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Neuro Model Based Controller For A Conical Tank Level Process

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ABSTRACT

The control of conical tank level process is complex because of its dynamics are nonlinear, time varying with change in gain of several orders. Hence in this work, modeling and control of conical tank level process is considered. First, the mathematical modeling of conical tank level process is developed and simulated. The entire operating region is divided into three linear zones to design a conventional PI controller. A small signal transfer functions are obtained for various operating regions by giving positive and negative step change in inflow rate. A conventional PI controller is designed using average of transfer function based on Z-N tuning method for each region. Simulation studies are carried out for both servo and regulatory problems. However, conventional controller will not give satisfactory results for varying operating points due to non linearity and time varying nature of conical tank level process. In this work, neuro model based controllers are designed using L-M algorithm and its outputs are compared with that of conventional PI controller through simulation studies for both servo and regulatory problems.

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INTRODUCTION

Liquid level control systems mainly control the manipulated parameter of liquid level, which in industry have a wide range of applications in various fields. In the industrial production process, there are many places need to control the liquid level, and make the liquid level maintain accurately for a given value. The traditional method is to use classical PID method. However, the practical application of the output is uncertain, in order to input well to follow the changes of output, then we need a continuously detect the number in time, to realize the liquid precise control. To implement a PID controller, three parameters (the proportional gain, Kp; the integral gain, Ki; the derivative gain, Kd) must be determined carefully. Many approaches have been developed to determine PID controller parameters for single input single output (SISO) systems. Among the well-known approaches is the Ziegler-Nichols (Z-N) method and the Cohen- Coon method.

Conical tanks are mostly used in various process industries, such as metallurgical industries, food processing industries, concrete mixing industries and wastewater treatment industries. A conical tank is basically a nonlinear process due to the change in the area of cross section and the level system with change in shape. Conventional controllers are commonly used in process industries as they are simple, robust and familiar to the field operator. Real time systems are not precisely linear but may be represented as linearized models around a nominal operating point. The controller parameters tuned at that operating point may not reflect the real-time system characteristics due to variations in the process parameters. The variations in the process parameters can be overcome by continuous adjustment of the controller parameter's using intelligent techniques like Artificial Neural Network (ANN).

2 Mathematical Modelling:

A mathematical model is a description of a process using mathematical concepts. The process of developing a mathematical model is termed as mathematical modeling. Mathematical modeling is used to explain the identified system and to study the effects of different components, and to make predictions about the process behavior. Mathematical models ca n take many forms, including but not limited to dynamical systems, statistical models, differential equations, etc. In this paper the proposed system includes the conical tank process whose area is variable throughout the height. The mathematical model of the conical tank is determined by the following assumptions.

➢ Level as the control variable

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- Inflow to the tank as the manipulated variable. This can be achieved by controlling the input flow of the conical tank.

Inflow rate of the tank (F_{in}) is regulated using the valve and the input flow through the conical tank. At each height of the conical tank the radius may vary. This is due to the shape of the tank. The difference between the inflow and the out flow rate will be based on the cross section area of the tank and level of the tank with respect to time. The flow and the level of the tank can be regulated by proper modeling the tank. Operating Parameters are,

Fin - Inflow rate of the tank
Fout - Outflow rate of the tank
H - Total height of the conical tank.
R - Top radius of the conical tank
h - Nominal level of the tank
r - Radius at nominal level

Mass balance Equation is given by

Fin - Fout = A dh/dt

dh/dt= (Fin – Fout) / A (1)

Outflow rate of the tank, Fout = b√(h) (2)

Where, b is a valve coefficient

By substituting the values and considering the cross sectional area of the tank at any level h.

Cross sectional area of the tank, $A = \pi r^2$

$$A = \pi R^2 h^2 / H^2 \quad (3)$$

Where radius, r = (Top radius of the conical tank)^2(Nominal level of the tank)^2 /(Total height of the conical tank)^2

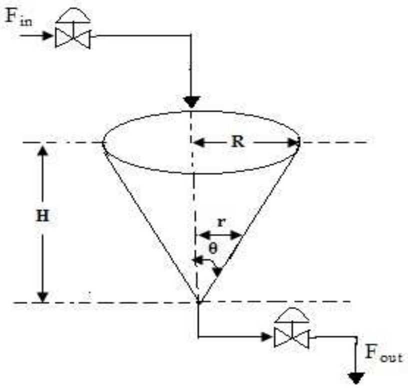

Fig. 1: Schematic diagram of the conical tank level process.

3. Design of PI Controller:

PI stands for Proportional-Integral controller. The individual P, I terms compose the standard two-term controller. Even complex industrial control systems make the use of a control network whose main control building block is a PI controller. The two-term PI controller has survived the changes of technology from the analog era into the digital computer control system age in a satisfactory way. It was the primary controller to be produced as a mass for the high market volume that existed in the process industries. PI controller is as type of feedback controller whose output, a control variable (CV), is generally based on the error (e) between some user defined set-point (SP) and some measured process variable (PV). Each element of the PI controller refers to a particular action to be taken on the error.

Design of PI controller using Zeigler-Nichols (Z-N) method

The PI mode of control is described by the relationship

$$u(t) = K_c e(t) + \frac{K_c}{T_i} \int_0^t e(t)dt + \text{bias} \quad (4)$$

The adjustment of the controller to achieve satisfactory control is called tuning. Ziegler Nichol's has proposed an open-loop tuning method called process reaction curve method. Optimum control setting can be obtained for various modes of control by using process reaction method. Process reaction curve method is to approximate a higher order process as first order with dead time. The open-loop response of the process is obtained as 'S' shaped curve or sigmoid curve as shown in Fig.2.

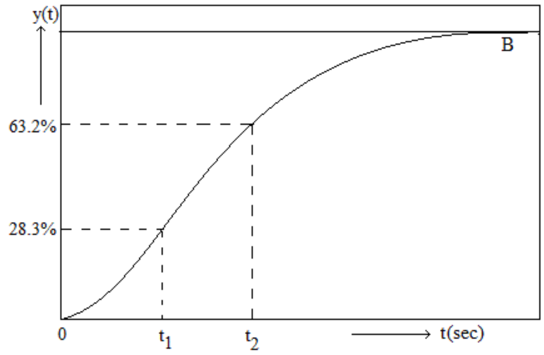

Fig. 2: Typical process reaction curve.

The process parameters are obtained using two point method (Wayne Bequette, 2010).

Time constant $\tau = 1.5(t_2 - t_1)$ (5)

Dead time $t_d = t_2 - \tau$ (6)

Process gain $K_p = \dfrac{\Delta\,\text{Output}}{\Delta\,\text{Input}}$ (7)

Time instant t_2 is obtained from 63.2% of the final steady state value. Similarly t_1 is obtained as 28.3% of the final steady state value (B).

The PI controller parameters can be determined using Zeigler – Nichols (Z-N) tuning method. The Z-N tuning parameters are given below:

Controller agin $K_c = \dfrac{0.9\tau}{t_d * K_p}$ (8)

Integral time $T_i = 3.33 * t_d$ (9)

However, conventional linear controllers will not give satisfactory response for the change in operating conditions. This necessitates the design of nonlinear controllers.

Neural Modeling:

From the previous discussion it is clear that the modeling and control of conical tank level process is not simple. Hence, neural network has the capacity to capture the nonlinear dynamics and model mismatch of the conical tank level process. The forward and inverse neuro models are developed using Levenberg – Marquardt algorithm.

4.1 Generation of Input-Output data:

By changing the inflow rate to the conical tank as PRBS sequence as shown in Fig.3 is given to the conical tank and the corresponding output is obtained as shown in Fig.4.The identification data set, containing N = 1000 samples with sampling time of 15 sec. The data matrix Z was constructed from the identification data set as

$$Z = \begin{bmatrix} Fin_1, Fin_2, \ldots. Fin_{1000} \\ h_1, \quad h_2, \ldots. \quad h_{1000} \end{bmatrix}^T$$

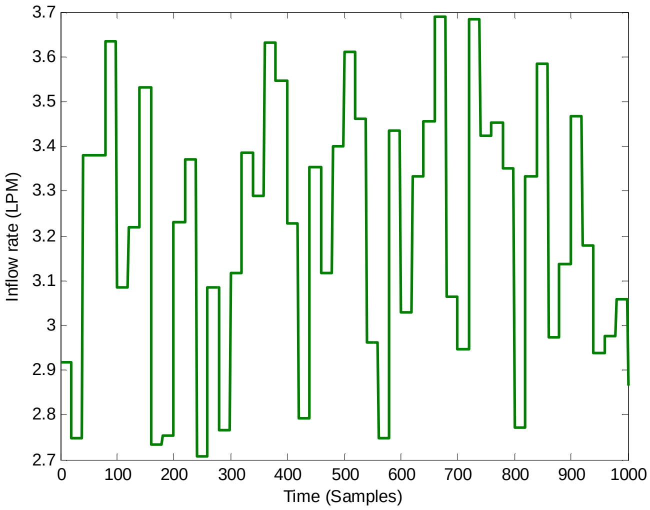

Fig. 3: Random input to the conical tank level process

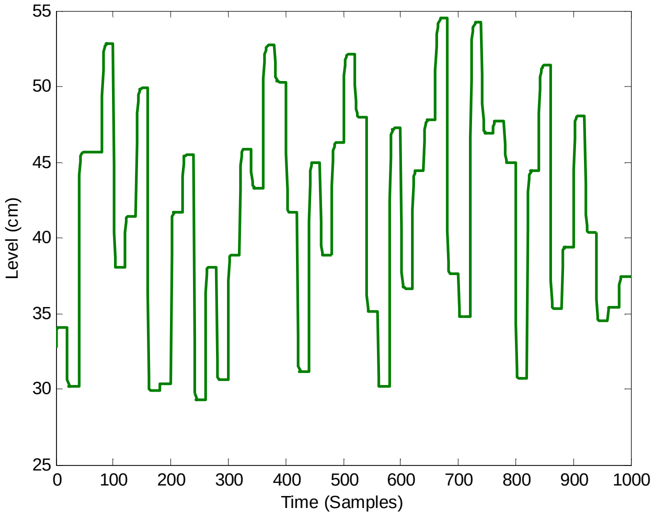

Fig. 4: Response for the conical tank level process

Forward Neural Model:

The neural network approach is trained to represent the forward dynamics of the conical tank level process. The network is trained using delayed outputs and delayed input. The Activation function for the hidden layer is Tansigmoidal, while for the output layer linear function is selected and they are bipolar in nature. The block diagram of forward neural network model is shown in Fig.5. The Levenberg Marquardt (LM) learning algorithm does the correct choice of the weight. The parameters used for training is given below:

Input vectors : [h(k-1) h(k-2) fin(k-1)]
Output vector : $\hat{h}(k)$
Sampling interval : 1 sec
Learning rate : 0.1
Training parameter goal : 1e-3

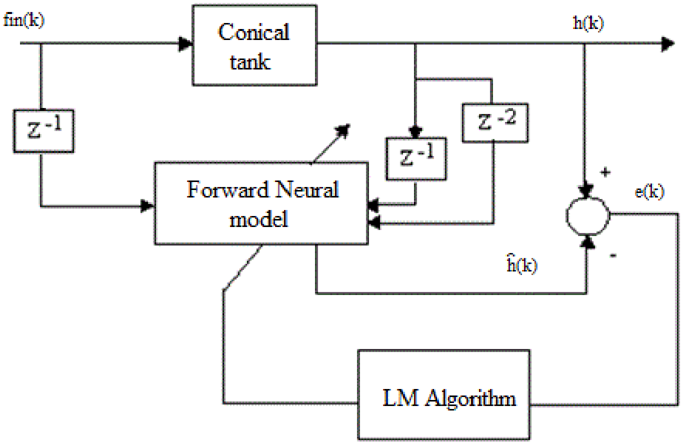

Fig. 5: Block diagram of forward neural model of conical tank level process.

Training and Model validation of forward Neural Model:

The data set used for training is sufficiently rich to ensure the stable operation, since no additional learning takes place after training. During training the NN learns the forward of the conical tank dynamics by fitting the input-output data pairs. This is achieved by using the LM algorithm [1]. The training pattern of MSE is shown in Fig.7 and this error goal is attained within 348 epochs. The simulated forward model output is shown in fig.6. It is observed from Fig.6 that forward model output exactly matches with output of the actual process. Hence, the neural network has the ability to model forward dynamics of the conical tank process, which can be used for developing the model based controllers.

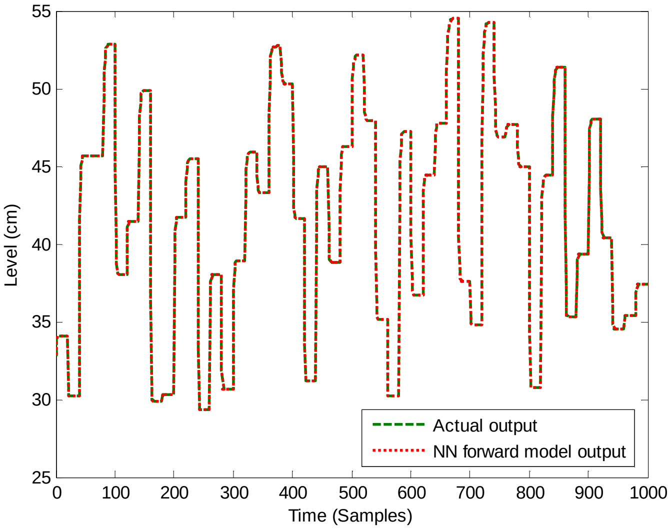

Fig. 6: Response of forward neural model and Actual process output

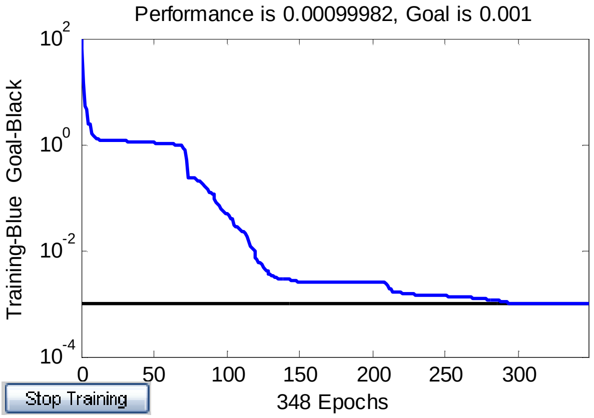

Fig. 7: Variation of MSE for forward neural model during training

Direct Inverse Neural Model:

The neural network approach is also trained to capture the inverse dynamics of the conical tank level process. The network is trained using current output and delayed sample of outputs and delayed input of conical tank level process. The Activation function for hidden layer and output layer are bipolar tansigmoidal and bipolar pure linear are used to give the desired output as inflow rate, which is input signal for the conical tank level process. The Levenberg Marquardt (LM) learning algorithm does the correct choice of the weight. The block diagram of direct inverse neural model is shown in Fig.8(a). The parameters used for training is given below:

Input vectors : [h(k) h(k-1) fin(k-1)]
Output vector : $\hat{f}in(k)$

Sampling interval : 1 sec
Learning rate : 0.1
Training parameter goal : 1e-6

Training and model validation of inverse neural model:

During training the NN learns the inverse of the conical tank dynamics by fitting the input-output data pairs. This is achieved by using the LM algorithm. The training pattern of MSE is shown in Fig.9 and this error goal is attained within 225 epochs. It is clear from Fig.8(b) that the inverse model output exactly matches with input of the actual model. Hence the neural network has the ability to model inverse dynamics of the conical tank process, which can be used for developing model-based controllers.

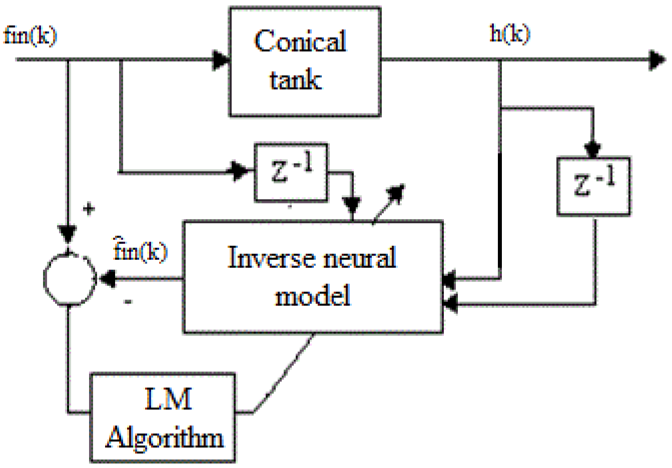

Fig. 8(a): Block diagram of direct inverse neural model

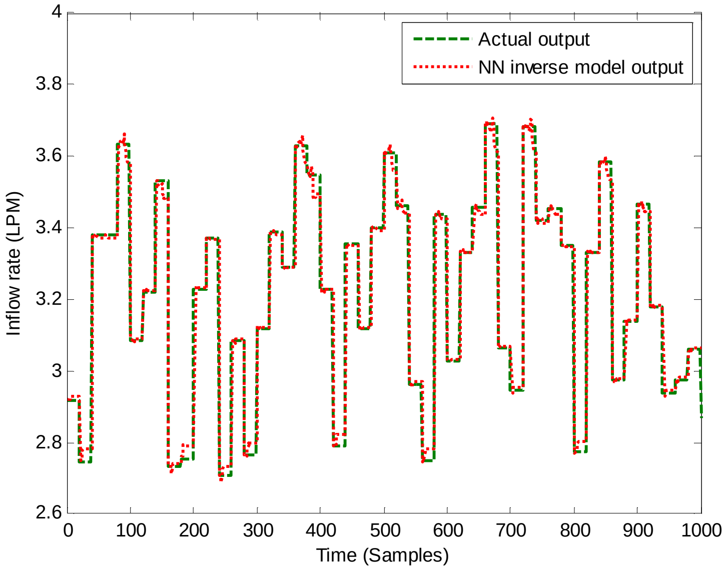

Fig. 8 (b): Response of inverse neural model and Actual process output.

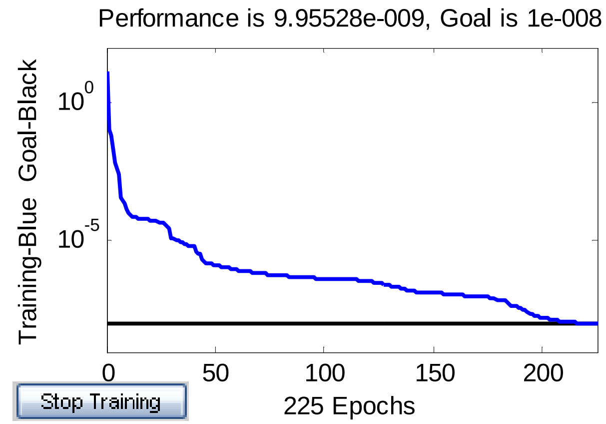

Fig. 9: Variation of MSE for inverse neural model during training.

Design of controllers:

5.1 Design of Local Linear PI Controller:

The design of local linear controller in each of the zones requires the knowledge of process gain (Kp), time constant (τ_p) and dead time (td). The gain is estimated as the ratio of change in the level of the tank to the change in inflow rate. The time constant of the model is evaluated in each zone from the simulation result on an actual nonlinear system for transient response for step change of the inflow rate around the nominal operating point. The average values of the parameters for the increased and decreased step change are taken in each of the zones. The local linear PI controller is designed in each zone using Z-N tuning method. Table I gives the linear model parameters and the controller parameters in each zone.

Table I: Process and Controller Parameter Settings for Various Zones

Zone	Nominal operating point	k_p	τ_p (min)	td	k_c	T_i (min)
Region1 (30-40 cm)	30	21.9	41.88	1.317	1.306	4.385
Region2 (40-50cm)	40	25.31	85.37	1.662	1.826	5.53
Region3 (50-60 cm)	50	28.2	147.4	2.287	2.056	7.615

Transfer function for Region 1

$$G_p(s) = \frac{21.9}{41.88s+1}e^{-1.317s}$$

Transfer function for Region 2

$$G_p(s) = \frac{25.31}{85.37s+1}e^{-1.662s}$$

Transfer function for Region 3

$$G_p(s) = \frac{28.2}{147.4s+1}e^{-2.287s}$$

5.2 Design of Direct Inverse Neuro Controller:

In the direct inverse control technique, the inverse model acts as the controller in cascade with the system under control, without any feedback. In this case the neural network, acting as the controller. In this control scheme the desired setpoint acts as the desired output which is fed to the network together with the past plant inputs and outputs to predict the desired current plant input.

5.3 Design of Neural Internal Model Controller:

The neural internal model control approach is similar to the direct inverse control approach above except for two additions. First is the addition of the forward model placed in parallel with the plant, to cater for plant or model mismatches and second is that the error between the plant output and the neural net forward model is subtracted from the set point before being fed into the inverse model. The other data fed to the inverse model is similar to the direct method. A filter can be introduced prior to the controller in this approach to incorporate robustness in the feedback system, especially where it is difficult to get exact inverse models. The structure of NNIMC is shown in Fig.10.

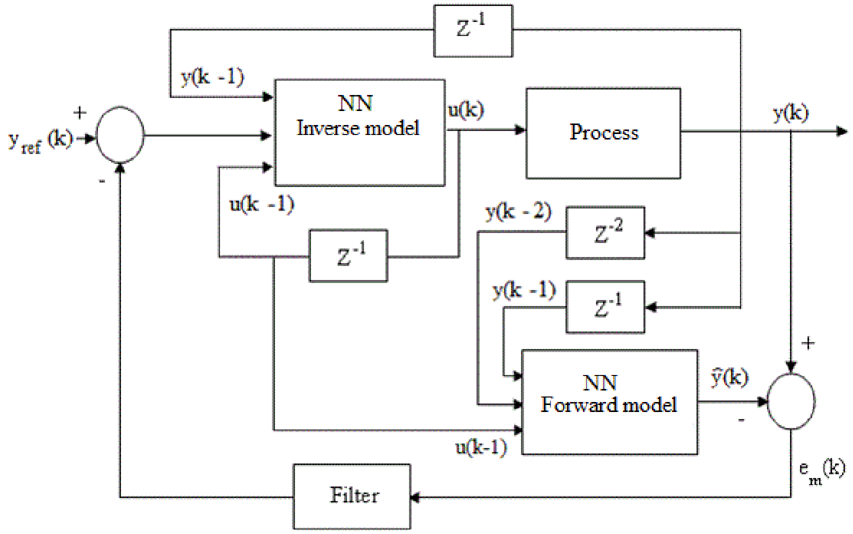

Fig. 10: structure of NNIMC for conical tank level process.

RESULTS AND DISCUSSIONS

The simulated controlled variable (h) profiles and the manipulated variable (Fin) profiles, for PI controller, NN DIC and NN IMC are shown in Fig.11, 12 , 13 and Fig.14, 15, 16 respectively for servo and regulatory response. PI controller exhibits large Integral Square Error (ISE), Integral Absolute Error (IAE) and settling time. NN DIC improves the performance of PI controller but it produces more offset at the operating point of 50 cm. However, from Fig.11, 12 and 13, it is clear that NN IMC is accurate enough to control the desired operating point. The performance measures for servo response of conical tank level process with PI controller, NN DIC and NN IMC are given in Table I. It reveals that NN IMC gives superior results for conical tank level process.

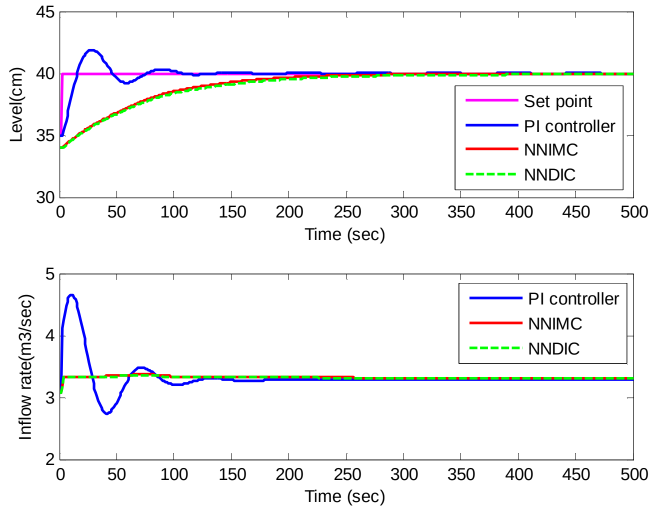

Fig. 11: Servo response of conical tank level process (region 1).

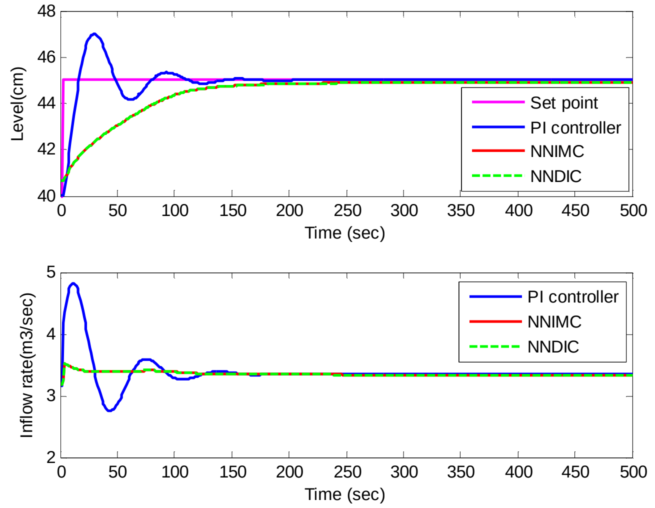

Fig. 12: Servo response of conical tank level process (region 2).

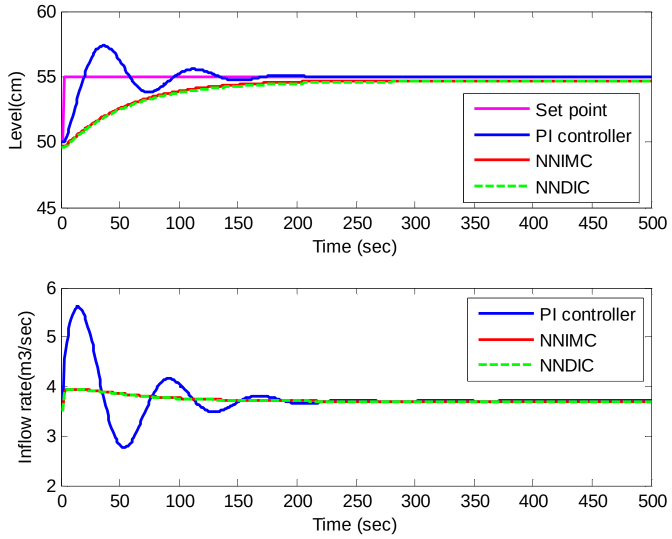

Fig. 13: Servo response of conical tank level process (region 3).

Table I: Performance measure for servo response.

Controller	Integral Square Error			Integral Absolute Error			Settling time		
	SP change 35 to 40	SP change 40 to 45	SP change 50 to 55	SP change 35 to 40	SP change 40 to 45	SP change 50 to 55	SP change 35 to 40	SP change 40 to 45	SP change 50 to 55
PI	1827	1007	1304	941	429	559	453	211	215
NNDIC	1409	530	999	480	344	462	268	182	209
NNIMC	1316	525	918	434	304	423	266	179	205

The step change in the inflow to the conical tank of 10 % is applied at 1000th second as load and the corresponding variation in level (h) is obtained. The weakness of the PI controller and NN DIC can be seen in Fig.14, 15 and 16. NNDIC fails to give satisfactory results for regulatory problems. When the disturbance is applied, PI controller produces large ISE and IAE but NN IMC produces lesser ISE and IAE and smaller settling time with zero offset. The performance measures for regulatory responses of conical tank level process using PI controller and NN IMC are given in Table II.

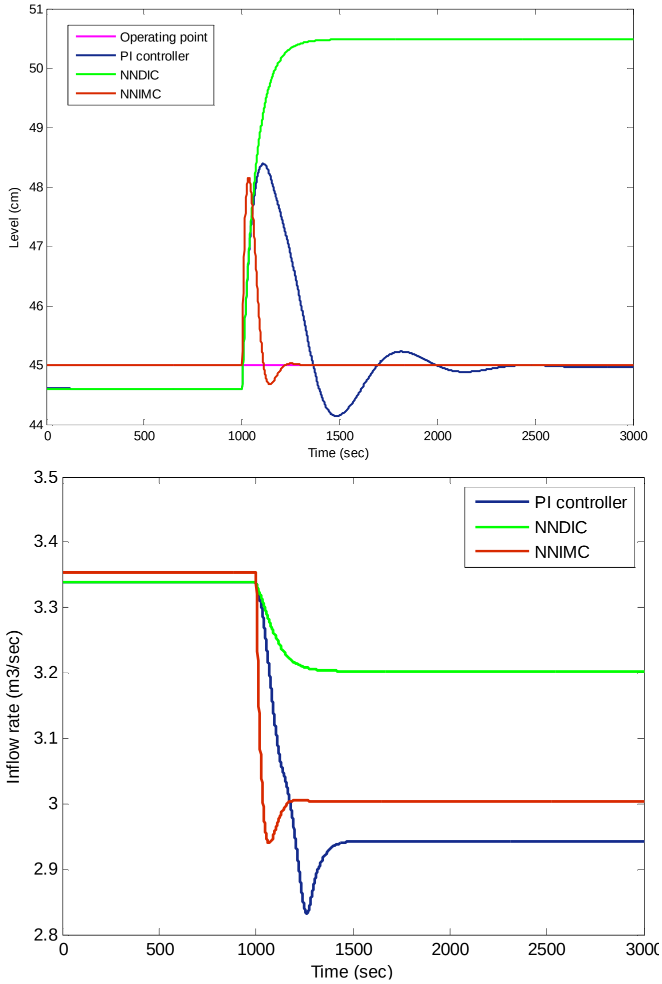

Fig. 14: Regulatory response of conical tank level process for the operating point of 45 (10 % increasing in inflow applied at 1000th sec).

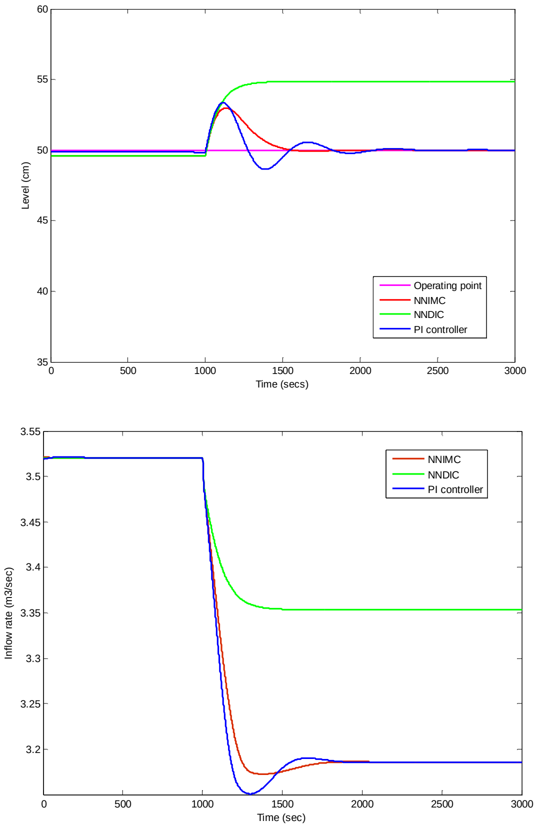

Fig. 15: Regulatory response of conical tank level process for the operating point of 50 (10 % increasing in inflow applied at 1000th sec).

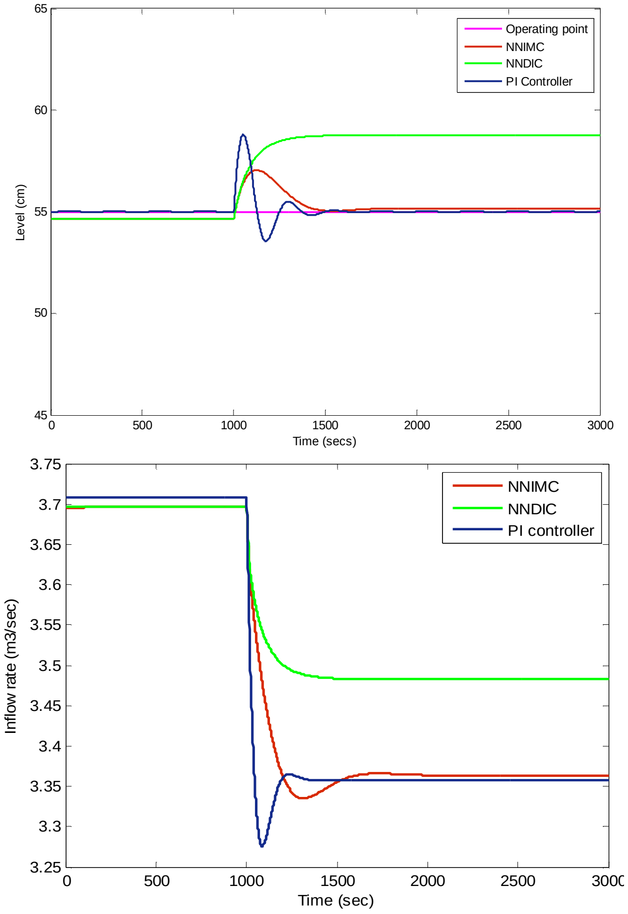

Fig. 16: Regulatory response of conical tank level process for the operating point of 55 (10 % increasing in inflow applied at 1000th sec).

Table II: Performance measure for regulatory problem.

Controller	Integral Square Error			Integral Absolute Error			Settling time		
	Operating point 45	Operating point 50	Operating point 55	Operating point 45	Operating point 50	Operating point 55	Operating point 45	Operating point 50	Operating point 55
PI	7861	10537	5437	2437	1214	1123	1410	1098	580
NNIMC	6945	8121	3320	1270	1007	986	455	595	570

Conclusion:

In this paper, the direct inverse control and internal model control are developed for a conical tank level process using neural network. The servo response of conical tank level process at various operating points shows that the NN IMC produces better result when compared with NNDIC and PI controller. The simulated regulatory responses of conical tank level process by varying Fin at the operating point of 45,50 and 55cm shows that the NN IMC performance is better in terms of lesser integral square error value, lesser Integral absolute error and having faster settling time when compared with NNDIC and PI controller. The overall results reveal that NN IMC outperforms for both servo and regulatory problems of conical tank level process.

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