation in the area of cross section of the tank system with its change in shape. The model of the process is identified using standard step response based system identification technique and it is approximated to be first order plus dead time (FOPDT) model. From the results it is observed that fuzzy controller shows much better integral absolute error (IAE) and integral squared error (ISE) performance criteria than the conventional controller.

Keywords: Internal Model Control (IMC), PID Controller, Neural networks

1. INTRODUCTION

With the development of cutting edge technology, the interest on the study of non-linear system is increased because of the fact that most industrial processes are inherently non-linear which includes large time delays and lags and strong interactions. Despite the advent of many complicated control theories and techniques, PID controller is the classical control algorithm in the field of process control and it still predominates in the process industries due to its robustness and effectiveness for a wide range of operating conditions and partly to its functional simplicity [1]. For designing the controllers, the process dynamics are described adequately by a first-order plus time delay (FOPTD) model. The PID tuning method was proposed by [2] and Astrom et al. reported an excellent review on the design of PID controllers. Chidambaram et al [3] designed the PID controllers for unstable FOPTD model. Padma Sree et al. [4] proposed a simple method for PI/PID controller settings for stable FOPTD and also for unstable

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FOPTD systems. Cvejn [5] presented the PI/PID controller settings for the first order systems with dead time, based on the modulus optimum criterion. The settings provide fast closed-loop response to changes of the reference input. Although optimal values of the parameters are valid for the reference tracking problem, a compensation of the disturbance lag that preserves the stability margin is proposed for the disturbance rejection problem.

The conventional PID provides convenient tuning parameter to adjust the response, robustness and speed of the closed-loop system because it has only one tuning parameter. But when the characteristics variation and uncertainty factors are included in the control system, it is difficult to accomplish satisfactory control performance by using conventional PID controllers [6]. For this reason, free intelligent control schemes have gained the researcher attention. In recent years, Artificial Neural Networks (ANNs) have become an attractive tool to construct complex nonlinear process models [7], great capability to solve the complex nonlinear mathematical problems [8].The ability of neural networks to represent nonlinear relations leads to the idea of using networks directly in a model-based control strategy. Chen [9] described an improved conventional PID control scheme using linearization through a specified neural network for control of nonlinear processes. The linearization of the neural network model is used to extract the linear model for updating the controller parameters Tokuda et al [10] designed a method of multi loop PID controllers with neural net based decoupler for nonlinear multivariable systems with mutual interactions. This method consists of a decoupler given by the sum of a static decoupler and a neural-net based decoupler, and multiloop PID controllers. The results confirmed that the training efficiency was improved instead of the complicated trail-and-error in designing the user-specified parameters included in the neural networks. Fuatalarcin [11] developed a IMC based on NN to adjust control parameters for roll motions of a container ship. Tarun et al. [7] established the ANN based IMC controller with modified BP algorithm for both set point and regulatory control problems of a CSTR .This approach provides accurate control for non linear processes without explicit model identification and linearization. Shahrakia et al [12] analysed a PID neural network and compared with Cancellation and pole placement algorithms through computer simulation and experimental study and proved that PIDNN requires less trial and error for tuning and has more robust performance

In this work, a neural based PID controller is designed for controlling liquid level in a conical tank. The process model is experimentally determined from step response analysis. The performances are compared with that of the conventional controller, based on Integral Squared Error (ISE) and Integral Average Error (IAE).

The paper is organized as follows, the developed model elucidated in section II, system identification is presented in section III, IMC and neural based PID controller design is elaborated in section IV and V, and finally results and discussion are appended in section VI.

2. MODELING OF THE SYSTEM

The conical tank system which exhibits the non linearity is taken to find out the model for simulation. Owing to the non linearity, the process dynamics are analyzed in four segments to obtain effective models for the operating ranges. The operating regions are chosen as 0-15 cm as model 1, 15-27 cm as model 2, 27-36 cm as model 3 and 36-43 cm as model 4. The corresponding mathematical models are found for these sections.

The real time system has a conical tank, reservoir and water pump, current to pressure convertor, compressor, Differential Pressure Transmitter (DPT), ADAM module 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 the I/P converter through digital to analog converter (DAC) of ADAM module. 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 which is calibrated for 0-43 cm and is converted to an output current range of 4-20 mA. This output current is given to the controller through analog to digital converter (ADC) of ADAM module. The ADAM module is used for interfacing the personal computer with the conical tank system thus forming a closed loop. The module can be operated manually with the console software provided and also with programming software like LabVIEW, MATLAB, etc. The schematic diagram for process layout is shown in Figure 1.

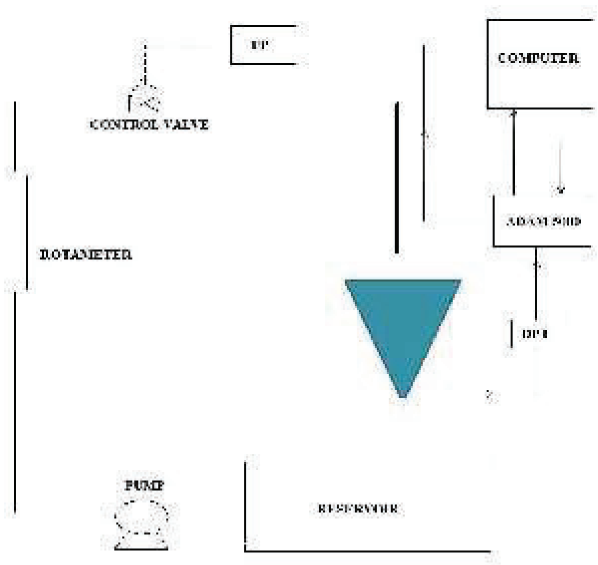

Fig. 1 Schematic diagram of conical tank system

3. SYSTEM IDENTIFICATION

System identification is normally done by step response methods. The maximum flow rate is maintained at 7 LPM. Four responses covering the full height of the conical tank are obtained as model 1 for 0-15 cm, model 2 for 15-27 cm, model 3 for 27-36 cm and model 4 for 36-43 cm. The models are obtained by two-point method and Sundaresan-Krishnaswamy method [13] and the simulated response of the models are found to be more coincide with real time responses. From the structure, the model is predicted to be similar to first order plus time delay (FOPDT) system and it is given as

$$G(s) = \frac{ke^{-\theta s}}{\tau s+1} \tag{1}$$

Where, k is the process gain ,θ is time delay ,τ is time constant

The models are estimated as, Model 1: (0-15 cm) $$G(s) = \frac{2.14e^{-10.703s}}{4.11s+1} \tag{2}$$

Model 2: (15-27 cm) $$G(s) = \frac{1.71e^{-13.68s}}{8.978s+1} \tag{3}$$

Model 3: (27-36 cm) $$G(s) = \frac{1.28e^{-15.71s}}{11.99s+1} \tag{4}$$

Model 4: (36-43 cm) $$G(s) = \frac{e^{-17.96s}}{14.72s+1} \tag{5}$$

The comparison of real time and simulation response curves for model 1, model 2, model 3 and model 4 are shown in Fig.2, Fig.3, Fig.4 and Fig.5 respectively

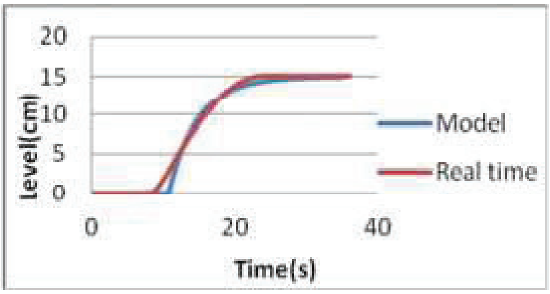

Figure 2: Comparison of real time and simulated responses of model 1

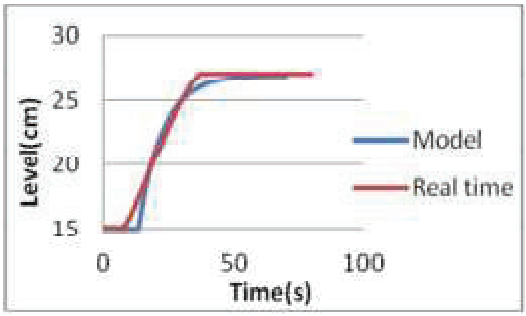

Figure 3: Comparison of real time and simulated responses of model 2

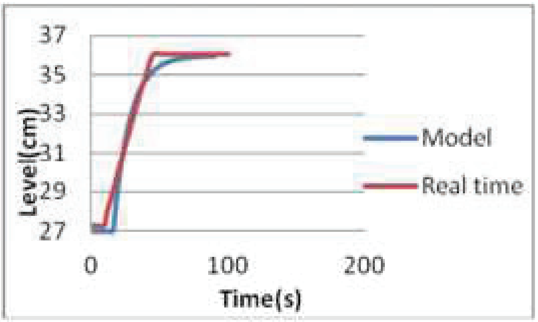

Figure 4: Comparison of real time and simulated responses of model 3

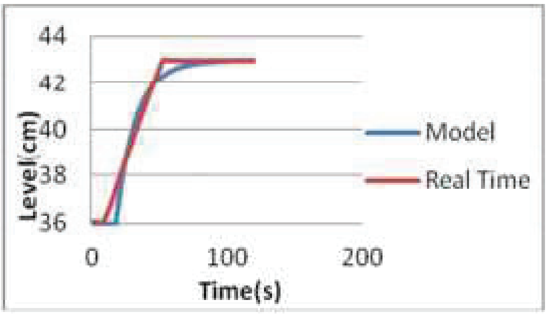

Figure 5: Comparison of real time and simulated responses of model 4

4. DESIGN OF IMC PID CONTROLLER

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 and τ_I for a PID controller. The IMC technique is one of the recent traditional tuning techniques that yield better values among the techniques available for conventional methods. For a FOPDT model, the IMC tuning values based on Chien and Fruehauf [14] is given as

$$K = \frac{\tau + \frac{\theta}{2}}{\tau_c + \frac{\theta}{2}} \quad (6)$$

$$\tau_i = \tau + \frac{\theta}{2} \quad (7)$$

$$\tau_d = \frac{\tau\theta}{2\tau + \theta} \quad (8)$$

With the conditions $\frac{\tau_c}{\theta} > 0.8 \,\&\, \tau_c > 0.1\tau \; 2)\, \tau > \tau_c > \theta \; 3)\, \tau_c = \theta$

Applying the technique, the IMC tuning parameters obtained are as shown in Table 1.

TABLE 1: CONTROL PARAMETERS

Parameters	Model 1	Model 2	Model 3	Model 4
$K_p = K_c$	0.174	0.344	0.4718	0.4095
$K_i = \frac{K_c}{\tau_i}$	0.018	0.0217	0.0237	0.0206
$K_d = K_c \tau_d$	0.404	1.335	2.238	1.8325

5. DESIGN OF NEURAL BASED PID CONTROLLER

The neural based PID control consists of conventional PID control and neural network, which combines the excellence of PID and neural network. The structure of the neural based PID control system is shown in Fig. 6.The neural network inputs are set point, error signal and the controller output. The data are collected from the closed loop response with conventional PID controller. The error signal data is taken as input and the controller output data is taken as target. These data are used to train the neural network. The Levenberg-Marquardt training algorithm is used for training the network. Once trained, the output of the neural network will be the optimal values of proportional gain K_p, integral gain K_i and derivative gain K_d.

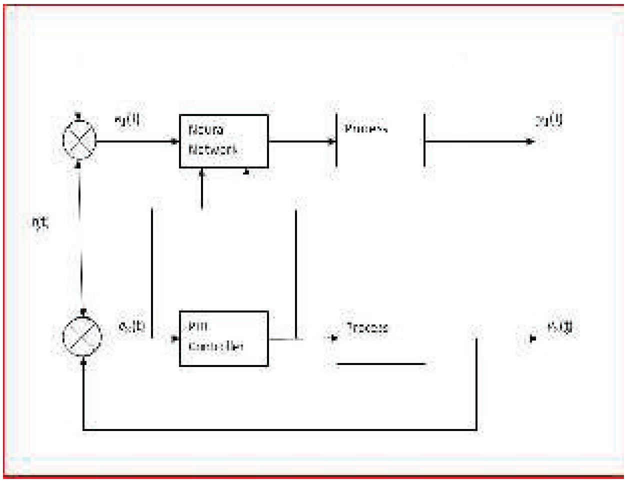

Figure 6: Block diagram of neural based PID controller

6. RESULTS AND COMPARISON

Both the conventional PID controller and neural based PID controller are implemented in the model and simulated using SIMULINK. The comparative responses are shown in Figure 7, Figure 8, Figure 9 and Figure 10.

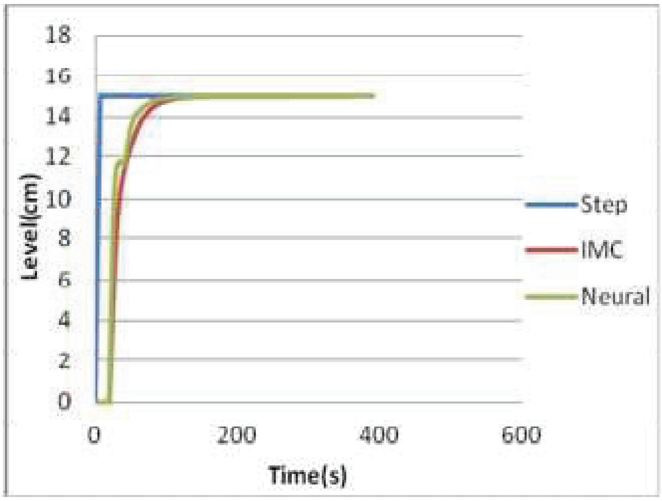

Figure 7: Comparison of responses of PID and NN based PID controller for model 1

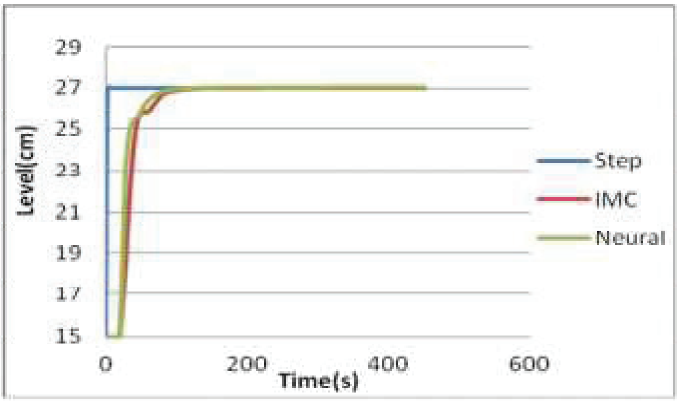

Figure 8: Comparison of responses of PID and NN based PID controllers for model 2

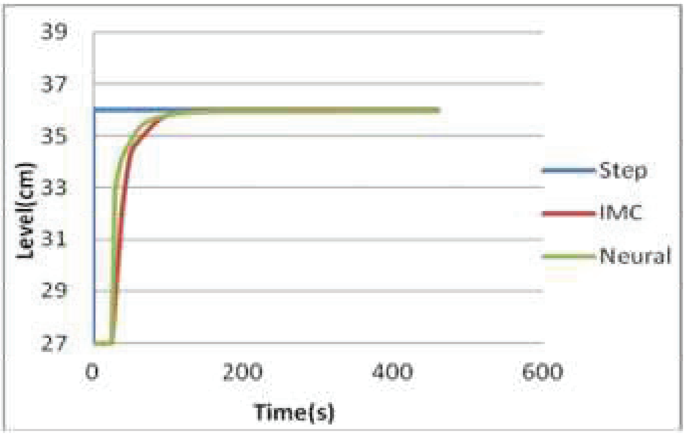

Figure 9: Comparison of responses of PID and NN based PID controllers for model 3

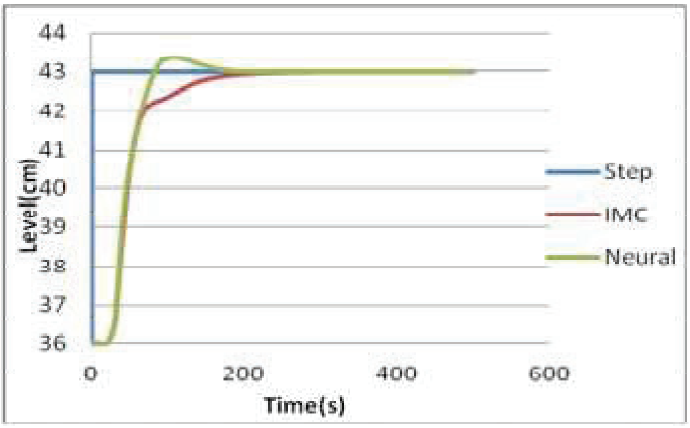

Figure 10: Comparison of responses of PID and NN based PID controllers for model 4

From the graph it is observed that the NN based controller shows faster settling time and less over shoot compared to IMC controller for set point tracking. Comparison of responses on the basis of ISE and IAE values reveals that the performance of NN based controller is much better than IMC controller and the results are shown in Table 2.

TABLE 2: PERFORMANCE INDICES

	Controller	ISE	IAE
Model 1	PID	394.56	70.57
	NN based PID	365.31	63.26
Model 2	PID	305.32	53.64
	NN based PID	258.09	45.30
Model 3	PID	455.32	75.67
	NN based PID	364.31	62.03
Model 4	PID	366.73	62.34
	NN based PID	359.53	59.02

7. CONCLUSION

In this paper, a neural based IMC controller for the level control of conical tank system is presented. Comparison of the proposed controller with conventional PID controller highlights its superiority. The response curve for different model of the system thus obtained using the neural controller is compared with response obtained by a conventional controller. For each set point, the proposed controller gives lower ISE and IAE than the other control scheme. Comparing the performance of responses, the neural control scheme performs very well and thus can be used for nonlinear varying processes.

References

[1] Wu W, Yuan J, Cheng L. Self-tuning sub-optimal control of time-invariant systems with bounded disturbance.*proc.of the 2005 American Control Conference,*vol.2, 2005, p.876-882.
[2] Ziegler JG, Nichols NB. Optimum settings for automatic controllers. *ASME Transactions , 64,759.*
[3] Chidambaram M. Control of unstable systems: A review.*Journal of Energy, Heat and Mass transfer,* 19,49.
[4] padma Shree R, Srinivas MN, Chidambaram M. A simple method of tuning PID controllers for stable and unstable FOPTD systems, *Computers and Chemical Engineering.*vol 28,issue 11, 2004, p.2201-2218.
[5] Cvejn J. PI/PID controller design for FOPTD plants based on the modulus optimum criterion. *ICCC,(12),*2011.
[6] Ying-ming Li, Ming-dong Hou, Jie-ping Hu. An Adaptive IMC-PID Control Scheme based on Neural Networks. *WRI Global Congress on Intelligent systems GCIS,* 2009, p.31-35.
[7] Tarun Varshney, Ruchi Varshney, Satya Sheel. ANN based IMC scheme for CSTR. *International conference on advances in computing, Communication and Control (ICAC3), 2009, p.543-546.*
[8] Hornik K, Stinchcombe M, White H. Multiplayer feedforward neural networks are universal approximators.*Neural Networks 2,*1989, p.359.
[9] Junghui Chen, Tien-Chih Huang. Applying neural networks to online updated PID controllers for nonlinear process control. *Journal of process control 14,* 2004, p.211-230.
[10] Makoto Tokuda, Toru Yamamoto, Yoshimi Monden. A Design of multiloop PID controllers with a Neural-Net based decoupler. *Asian Journal of Control, Vol.7,No.3,* 2005, p.275-285.
[11] Fust Alarcin. Internal model control using neural network for ship roll stabilization. *Journal of Marine Science and technology, Vol.15, No.2,*2007, p.141-147.
[12] Shahraki F, Fanaei MA, Arjomandzadeh AR. Adaptive System Control with PID Neural Networks. *Chemical Engineering transaction, Vol 17,* 2009, p.1395-1401.

[13] Sundaresan KR, Krishnaswamy RR. Estimation of time delay, time constant parameters in time, frequency and laplace Domains. *Can J.Chem.Eng,vol 56,* 1978, p.257.

[14] Chien IL, Freuhauf PS. Consider IMC tuning to improve controller performance. *Chemical Engineering Progress,* 1990, p.33-41.