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Neural network model for IMC based PI controller for a nonlinear pH process

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Abstract : The control of pH is one of the most difficult challenges in the process industry because of the severe nonlinearities in the behaviour of the system. Different approaches for the pH control are proposed in various literatures. In the present study, control of pH using internal model controller for a neural network model based pH process is proposed. Modelling of the pH process is supposed to be a difficult task because one needs to have knowledge about the components and their nature in the process stream in order to model its dynamics. I this work, neural network model is proposed using the first principle equation of the nonlinear pH and used for controlling the pH process effectively using IMC based PI.

Keywords : Neural network; Internal model control based PI; pH process.

INTRODUCTION

Nearly all process plants in industries generate a wastewater effluent that must be neutralized prior to discharge or reuse. Therefore, pH control is needed in just about every process plant and yet a large percentage of pH loops perform poorly in practical cases. Results of this are lesser product quality, environmental pollution, and material waste. Examples of areas where pH control processes are in extensive use are water treatment plants, many chemical processes, production of pharmaceuticals and biological processes. With ever increasing demands to improve plant efficiency, effective and continuous pH control is extremely required. A control of pH process is highly nonlinear because the pH value versus the reagent flow (i.e., acid flow or base flow) has a logarithmic relationship.

Modelling of the pH process is supposed to be a very difficult operation because one needs to have knowledge about the components and their nature in the process stream in order to model its dynamics. Otherwise assuming some fictitious components and parameters defining their nature as linear model is needed, which might not be accurate in all cases. A model for the pH neutralization process with a single-acid single base system was developed [1]. This model has been widely accepted in the literature for process identification. A generalized model for pH system with an arbitrary number of acids and bases using the reaction invariant concept[2] was also attempted.

Neural network falls under the category of intelligent control and hence used for nonlinear application. Model Predictive Control Using Neural Networks[3] was attempted in literatures. Modelling of real pH Neutralization Process using Multiple Neural Networks (MNN) Combination Technique was also done[4]. Internal Model Control for PID Controller Design was already done[5],[6] to show that its better features in practical case. IMC Based PID Controller Design for a Jacketed CSTR was also done[7]. Here in this work, neural network model is done based on the input output data's of the system. Once an adequate ANN process model was developed, suitable control structure which could accommodate the model is chosen. That is internal model control based on PI controller.

Rest of the paper is as follows

Section 2 deals with the description of the process. Neural network modelling for pH process is dealt in section 3. The controller part of the pH process is done using IMC based PI controller which is dealt in section 4. Simulation studies carried out on simulink base of matlab is dealt in section 5 and conclusion is drawn in section 6.

DISCRIPTION OF THE PROCESS

Modelling of the pH process is supposed to be a very difficult operation because one needs to have knowledge about the components and their nature in the process stream in order to model its dynamics. Otherwise assuming some fictitious components and parameters defining their nature as linear model is needed, which might not be accurate in all cases. A model for the pH neutralization process with a single-acid single base system was developed[7]. This model has been widely accepted in the literature for process identification. A generalized model for pH system with an arbitrary number of acids and bases using the reaction invariant concept[8] was also attempted.

The system under consideration is a continuously stirred tank reactor (CSTR), in which a strong acid (Hydro Chloric acid) neutralised by adding a strong base (Sodium Hydroxide) continuously in a CSTR. The flow rate of strong base is manipulated to get the required pH. Material and ionic balance gives a set of linear differential equations and nonlinear static equation which is used for simulation.

$$V\frac{dx_a}{dt} = F_aC_a - (F_a + F_b)x_a \quad (1)$$

$$V\frac{dx_b}{dt} = F_bC_b - (F_a + F_b)x_b \quad (2)$$

$$x_b - x_a + 10^{-pH} - 10^{(pH-pK_w)} = 0 \quad (3)$$

where x_a and x_b are state variables, F_b is the manipulated variable and pH is the system output. The remaining symbols in the above equations are defined in TABLE 1. The simulink model of the pH process is obtained from the equation (1) to (3) as shown in Figure 1. The steady state characteristic titration curve for the acid base system generated by simulink model for variation in the base flow rate (F_b) from 0 to 60 Lit /hr is shown in Figure 2.

NEURAL NETWORK MODELLING

The term artificial neural network originates from research which attempted to understand and proposed very simple model of the operation of the human brain. This gives NNs several characteristics which are appealing for the modelling and control of non-linear systems. This generalization property makes it possible to train a network on a representative set of input/ target pairs and get good re-

TABLE 1 : System specifications

Variable/parameters	Nominal Value
Volume of reactor	5.7 lit
Flow rate of acid, F_a	20 lit/hr
Conc. Of acid, C_a	0.2N
Conc. Of base, C_b	0.2N
Equilibrium constant for water dissociation, K_w at 25 ^{O}C	10^{-14}

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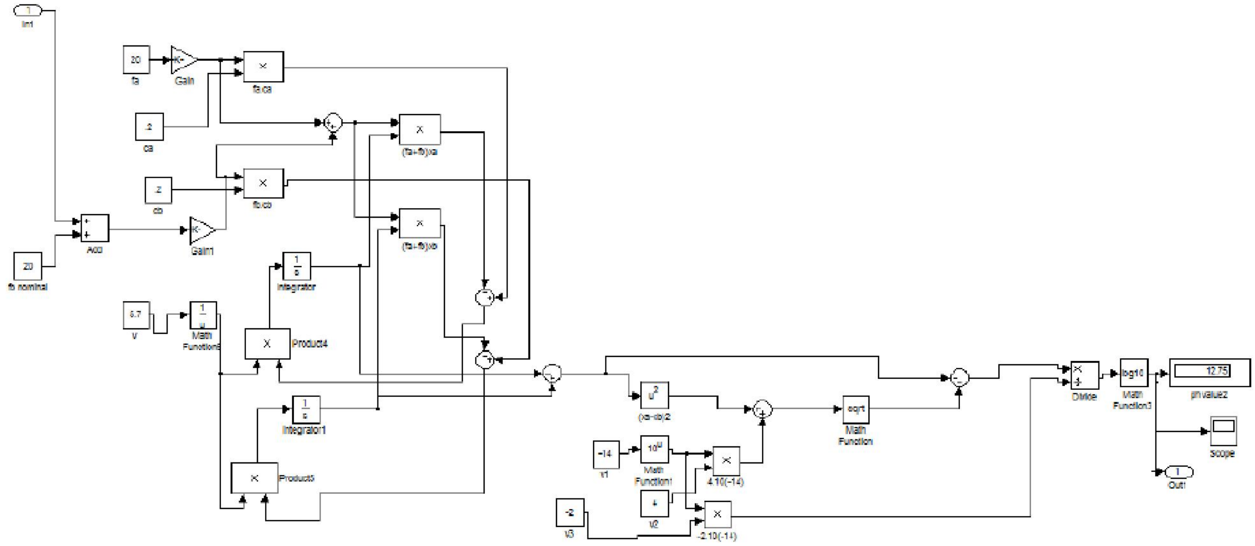

Figure 1 : Simulink block of the nonlinear pH process used

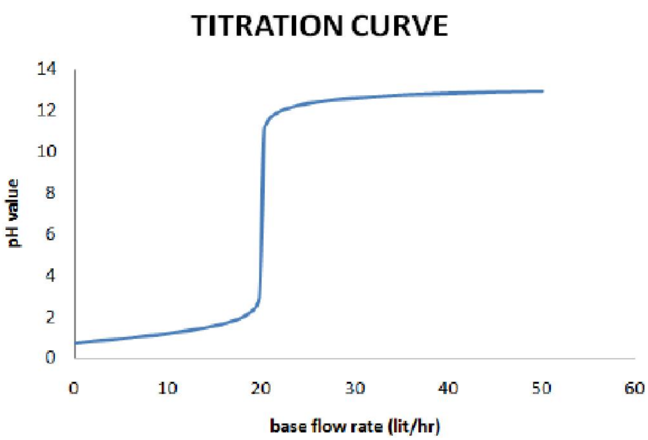

Figure 2 : Steady State characteristic titration curve of process considered

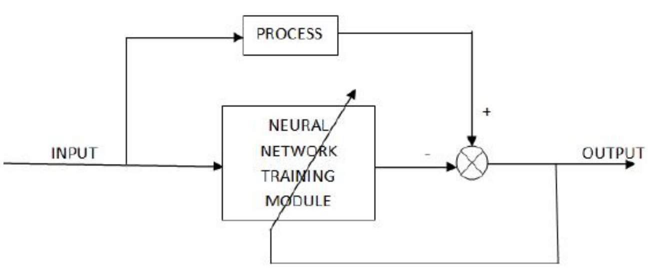

Figure 3 : Training of neural network module

sults without training the network on all possible input/output pairs.. Neural network models may be derived from measured Input output data of the plant. Usually, special open-loop experiments are performed to provide the data to train the neural nets. Here, some input is fed to the process and its output is collected. These collected data's are given to the neural network training module and the NN was trained until zero error occurred as shown in Figure 3.

Here we have chosen a feedforward network with tan sigmoid activation functions. This class of neural networks is well known and relatively well understood. Feedforward nets are easily implemented under real-time conditions. A disadvantage is that the training effort is usually high. Feedforward nets with at least one hidden layer have the capability to approximate any desired nonlinear mapping to an arbitrary degree of accuracy. The hidden layer considered consist of 30 neurons each, while the output layer consists of one neuron. The function used to train the neural network block is given below.

net=newff(minmax(pn),[30 1], {'tansig','purelin'} ,'trainlm').

INTERNAL MODEL CONTROL BASED PI CONTROLLER

The IMC uses a model based procedure, where a process model is to be embedded in the controller. The IMC structure is rearranged to get a standard feedback control system so that open loop unstable system can be handled. This is done to im-

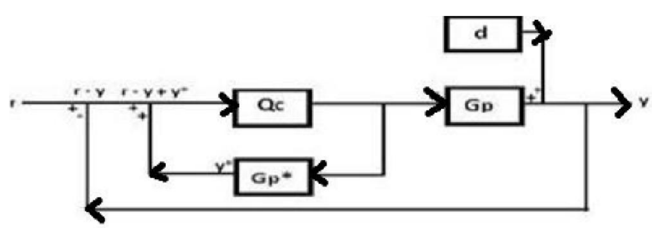

Figure 4 : Block diagram of IMC based PI controller

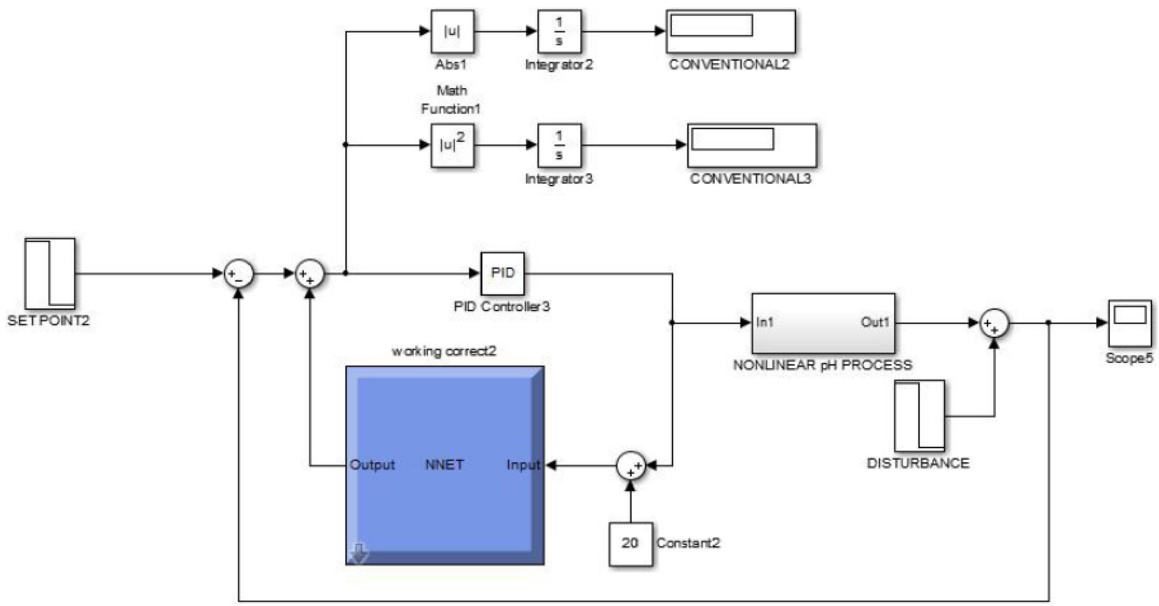

Figure 5 : Simulink block of neural network for IMC based PI controller

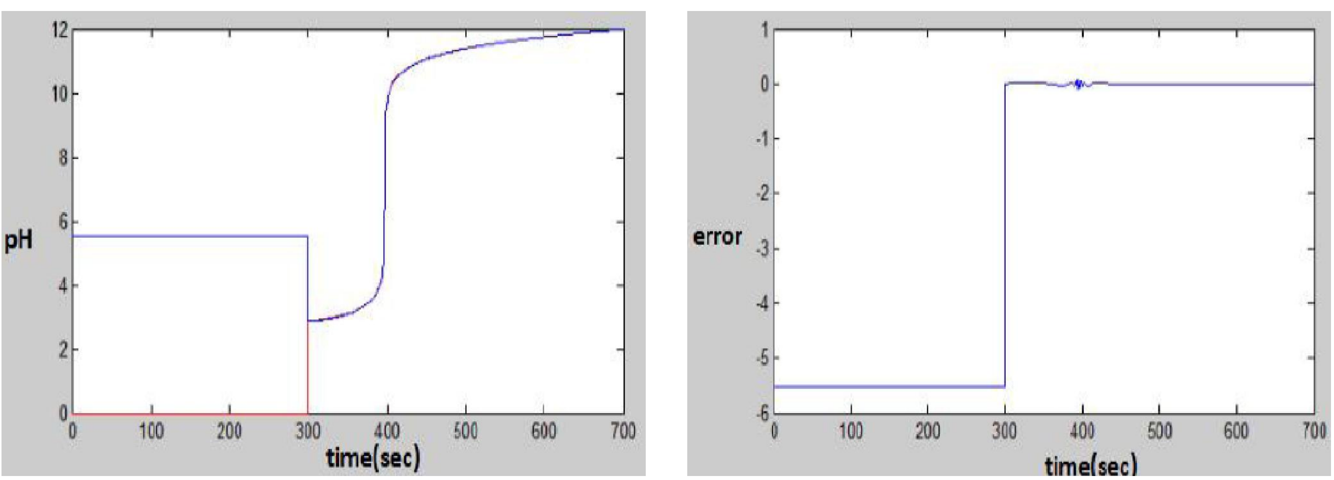

Figure 6 : Testing process for trained NN module

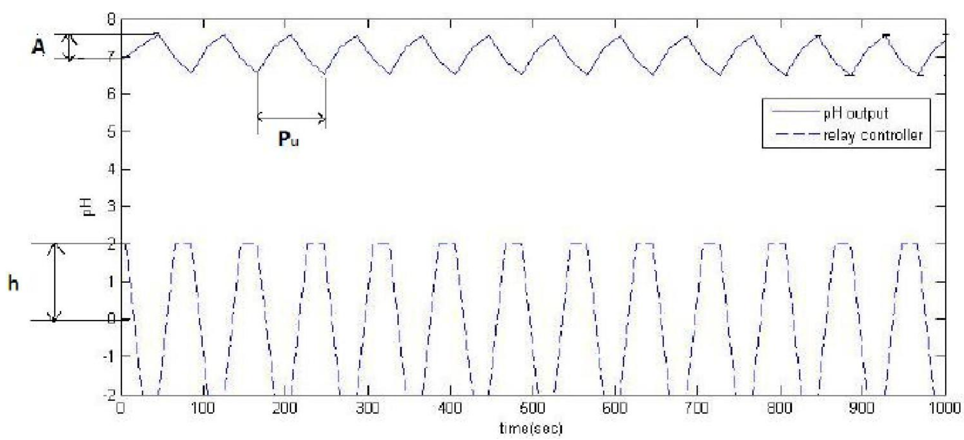

Figure 7 : Relay feedback test for pH process

prove the input disturbance rejection. The IMC based PI structure uses the process model as in IMC design. In the IMC procedure the controller $Q_c(s)$ is directly based on the invertible part of the process transfer function. IMC based PI procedures uses an approximation for the dead time. And if the process has no time delays it gives the same performance as does the IMC.

The block diagram of IMC based PI is shown in Figure 4. Here r(s) stands for input and y(s) stands for output. Here, the process model is G_p*(s)for an actual process plant G_p(s). The controller Q_c(s)is used to control the process in which the disturbances d(s)enters into the system at random time. In this work, the G_p*(s) is modelled using neural network where the NN module is trained to function similar to the process. Once trained, the above block diagram is to be constructed to understand the controller performance.

Figure 5. shows how the IMC based PI controller was constructed to control the nonlinear pH process using simulink. Since the system is nonlinear an intelligent controller based on NN can do better performance. This is tested by modelling the a NN module based PI controller.

SIMULATION STUDIES

The system is trained by providing a random input and the data's are collected for training. Once trained the module is tested at 300 sec. In the Figure 6 the output for testing data represents the simulated output of the neural network for the test data and the actual output of the subsystem. The error between the actual output of the system and the simulated output of the neural network is also shown.

Figure 7 illustrates the typical response curves for pH process for relay feedback test. The test provides ultimate gain (k_{cu}) and ultimate period (P_u) of the pH process at nominal operating point. Here h stands for height of relay control action and (A) stands for amplitude of plant response. Controller tuning to find K_c and T_i via the above mentioned relay feedback test is attractive, because it is operated under closed-loop and no priori knowledge of system is needed. The PI controller tuning parameters are obtained using Zeigler-Nichols method as shown in the equation (4) to (6).

$$k_{cu} = \frac{4h}{\pi A} \tag{4}$$

$$K_c = 0.45\, K_{cu} \tag{5}$$

$$T_i = \frac{P_u}{1.2} \tag{6}$$

The simulation results of conventional PI, NN-IMC Based PI Controller are shown in Figures (8-10) respectively. The simulation results show that the NN-IMC based PI controller has less overshoot and fast response compared to the conventional PI. The response for the Set point change from pH 7to pH 5 is shown in Figure 8. Here, it is found that NN-IMC based PI shows a much better response by achieving the set point at a much faster rate than PI.

The response for the Set point change from pH 7to pH 8 is shown in Figure 9. Here, it is found that

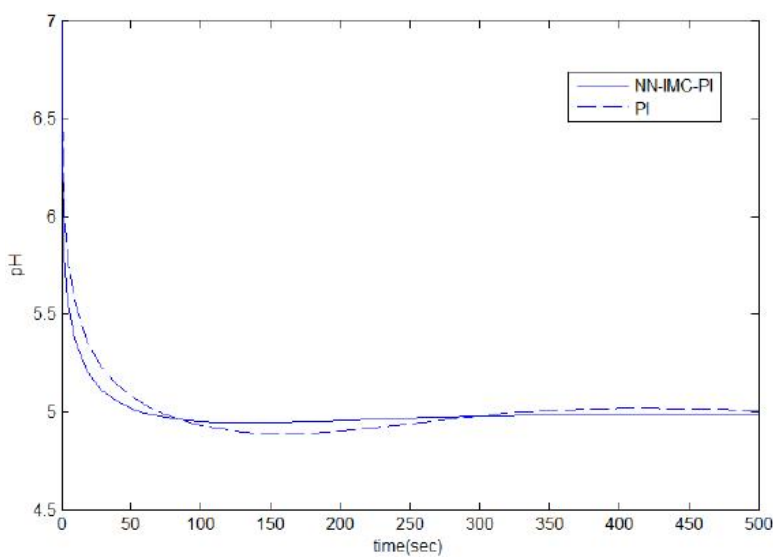

Figure 8 : Servo response for pH change from pH 7 to pH 5

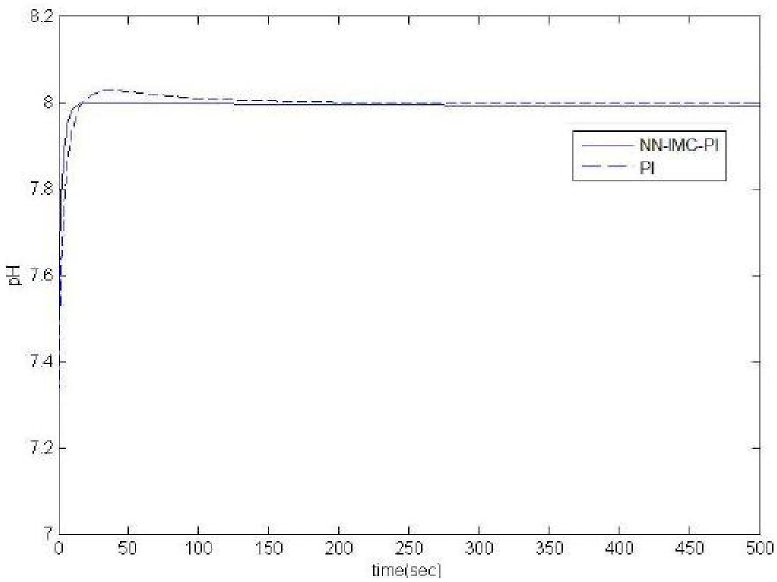

Figure 9 : Servo response for pH change from pH 7 to pH 8

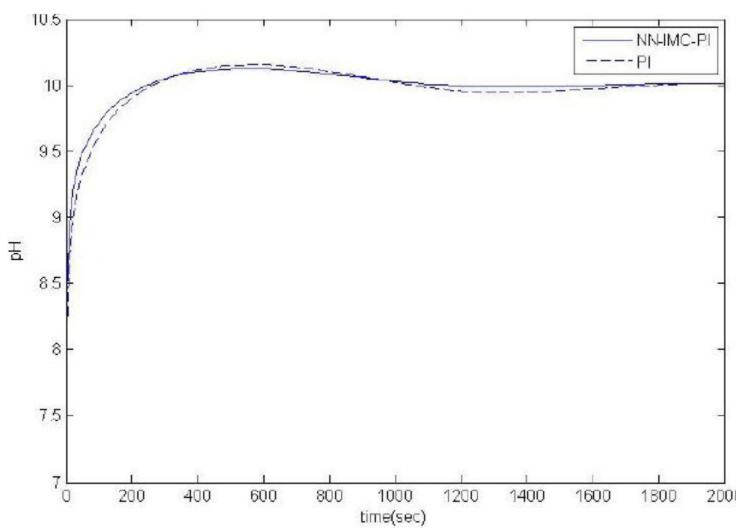

Figure 10 : Servo response for pH change from pH 7 to pH 10

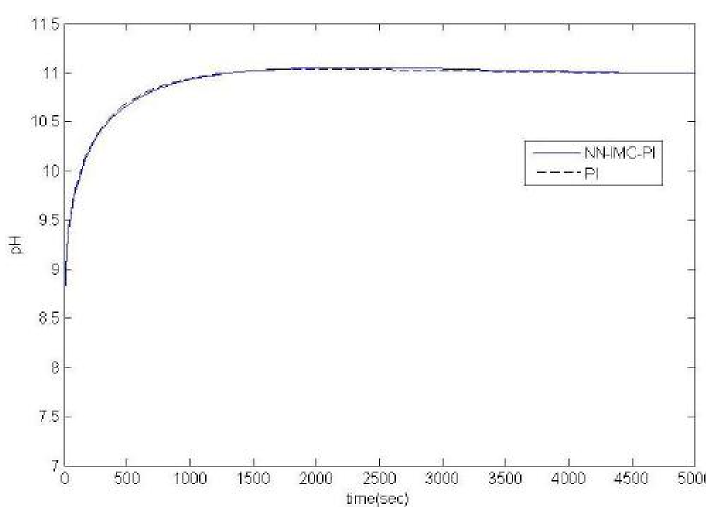

Figure 11 : Servo response for pH change from pH 7 to pH 11

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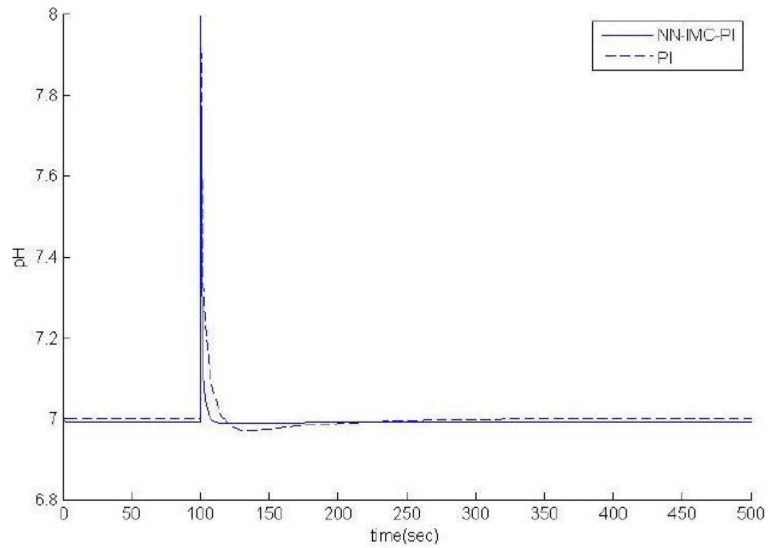

Figure 12 : Regulatory response for disturbance of +1 pH

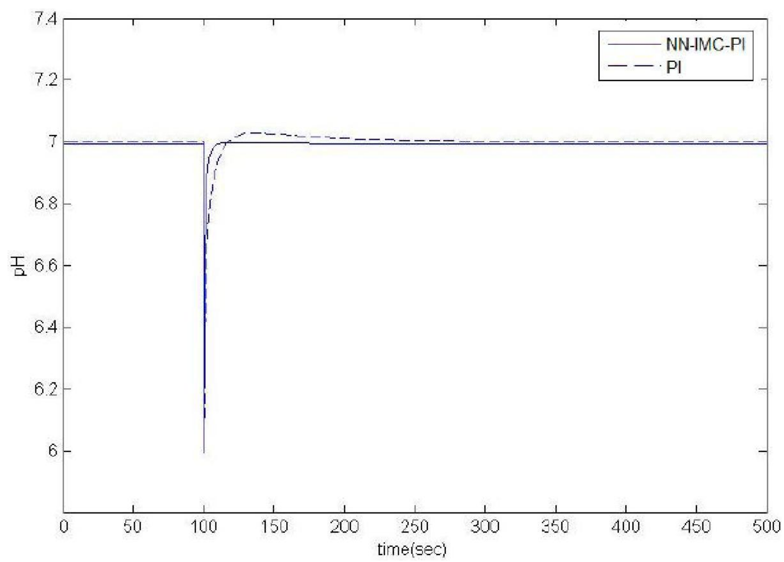

Figure 13 : Regulatory response for disturbance of -1 pH

NN-IMC based PI shows a much better response by achieving the set point at a much faster rate than PI.

The response for the Set point change from pH 7to pH 10 is shown in Figure 10. There is a nonlinear transition in the system. Here, it is found that NN-IMC based PI shows a better ISE and IAE values than PI.

The response for the Set point change from pH 7to pH 11 is shown in Figure 11. There is a nonlinear transition in the system. Here, it is found that NN-IMC based PI shows a better ISE and IAE values than PI.

In many practical cases the effluent from waste water treatment plant must be neutralized to pH 7 to maintain the environmental limits. A simulation work is considered in our work as shown in Figure 12,13 where a solution entering the CSTR has a pH of 8. Here, it is found that NN-IMC based PI shows a better ISE and IAE values than PI. Similarly a simulation work is considered in our work where a solution entering the CSTR has a pH of 6. Here, it is found that NN-IMC based PI shows a better ISE and IAE values than PI.

The performance analysis for servo and regulatory response was also done by obtaining the ISE and IAE values as shown in TABLE 2 and TABLE 3 for the controllers and it also concludes that NN-IMC based PI shows very low ISE and IAE values

TABLE 2 : Performance analysis for servo response

SP Change	NN-IMC-PI Controller		PI Controller	
	IAE	ISE	IAE	ISE
7-5	21.96	7.343	39.21	12.96
7-6	2.643	0.6174	5.056	1.137
7-8	2.58	0.5997	5.056	1.137
7-9	21.39	7.11	39.21	12.96
7-10	152.9	63.28	205.8	89.33
7-11	489.6	387.7	494.3	425.2

TABLE 3 : Performance analysis for regulatory response

Disrubance rejection for operating point of 7 pH	NN-IMC–PI Controller		PI Controller	
	IAE	ISE	IAE	ISE
8pH	1.632	0.4216	5.053	1.137
6pH	1.591	0.4123	5.053	1.137

PI – proportional and integral controller; NN – neural network; IMC – internal model control; NN-IMC-PI – neural network for internal model controller based PI

compared with PI. Hence we find that control of pH process using NN-IMC based PI shows better response than PI. When NN-IMC based PI was applied on the pH process it improved the speed of the response and there was no steady state error.

CONCLUSION

For practical applications on an actual process in industries, IMC based PI controller algorithm is simple and robust to handle the model inaccuracies. Since NN includes little intelligence, it can handle nonlinearities. For this reason, NN model is incorporated so that robustness to model inaccuracies is obtained. So we can conclude that IMC-PI along with neural network shows better performance with low ISE and IAE values for set point change and regulatory response on a pH process.

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