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Challenges in Biochemical Engineering and Biotechnology for Sustainable Environment

Design and Implementation of Neuro Controllers for a Two-Tank Interacting Level Process

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Abstract: The control of liquid level in tanks and flow between tanks is a basic problem in the process industries. Almost all theprocesses in the industries are non-linear in nature. Designing a controller for a non-linear process is an important problem. The problem of level control in interacting tank processes are system dynamics and interacting characteristics. In interacting process, dynamics of tank1 affects the dynamics of tank2 and vice versabecause flow rate depends on the difference between the liquid levels (h_1 and h_2). In this paper, a real-time two-tank interacting level process is taken-up for study. The mathematical model of a two-tank interacting process is derived. The hydraulic resistances (R_1 and R_2) are obtained using Experimental data. The servo and regulatory responses are obtained with conventional PI controller. A neural network based direct inverse and internal model controllers are designed for a two-tank interacting process and its performance is compared with conventional PI controller. To develop model based neuro controllers forward and inverse neuro model are developed, trained and validated. Simulation studies are carried out with direct inverse neuro and internal model neuro controllers for servo and regulatory problems. It is observed that, direct inverse neuro and internal model neuro controllers are giving better results when compared to conventional PI controller.
Keywords— Two-tank interacting process, PI controller, Non-linear, Inverse control and Internal model controller.

1. Introduction

Level control is very important for the successful operation of most process control, chemical and biochemical industries. PI controllers are popular in industrial applications, as they are easy to install and resonably robust. In the recent years, there have been significant advances in control system design for non-linear processes. One such method is the non-linear inverse model based neural control strategy[1]. Neural networks (NN) have the potential to approximate any non-linear system including their forward & inverse dynamics. The direct inverse NN control strategy utilizes the process inverse model as controller. For training the neural network, the process input-output data is generated by applying a uniform random number on a white box model of the two-tank interacting process. The BPN Levenberg-Marquardt algorithm is used to train the neural networks.

2. Two-Tank Interacting Process

Fig.1 shows the photograph of the laboratory level process station. It consists of three pumps, two motorized control valves, six process tanks, two overhead tanks, two differential pressure transmitters, five level transmitters and rotameters. Instrumentation panel consists of two PID controllers, main power supply switch, pump switches, motorized control valve switches and auxiliary switches for individual component

Table I.Dimensions and variables for two-tank interacting process.

Operating conditions	Area (cm^2)	Hydraulic resistance (R_1) min/cm^2	Hydraulic resistance (R_2) min/cm^2
50-60%	113.0973	0.0300	0.0114
60-70%	113.0973	0.0300	0.0114

Fluid level in the tank is measured by level transmitter(LT). Output of LT is given to the data acquisition setup. It consists of ADC and DAC. The differential pressure level transmitter(DPLT) measures the flow by sensing the difference in level between the tank. The DPLT then transmits a current signal(4-20mA) to the I/V converter. The output of the I/V converter is given to the interfacing hardware associated with the personal computer (PC). A control algorithms are implemented in Lab view software. It compares and takes corrective action on the motorized control valve. Based on the valve opening flow rate is manipulated. Rotameter can visualize the flow rate. The controller compares the controlled variable against set point and generates manipulated variable as current signal(4-20mA). Here the controlled variable is the level(h_2) and the manipulated variable is the flow rate(q_{in}). The Control valve gives restriction to the flow through the pipeline and hence the desired level is achieved.

Fig.1.Piping and Instrumentation diagram of two-tank interacting process.

3. Mathematical Modelling of A Two-Tank Interacting Level Process

Consider the process consisting of two interacting liquid tanks in the Fig.2. The volumetric flow into tank1 is q_{in}(cm^3/min), the volumetric flow rate from tank1 to tank2 is q_1(cm^3/min), and the volumetric flow rate from tank2 is q_o(cm^3/min). The height of the liquid level is h_1(cm) in tank1 and h_2 in tank2(cm). Both tanks have the same cross sectional area denotes the area of tank1 is A_1(cm^2) and area of tank2 is A_2(cm^2), q_{L1} is the inflow of tank1 as load disturbance(cm^3/min)and q_{L2} is the inflow of tank2 as load disturbance(cm^3/min)^2.

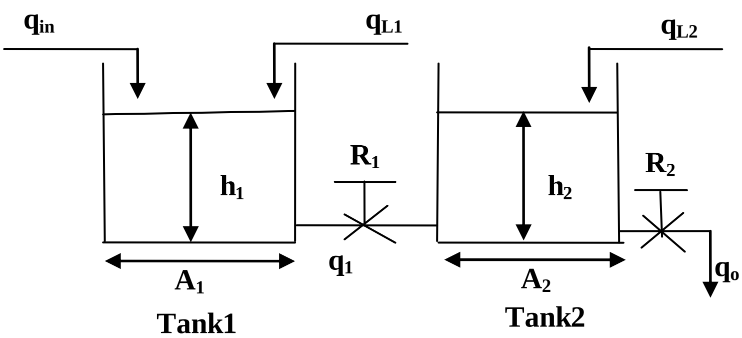

Fig.2.Two-tank interacting process.

For tank 1
$$A_1 \frac{dh_1}{dt} = q_{in} - \left(\frac{h_1 - h_2}{R_1}\right) \quad (1)$$

For tank 2
$$A_2 \frac{dh_2}{dt} = \left(\frac{h_1 - h_2}{R_1}\right) - \left(\frac{h_2}{R_2}\right) \quad (2)$$

From the experimental open loop response the hydraulic resistances R_1 and R_2 values are calculated[3]. The hydraulic resistances of tank1 and tank2 for different operating conditions are given in Table II.

Table II. R_1 and R_2 values for different operating conditions.

Parameters	**Dimensions**	
	TANK1	**TANK2**
Area	113.0973cm^2	113.0973cm^2
Height	25cm	25cm
Diameter	12cm	12cm
Inflow rate q_{in}(MV)	0- 1666cm^3/min	0- 1666cm^3/min
Process variable(h_1 and h_2)	0-25cm	0-25cm

3.1. Simulated Open Loop Responses for Two-Tank Interacting Process

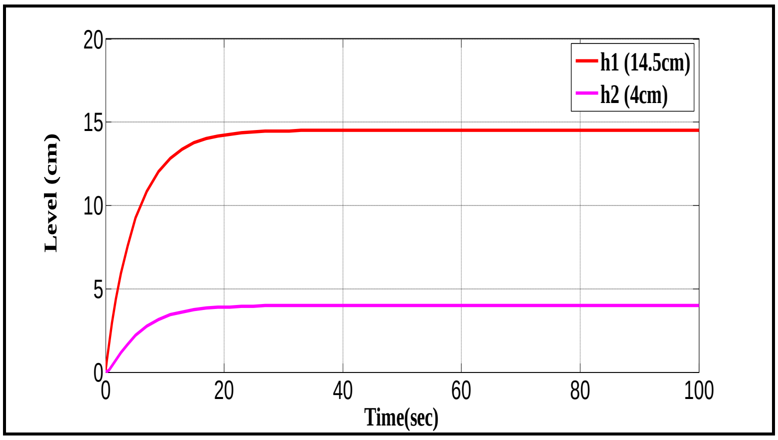

Fig.3.Simulated open loop response of h_1 and h_2 of interacting Process.

Fig.3 shows the Simulated open loop response of interacting process. The level (h_2) changes from 0 to 4cm, when applying a step input in q_{in}(21.05*16.66cm^3/min) also the level (h_1) changes from 0 to 14.5cm due to interaction. The simulated process reaction curve(PRC) of h_2 for step change in q_{in} for ±2cm is shown in

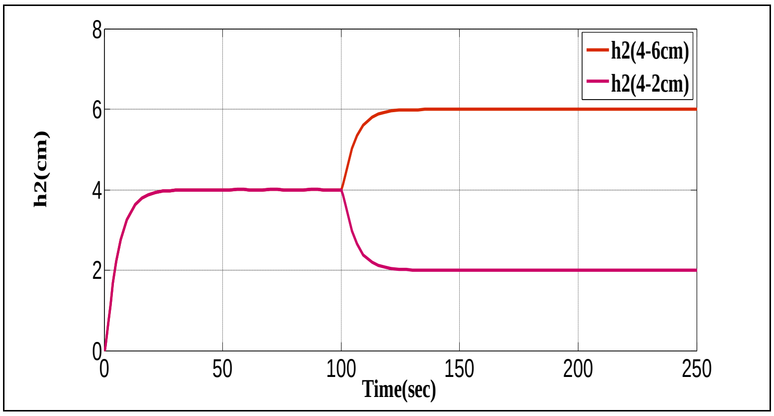

Fig.4.Simulated PRC of h_2 for step change in q_{in} for ± 2cm.

The transfer functions are obtained and tabulated in Table III. From the average transfer function, the controller parameters are obtained using Z-N tuning rule[4]. For two-tank interacting process the PI controller parameters are tabulated in Table IV.

Table III. Transfer function model of two-tank interacting process.

Step Input(q_{in})	Transfer Function	Average Transfer Function
Positive Step Input(q_{in})	$\frac{2}{4.5s+1}e^{-1.5s}$	$\frac{2}{4.5s+1}e^{-1.5s}$
Negative Step Input(q_{in})	$\frac{2}{4.5s+1}e^{-1.5s}$	

Table IV. PI controller settings for two-tank interacting process.

Mode	K_c	T_i(sec)
PI	1.35	4.995

4. Neural Modelling

Neural network has the capacity to capture the non-linear dynamics and model mismatch of the two-tank interacting process. The forward and inverse neuro models are developed using BPN Levenberg-Marquart algorithm[5].

4.1. Generation of Input-Output Data

By changing the flow rate as shown in Fig.5 is given to the process and the corresponding output is obtained as shown in Fig.6.

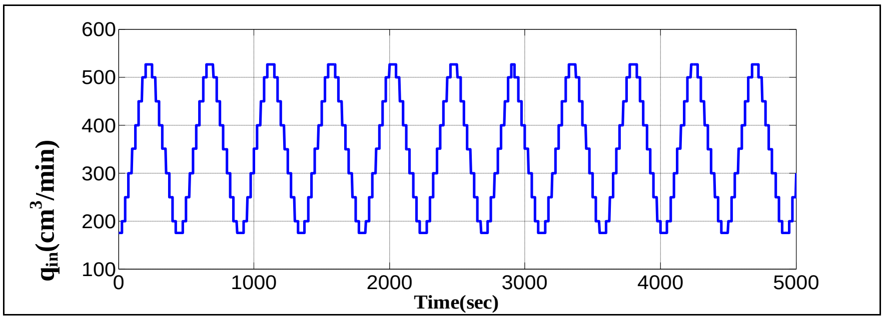

Fig.5.Random variation of flowrate.

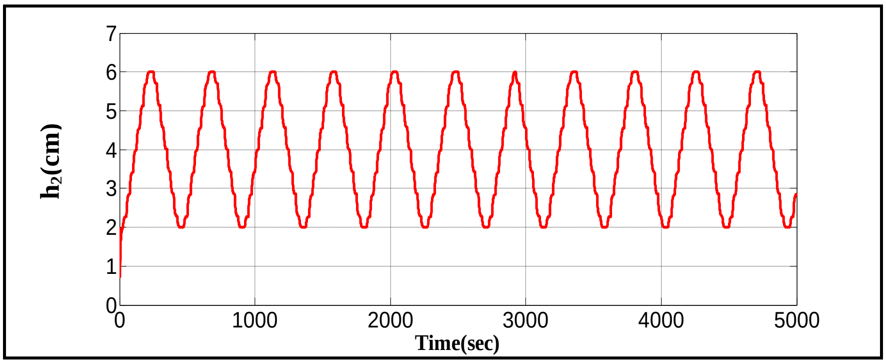

Fig.6.Random variation of level in tank2.

4.2 Forward Neural Model

The network is trained using delayed inputs and delayed outputs. The activation function for the hidden layer is tan-sigmoidal, while for the output layer linear function is selected and they are bipolar in nature[6]. The procedure for training a forward model consists of placing a NN in parallel with the plant as shown in Fig.7. Here the error resulting from the mismatch between plant and model is used to change the weights of the NN through an appropriate algorithm[7]. The procedure of training a neural net to represent the forward dynamics of a system is referred to as forward modeling and the models obtained from this procedure are called the forward models.

The parameters used for forward modeling:
input vectors : $[q_{in}(k-1)\ q_{in}(k-2)\ h_2(k-1)\ h_2(k-2)]$
Output vector : $\hat{h}_2(k)$
Training algorithm : BPN Levenberg-Marquardt algorithm
Activation function : Hidden layer- Tan-sigmoid function
Output layer- pure linear function
Sampling interval : 25sec

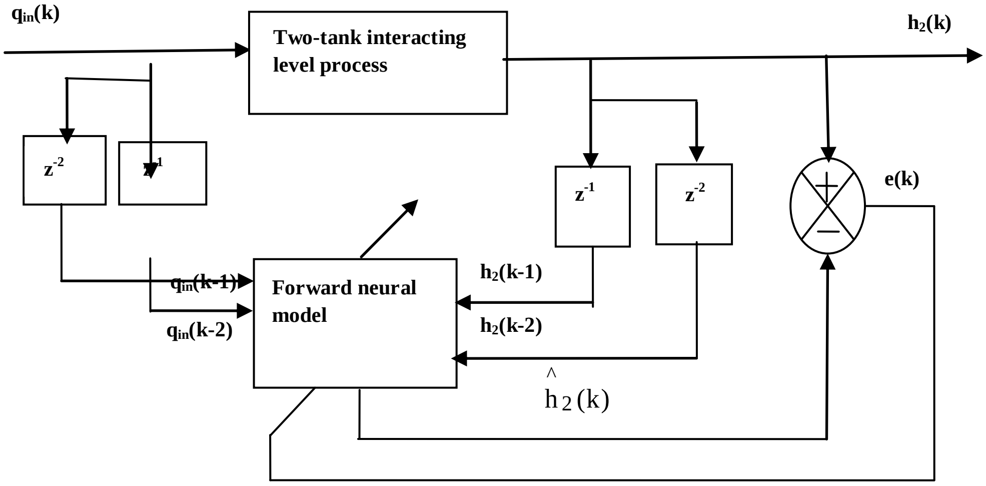

Fig.7.Block diagram of forward neuro model of two-tank interacting process.

4.2.1 Validation of forward model

Fig.8 shows the NN forward model for a two-tank interacting process. Forward neuro model is obtained by using delayed inputs and delayed outputs. The model output is compared with actual process output. It is clear from the Fig.8 that the forward model output exactly matches with the actual process output. The training pattern of MSE is shown in Fig.9.

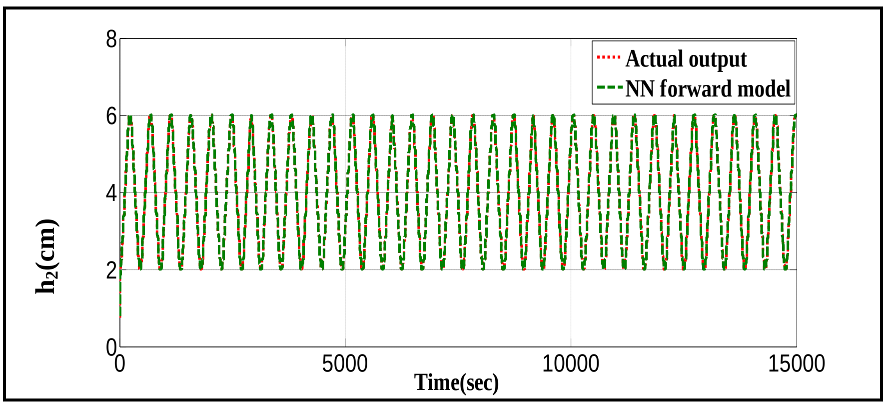

Fig.8.Comparison of NN forward model with actual output.

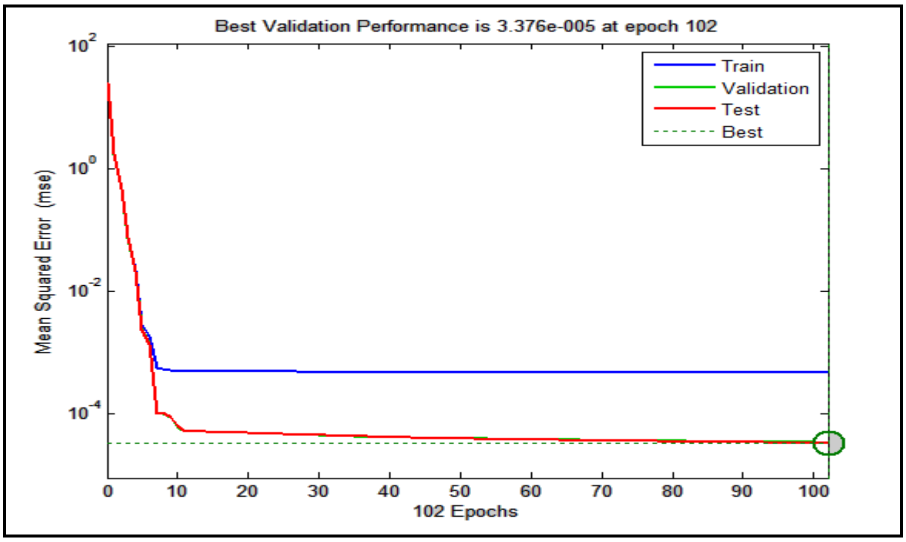

Fig.9.Variation of MSE for forward neural model during training.

4.3 Inverse Neural Model

The inverse neural network is shown in Fig.10. Inverse models are very important since they are part of many control structures. The simplest approach is the direct method which is closely related to forward modelling. Inverse models are basically the neural net structure representing the inverse of the system dynamics at the completion of training. The training procedure in this case is called inverse modelling.The network is trained using delayed sample of outputs and delayed inputs[5]. The activation function for hidden layer is Tan-sigmoidal function and output layer is pure linear function.

The parameters used for inverse modeling:

Input vectors	:	$[q_{in}(k-1)\ q_{in}(k-2)\ h_2(k-1)\ h_2(k-2)]$
Output vector	:	$\hat{q}_{in}(k)$
Training algorithm	:	BPN Levenberg-Marquardt algorithm
Activation function	:	Hidden layer-Tan-sigmoid function Output layer-pure linear function
Sampling interval	:	25sec

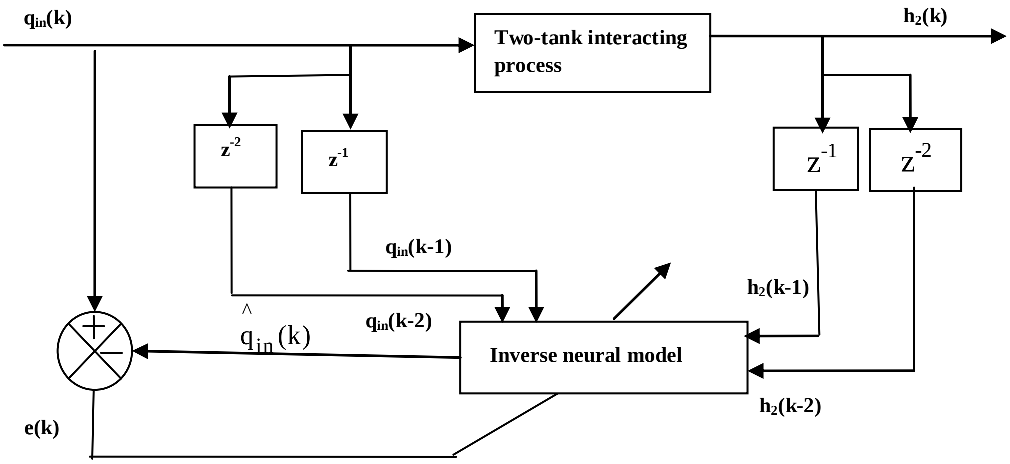

Fig.10.Block diagram of inverse neuro model of two-tank interacting process.

4.3.1 Training and model validation

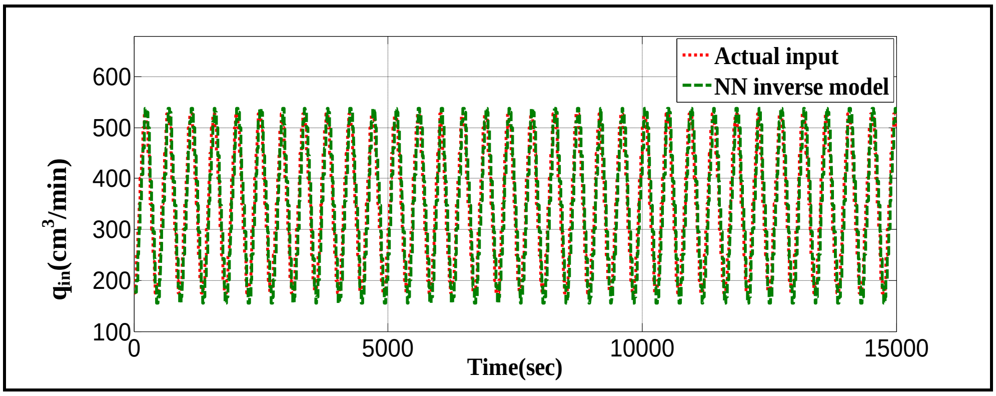

Fig.11.Comparison of NN inverse model with actual process input.

Fig.11 shows the NN inverse model for a two-tank interacting process. Inverse neuro model is obtained by using delayed inputs and delayed outputs. The model output is compared with actual process input. It is clear from the Fig.11 that the inverse model output exactly matches with the actual process input. The training pattern of MSE is shown in Fig.12.

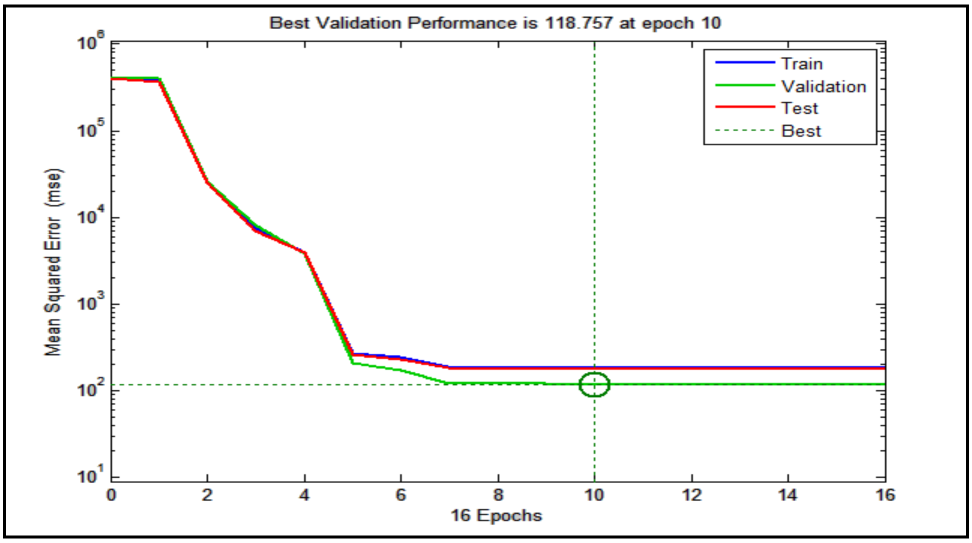

Fig.12.Variation of MSE for inverse neural model during training

4.4 Design of Direct Inverse Neuro controller

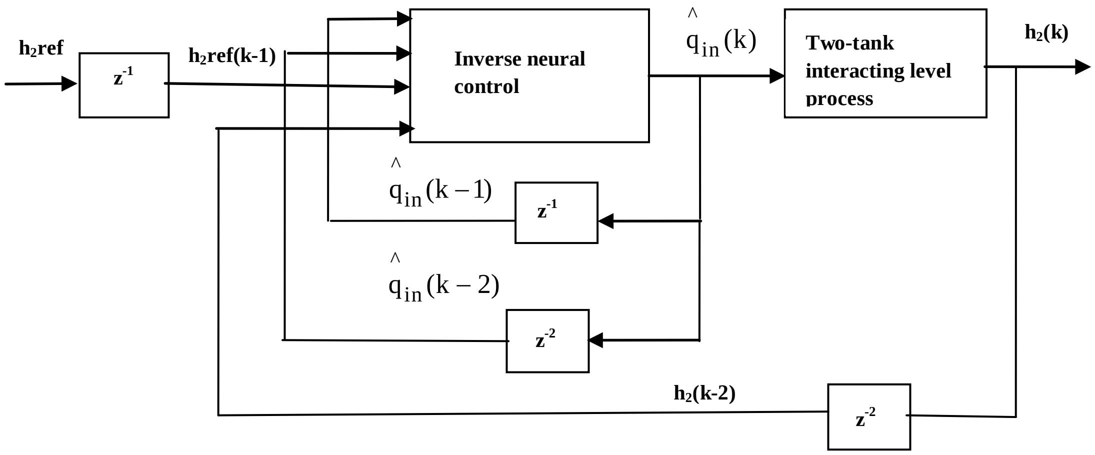

Fig.13.Block diagram of direct inverse neuro control of two-tank interacting process.

Direct inverse control is the simplest solution for control that consists of connecting in series the inverse model and the plant as can be seen in Fig.13.In the direct inverse control technique, the inverse model will act as the controller in cascade with the system under control, without any feedback. In the control scheme the desired set-point 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. In the ideal situation, with no modeling errors and disturbances, inverse controller yield perfect control with zero steady state error. It is fail to work for load disturbances.

4.5. Internal Model Neuro Controller

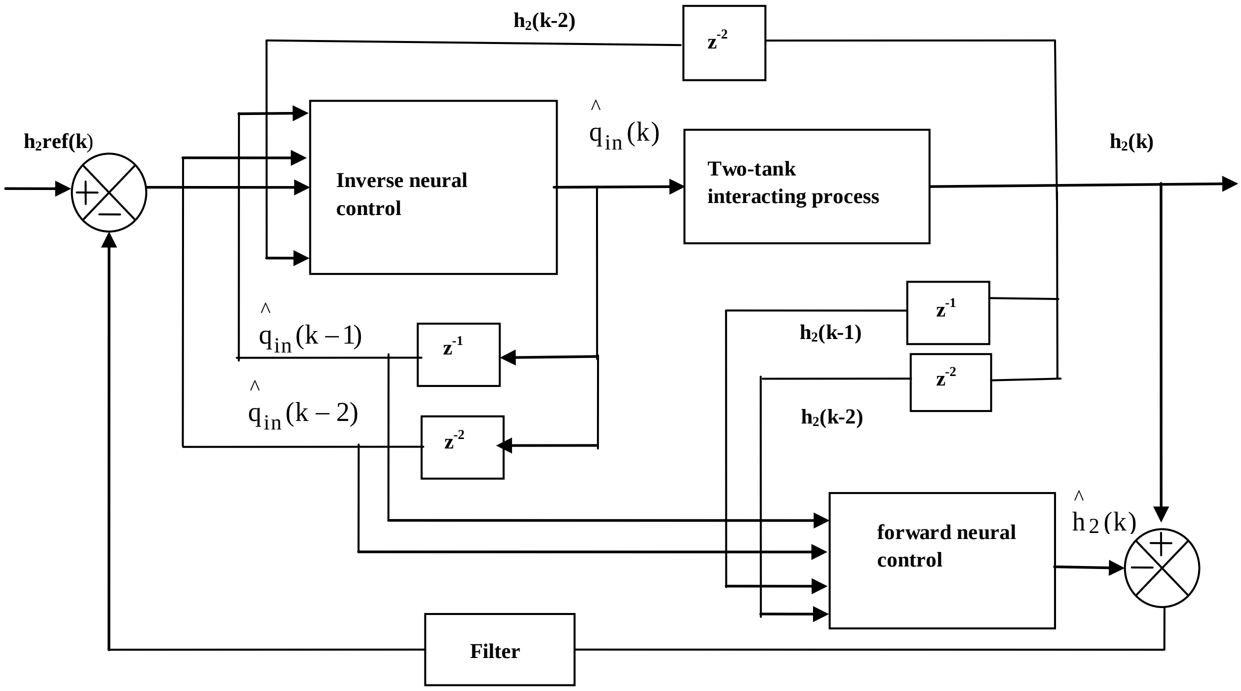

Fig.14.Block diagram of internal model neuro control of two-tank interacting process.

Fig.14 shows the internal model neuro controller for a two-tank interacting process. The internal model neuro control approach is similar to the direct inverse control approach 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. Second is the error between the plant output and the neural forward model is subtracted from the set-point before being fed into the inverse model. The IMC strategy however has a few drawbacks such as not being able to handle unstable processes and non-minimum phase systems[1]. 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. Some good feature is compensation for constant disturbances.

5. Simulation Results and Discussions

5.1 Servo Responses of Levels with PI and Neuro Controllers

Fig.15 shows the set point tracking for level (h_2) with PI, direct inverse and internal model neuro controllers from 4 to 6cm, 6 to 4cm, 4 to 2cm and 2 to 4cm.The level h_1 also increases from 14.5 to 21.8cm, 21.8 to 14.5cm, 14.5 to 7.3cm and 7.3 to 14.5cm due to interaction as shown in Fig.16. Also corresponding controller output q_{in} is shown in Fig.17. It is observed from figures that the PI controller takes more settling time for the level (h_2) and maximum integral square error. The direct inverse and internal model neuro controllers takes less settling time for the level (h_2) and thereby producing minimum integral square error**.** The performance measures are tabulated in Table V.

Table V.Comparison of performance measures of h_2 with PI and Neuro controllers.

Controllers	Servo response h_2(4)cm		Regulatory response h_2(4)cm				
			+8% from q_{L2}		-8% from q_{L2}		
	t_s (sec)	ISE	t_s (sec)	ISE	t_s (sec)	ISE	offset
PI	2200	2605	2000	651.2	2000	651.2	-
DIC	500	477.3	-	-	-	-	-
IMC	1000	497	500	375.5	500	207.6	0.1

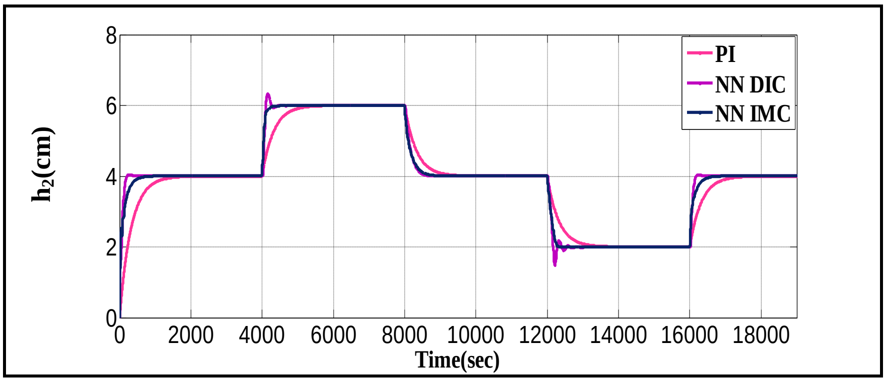

Fig.15.Servo response of tank2with PI, direct inverse andIMC controllers.

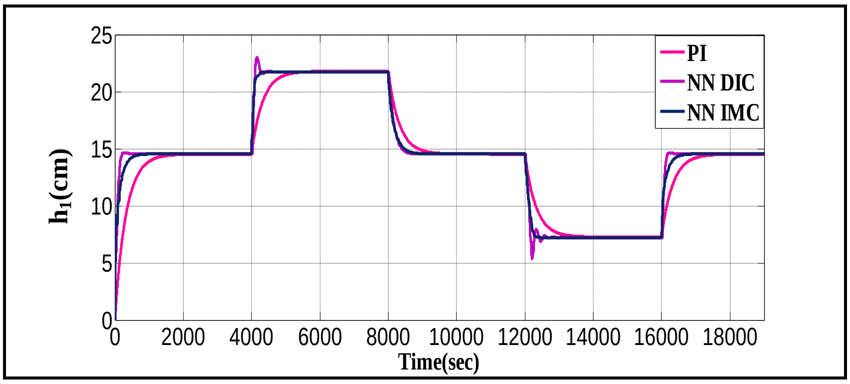

Fig.16.Servo response of tank1 with PI, direct inverseand IMCcontrollers.

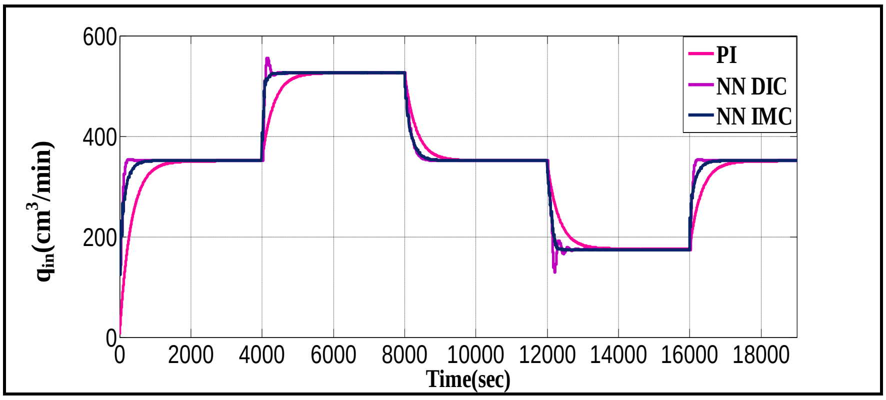

Fig.17.Response of PI, direct inverse and IMCcontrollers output q_{in} for Servoresponse.

5.2 Regulatory Response of Levels with Direct Inverse Neuro Controller(+8% load disturbance from q_{L2})

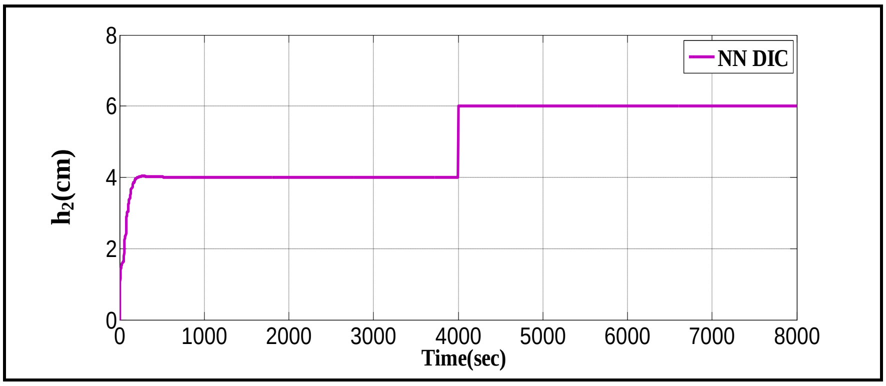

Fig.18.Regulatory response of tank2 with direct inverse neuro controller due to load variation in +8% from q_{L2}.

Fig.18 shows the regulatory response of h_2 with direct inverse neuro controller due to load variation in+8% from q_{L2}. The direct inverse controller is failing to work for load disturbances in the two-tank interacting process.

5.3 Regulatory Response of Levels with PI and IMC Controllers (+8% load disturbance from q_{L2})

A sudden load disturbance of +8% is given in inlet flowrate of tank2 at 4000th sample from q_{L2} as shown in Fig.2. Due to this level in h_2 increases from 4 to 6cm and controllers takes necessary action to reduce the flowrate, i.e from 350.8 to 175.4cm^3/min(referring Fig.21) thereby decreasing h_1 from 14.5 to 7.25cm(referring Fig.20). The performance measures are tabulated in Table V.

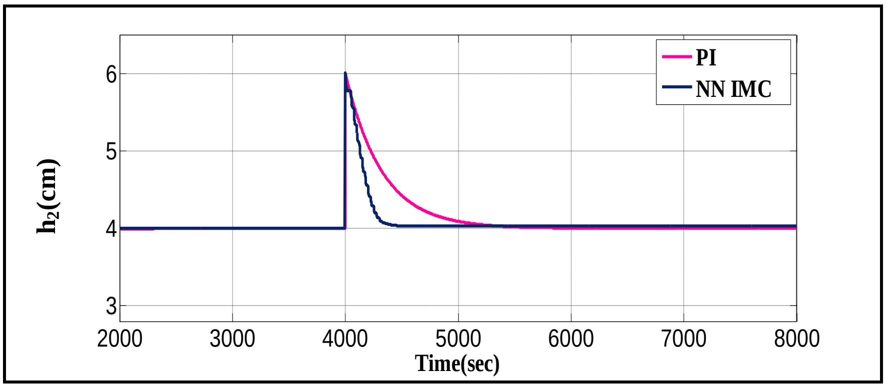

Fig.19.Regulatory response of tank2 with PI and IMC controllers due to load variation in +8% from q_{L2}.

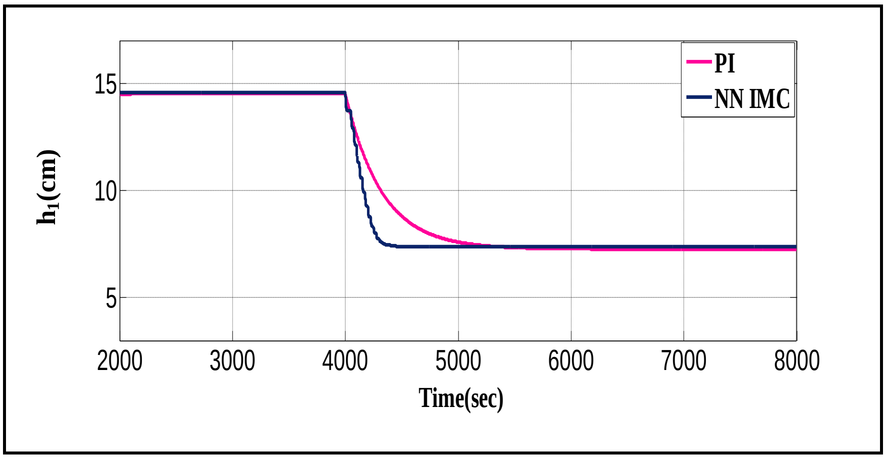

Fig.20.Regulatory response of tank1 with PI and IMC controllers due to load variation in +8% from q_{L2}.

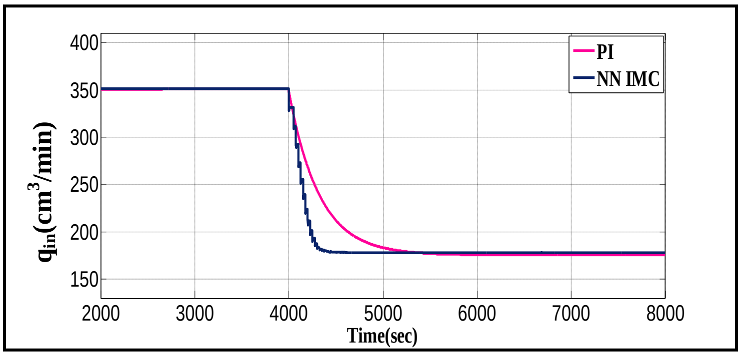

Fig.21.Response of PI and IMC output q_{in} for load variation in +8% from q_{L2}.

5.4 Regulatory Responses of Levels with PI and IMC Controllers (-8% load disturbance fromq$_{L2}$)

A sudden load disturbance of -8% is given in inlet flowrate of tank2 at 4000th sample from q_{L2} as shown in Fig.2. Due to this level in h_2 decreases from 4 to 2cm and controller takes necessary action to increase the flowrate, i.e from 350.8 to 526.3cm^3/min(referring Fig.24) thereby increasing h_1 from 14.5 to 21.8cm(referring Fig.23). The performance measures are tabulated in Table V.

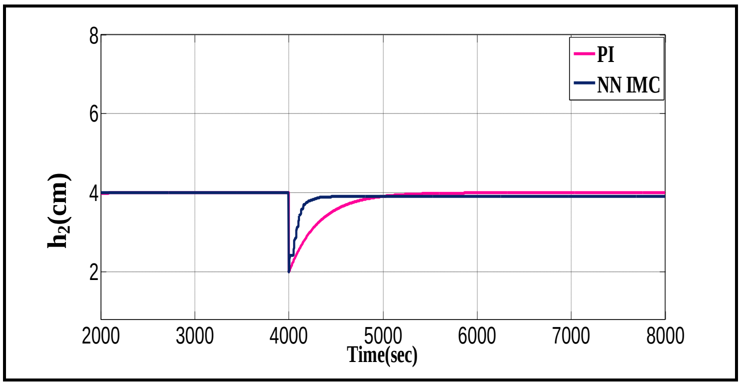

Fig.22.Regulatory response of tank2 with PI and IMC controllers due to load variation in -8% from q_{L2}.

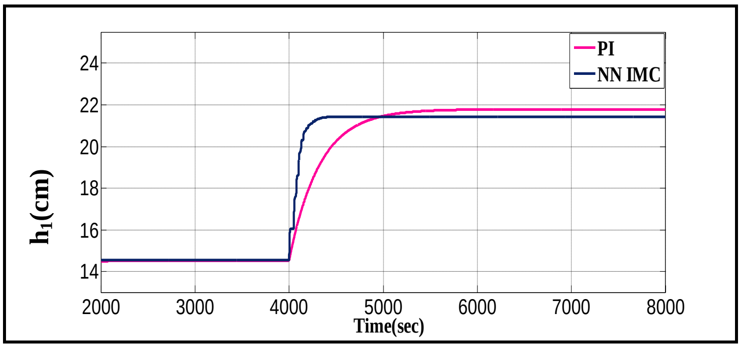

Fig.23.Regulatory response of tank1 with PI and IMC controllers due toload variation in-8% from q_{L2}.

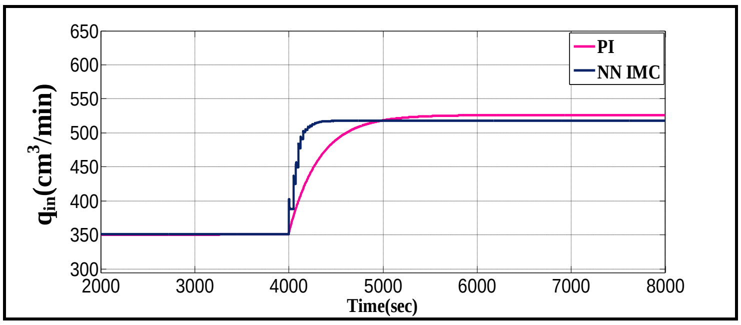

Fig.24.Response of PI and IMC controlleroutput q_{in} for load variation in -8% from q_{L2}.

5.5 Conclusion

In this work, the conventional PI and neuro controllers are developed for a two-tank interacting process. The Neural network based direct inverse and internal model controller are developed for a two-tank interacting process using BPN Levenberg-Marquardt learning algorithm.The servo response of two-tank interacting process shows that the direct inverse and internal model neuro controller performances are better than PI controller.The direct inverse controller is failing to work for load disturbances in the two-tank interacting process. The regulatory response of two-tank interacting process shows that the internal model controllerperformance is better in terms of less integral square error, faster settling time and better set-point tracking when compared with PI controller.

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