GREY WOLF OPTIMIZATION BASED DEEP NEURAL NETWORK INTERNAL MODEL CONTROLLER FOR A PH PROCESS

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Abstract

The pH process is challenging to control using conventional techniques because of its nonlinear and time varying process characteristics. This necessitates the design of model based control strategies for non-linear pH process. In this paper, Deep Neural Network is used to develop the forward and inverse models of pH process using its input-output data. The developed forward and inverse models are plugged into the Internal Model Control structure. To get the optimum performance, the number of hidden neurons in the hidden layers of DNN is determined using Grey Wolf Optimization. The effectiveness of the Grey Wolf Optimization based Deep Neural Network Internal Model Controller is contrasted with those of the Deep Neural Network Internal Model Controller and the traditional PI Controller.

Keywords: pH process, Non-linear, Grey Wolf optimization and Controller.

1. Introduction

Industrial processes show the complicated dynamics and nonlinear behaviour. It is known that all processes show some nonlinear behaviour. The application of model-based controllers that are efficient for processes whose nonlinearities cannot be ignored without adverse effects has recently attracted more industrial and academic interest. Since the dynamics of the pH process are extremely nonlinear and varying gain of several orders, Tight control of pH is also essential in the manufacturing of pharmaceuticals and waste water treatment [1]. Ali, E. [2] discussed the PI tuning method, globally linearizing control and gain scheduling controllers and the outcomes were compared. Kumar, A.A. et al.

[3] designed and implemented the pole placement technique based PI controller both in simulation and real time. The titration curve was obtained using CH_3COOH and NaOH.

Gustafsson,T.K. and Waller,K.V [4] elaborated an excellent overview of various adaptive control and non-linear methods for pH control. This study focuses on the useful advantages of ratio control and feed forward-feedback structure. Henson, M. A., and Seborg, D. E.[5] illustrated a pH neutralisation process with an Adaptive Nonlinear Output Feedback Control (ANOFC) approach. Over a variety of buffering conditions, the ANOFC produces excellent control of pH. For unquantified acid flow rate disruptions, the ANOFC works better than the PI and adaptive nonlinear controllers. Alina, B., and Madalina, C [6] designed IMC structure for wastewater pH neutralization process. They concluded that multi-model IMC algorithm is a feasible alternative for controlling pH process.

Palancar et.al., [7] developed a neural controller that consisted of forward and inverse model. By combining these two, the neural controller could calculate the required reagent flow for pH control. The controller was first tested with simulations and then implemented on a pilot-scale neutralization process. The buffering was changed during the test runs and the controller adapted to small and gradual buffer changes. Unfortunately the learning was not efficient enough for sudden and significantly big changes in the buffering [8]. Elarafi et al [9] described feasible modelling of the pH neutralisation plant using empirical methods, and compared the effectiveness of a predictive controller based on an ANN to conventional PID controllers. The feasible empirical model that came nearest to a second-order with dead time was identified. E.Sivaraman et al. [10] applied a NNIMC for a nonlinear pH process and their results were contrasted with those of a traditional PI controller and direct inverse neuro controller. Using the Levenberg-Marquardt method, the inverse and forward neuro structures are developed.

Meta-heuristic algorithm that mimics the leadership structure and hunting behaviour of grey wolves is called the Grey Wolf Optimizer (GWO). Given their position at the top of the food hierarchy, grey wolves are considered to be apex predators. They live in clusters, with each group averaging five to twelve residents. The group's members uphold a rigid social order. Alpha wolves are regarded as the most dominant members of the pack order. The omega wolves are under the authority of beta and delta, who are subordinates to alpha [11].

In this paper, Grey Wolf Optimization based DNN Internal Model Controller is designed and implemented for a nonlinear pH process. The introduction to the pH process and a review of relevant literature are elaborated in Section 1.The mathematical modelling of the pH process and an explanation of the process are described in Section 2. Section 3 discusses identification of process and controller parameters and the section 4 discusses Grey Wolf Optimization algorithm. The design procedure of GWO based DNN Internal Model Controller for a pH process is detailed in Section 5 of this article. The outcome and discussion of the current task are elaborated in Section 6, and the conclusion is reported in Section 7.

2. Process Description and Mathematical Modeling

A sodium hydroxide (NaOH) solution makes up the process stream, while an acetic acid (CH3COOH) solution makes up the titrating stream. An instantaneous chemical interaction between an acid and a base produces salt and water during the neutralisation process. The equivalence point is where the amounts of the bases and acids are equivalent, and this is where the process gain reaches its maximum value. The precision of the control system and the range capability of the reagent distribution system would be under extremely high demands if this system was to be controlled close to pH 7. The moderately high gain near neutrality makes it clear that the strong base/weak acid system is comparatively difficult to control. It should be emphasised that neutrality and the equivalence point don't always coincide. Thus the, a strong base- weak acid neutralisation procedure is taken up for the study.

The dynamic physical and chemical behaviour of pH in continuously stirred tank reactors was described by McAvoy et al. [12]. They created the dynamic formulae for the neutralisation of CH_3COOH and NaOH and then compared them to the findings of the experiments. The technique applies mass balance to individual components or groups of components.

The pH process's linear algebraic equation is written as

$$[H^+]^3 + (K_A + \zeta)[H^+]^2 + K_A(\zeta - \xi) - K_W[H^+] - K_A K_W = 0 \quad (1)$$

The following mass balances reveal the reaction symmetries, and. ζ and ξ

$$F_A C_A - (F_A + F_B)\xi = V\left(\frac{d\xi}{dt}\right) \quad (2)$$

$$F_B C_B - (F_A + F_B)\zeta = V\left(\frac{d\zeta}{dt}\right) \quad (3)$$

where [H+] has been the hydrogen ion concentration. The pH is finally determined as

$$pH = -\log_{10}([H^+]) \quad (4)$$

The following are the system specs at the nominal setpoint

Volume of the tank (V)	=	7.5 L
Inlet acid concentration (C_A)	=	0.2 mol/L
Inlet base concentration (C_B)	=	0.1 mol/L
Flow rate of acid (F_A)	=	0 - 0.5 L/min
Flow rate of base (F_B)	=	0.4 L/min
Acid equilibrium constant (K_A)	=	$1.8*10^{-5}$
Water equilibrium constant (K_W)	=	$1.0*10^{-14}$.

Solving equations (1), (2), (3), and (4) in modelling using MATLAB software for changes in the acid flow rate (FA) from 0-0.5 L/min results in the steady-state titration curve for the acid-base system. At an acid flow rate of roughly 0.2 L/min, the system's static nonlinear behaviour is readily noticeable. The pH value will change drastically from 11 to 7 even with a slight change in the acid flow rate in the region. Since this operating point is challenging to design the conventional controller.

By giving the step change in control variable, the process response curve is obtained. The parameters of the pH process at each zone are identified using this technique. The appropriate reaction curves have been determined for each of these regions after a step change in inflow is provided in both the negative and positive directions. The variable time constant (τ) and process gain (Kp) are obtained from these process reaction curves. At the setpoint of 8, both negative and positive step change in acid flow rate was applied to produce the PRC for zone 2. This result is shown in Figure 1. Table1 lists the process parameters that were attained for different zones. The pole placement method is used in the design of PI controller.

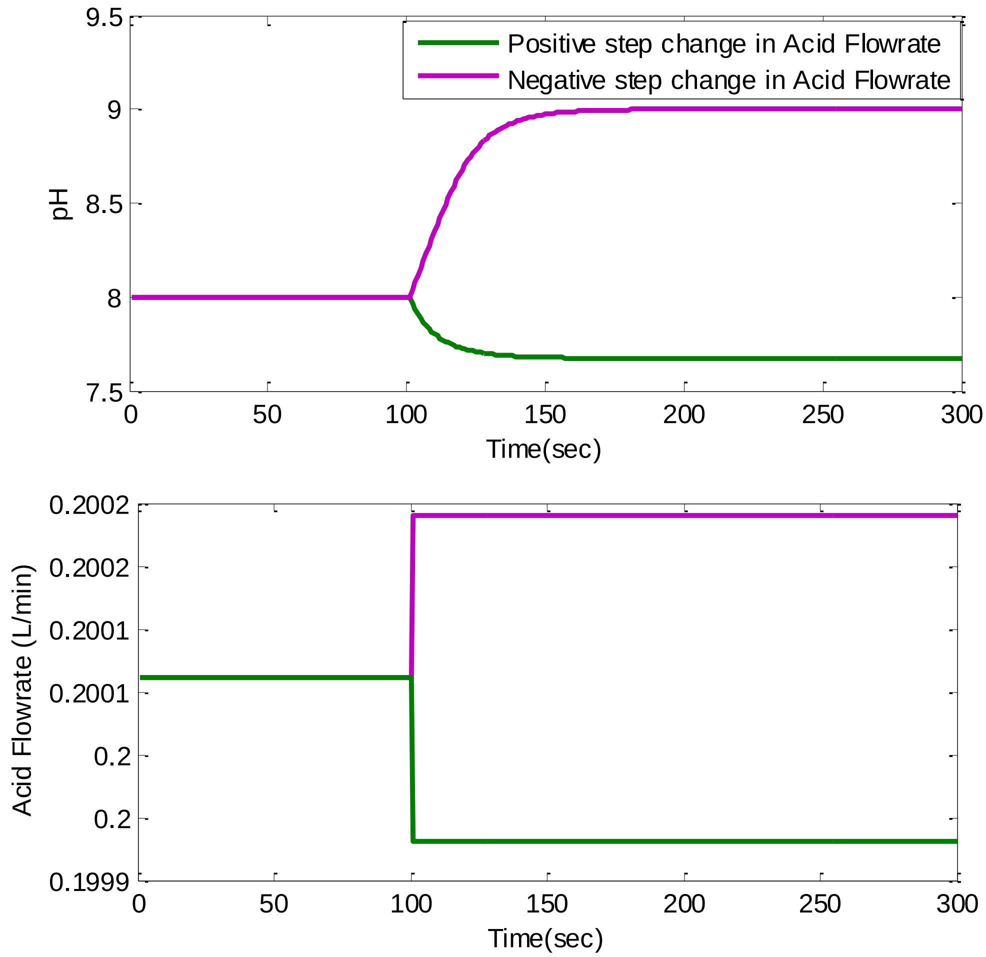

Figure 1. Process reaction curve for zone3.

Table 1. pH process parameters for various zones.

Zone	Nominal operating Point	Process Gain			Time constant		
		K_p $(+F_A)$	K_p $(-F_A)$	K_p (Average)	τ $(+F_A)$	τ $(-F_A)$	τ (Average)
1(13to11)	12	-37	-12	-24.5	22	9.6	15.8
2(11to 9.5)	10.25	-3520	-1012	-2266	20.5	10.5	15.5
3(9.5 to 8)	8.75	-2416	-7702	-5059	10.1	15.1	12.6
4 (8 to 6.5)	7.25	-98	-136	-117	10.2	19.5	14.85
5 (6.5 to 4.5)	5.5	-27	-97	-62	10.25	21.4	15.83

4. Grey Wolf Optimization (GWO)

The grey wolf is a member of the canid family (Canis lupus). Grey wolves are thought of as apex predators because they are at the summit of the food chain. Grey wolves typically prefer to live in groups. There are typically 5 to 12 individuals. They have a very rigid social dominant order, which is particularly interesting [13,14]. The social structure of grey wolves and their hunting method are numerically modelled in this work in order to create GWO and carry out optimization. The encircling motion can be mathematically modelled using the following equations.

$$\vec{D} = \left|\vec{C}.\vec{X}_p(t) - \vec{X}(t)\right|$$
$$\vec{X}(t+1) = \vec{X}_p(t) - \vec{A}.\overrightarrow{D}$$

where t denotes the present iteration, $\vec{A}$and $\vec{C}$denote coefficient vectors, $\overrightarrow{X_p}\,(t)$ denotes the prey's position vector, and $\vec{X}$denotes a grey wolf's position vector. The following formulas are used to determine vectors$\vec{A}$and $\vec{C}$:

$$\vec{A} = 2\vec{a}.\vec{r}_1 - \vec{a}$$
$$\vec{C} = 2.\vec{r}_2$$

where $\overrightarrow{r_1}, \overrightarrow{r_2}$ are random vectors in the range [0, 1] and elements of an are linearly reduced from 2 to 0 over the period of iterations. The first 3 acquired best solutions in GWO are currently stored and because of the locations of the best search agents, the other search agents are forced to update their positions. The following equations are suggested in this respect.

$$\vec{D}_\alpha = \left|\vec{C}_1.\vec{X}_\alpha - \vec{X}\right|,\ \ \vec{D}_\beta = \left|\vec{C}_2.\vec{X}_\beta - \vec{X}\right|,\ \ \vec{D}_\delta = \left|\vec{C}_3.\vec{X}_\delta - \vec{X}\right|$$

$$\vec{X}_1 = \vec{X}_\alpha - \vec{A}_1.(\vec{D}_\alpha),\ \vec{X}_2 = \vec{X}_\beta - \vec{A}_2.(\vec{D}_\beta),\ \vec{X}_3 = \vec{X}_\delta - \vec{A}_3.(\vec{D}_\delta),$$

$$\vec{X}(t+1) = \frac{\vec{X}_1 + \vec{X}_2 + \vec{X}_3}{3}$$

The mathematical representations of the social order in the GWO algorithm include encircling, attacking, and tracking prey.

5 Grey Wolf Optimization based DNN

The output layer, hidden layers, and input layer make up the main three elements of the DNN architecture. Fig.6 depicts the DNN architecture that has been suggested. The DNN is built with 2 hidden layers to perfectly learn the mapping connection between the output and input data by taking the effort of weight fitness into account. The DNN iteratively modifies the hidden neurons in the hidden layers during the training process using the GWO. This neural network continues to fit the decision boundary of the labelled training as the training trials rise. Equation (5) is used to calculate the overall number of nodes in the hidden layer.

$$N = \sqrt{a+b} + c \qquad (5)$$

where a denotes the number of nodes in the input layer, b is the number of nodes in the output layer, n is the number of nodes in the hidden layer, and c a fixed value between [1,10]. In the hidden layer of the DNN, an activation function is introduced to enable the non-linear fitness capability. The activation function we used, the sigmoid, is given as,

$$S = \frac{1}{1+e^{-x}} \qquad (6)$$

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The mapping function Mf activates the network's incoming data, which is referred to as x.

$$M_f = sigm\,(\omega_i X + \beta_i)$$

where, correspondingly, x and b stand for the weight matrices and the bias between the output layer and the hidden layer.

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5.1 Modelling using GWO-DNN Algorithm

The inverse and forward modelling of processes using GWO-DNN algorithms is described in this part. The created physical model is stimulated by uniformly perturbed random input signal. 1000 data points were gathered from the physical model. The forward and inverse models are developed using the common GWO-DNN structures.

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5.2 Forward Model using GWO-DNN algorithm

Forward modelling is the process of representing forward dynamics of the process. In order to predict the present output, the process's forward modelling makes use of the past inputs and outputs. In order to create a forward model of the pH process, acid flow rate and pH readings are taken into account. Figure 2 depicts the schematic representation of GWO-DNN forward model. The forward model is trained using the following values.

Input vectors	:	$[pH(k-1)\quad pH(k-2)\quad F_A(k-1)]$
Output vector	:	$p\hat{H}(k)$
Sampling interval	:	15 sec

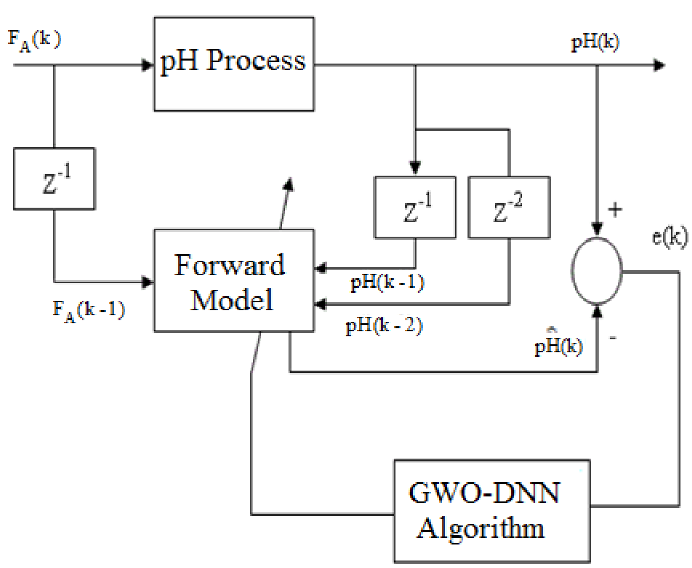

Figure.2. Schematic representation of GWO-DNN forward model.

5.3 Inverse Model using GWO-DNN Algorithm

Inverse modelling is the process of representing the inverse dynamics of the system. GWO-DNN Inverse model uses the current output, delayed input, and delayed outputs to train the inverse GWO-DNN model. Figure 3 depicts the schematic representation of GWO-DNN inverse model. The non-linear inverse model-based control scheme is one such way of control. This technique, however, heavily relies on the accessibility of the system's inverse, which is challenging to determine analytically for non-linear systems. Therefore, the inverse modelling and analysis can be developed using GWO-DNN. The inverse model is trained using the following values.

Input vectors	:	$[F_A(k-1) \quad pH(k) \quad pH(k-1)]$
Output vectors	:	$\hat{F}_A(k)$
Sampling interval	:	15 sec

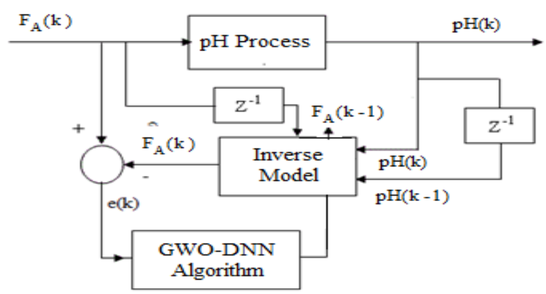

Fig.3. Schematic representation of GWO-DNN inverse model.

Forward and inverse models that have been created are used to create the Internal Model Control structure. Figure 4 shows the structure of IMC with developed GWO-DNN based forward and inverse models.

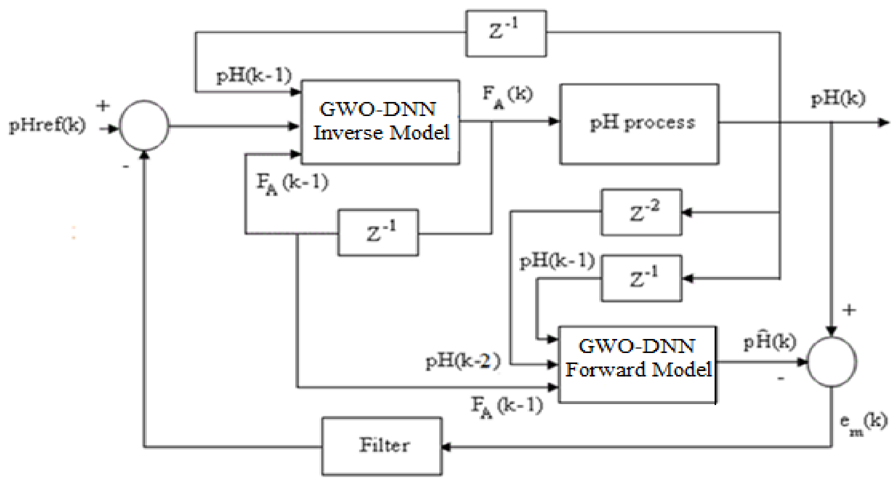

Fig. 4. Structure of IMC using GWO-DNN forward and inverse models.

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6. Results and Discussion

The controlled variable (pH) profiles and the manipulated variable (FA) profiles are presented in Figures.5 and 6, respectively. Large overshoot and setting time are produced by the PI controller. DNN IMC doesn't show any appreciable variations. The accuracy of GWO-DNN IMC is clearly visible around all operating conditions as shown in Figure 5. Table 2 lists the performance metrics for the servo response of the pH process using the DNN IMC, GWO-DNN IMC, and PI controller.

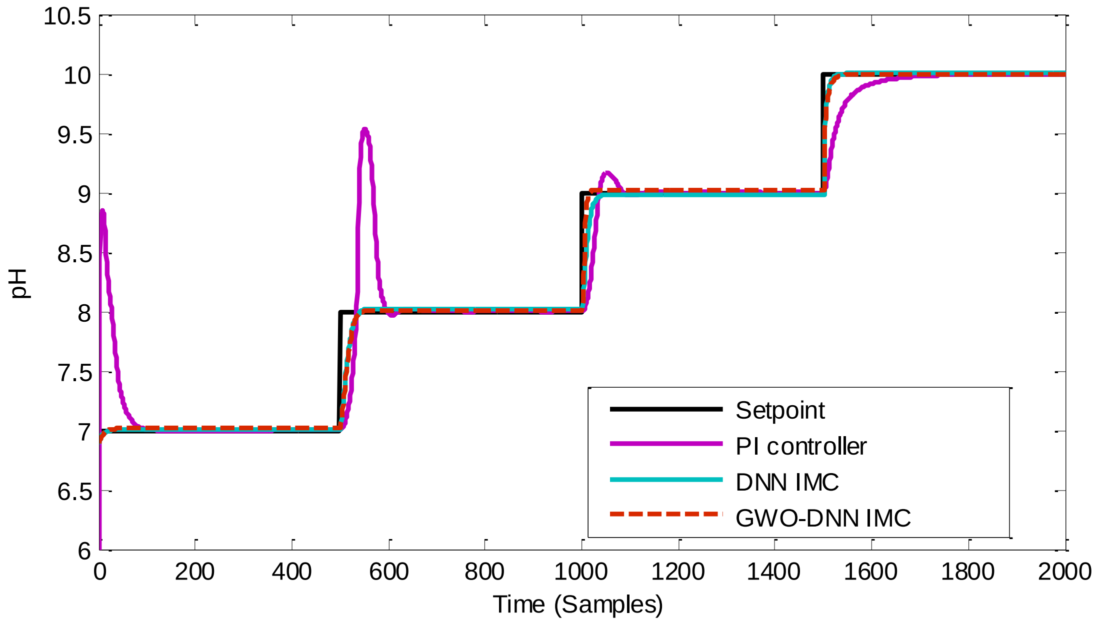

Figure.5. Servo Response of pH Process with PI, DNN IMC and GWO-DNN IMC.

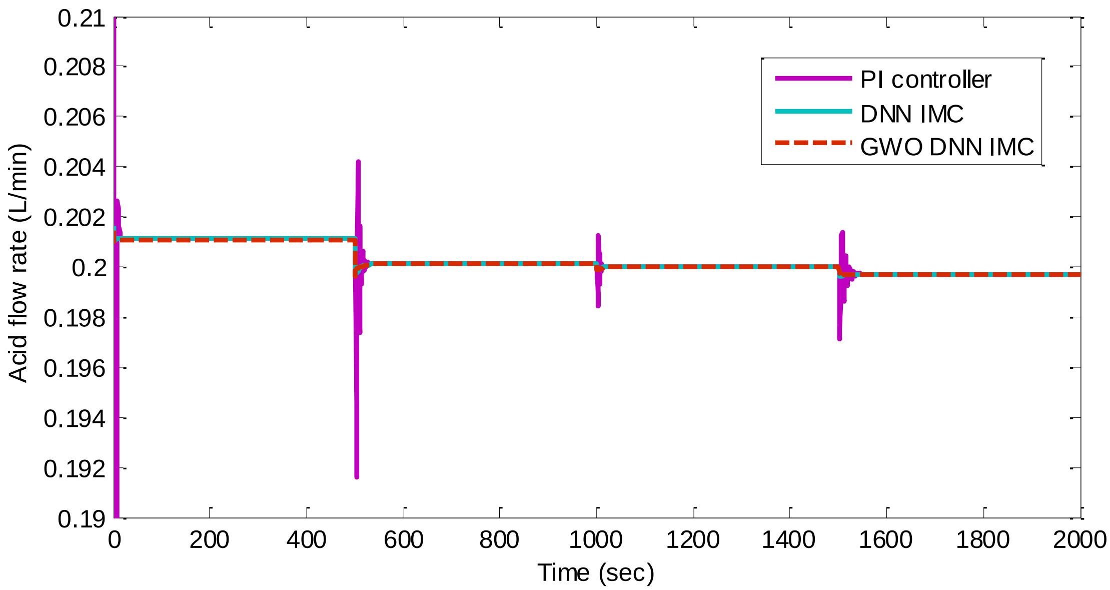

Figure.6. Controller Output of pH Process with PI, DNN IMC and GWO-DNN IMC for Set Point Tracking.

Table 2 Performance Measures of PI, DNN IMC and GWO-DNN IMC for Set-Point Tracking

SP Change in pH	ISE			Settling Time (Seconds)		
	PI	DNNIMC	GWO-DNN IMC	PI	DNNIMC	GWO-DNN IMC
7-8	15.88	9.32	9.37	112	59	54
8-9	11.31	7.46	5.28	185	52	22
9-10	4.45	3.53	3.25	303	50	45

The regulatory response of the pH process using the DNN IMC, GWO-DNN IMC, and PI controllers at the operating points of pH 9 and 7 is shown in Figures 7 and 9 and the associated controller outputs are presented in Figures 8 and 10 respectively. At the 250th second, a base flow rate step variation of 10% above the nominal value is applied, and the resulting pH variation is measured. Figures 7 and 9 show the shortcomings of the PI controller and DNN IMC. PI controller and DNN IMC generate massive IAE, ISE, and settling time when the disturbance is applied, whereas GWO-DNN IMC generates smaller IAE, ISE, and settling time with zero offset. Table 3 lists the performance metrics for the regulatory reaction of the pH process using the DNN IMC, GWO-DNN IMC, and PI controller.

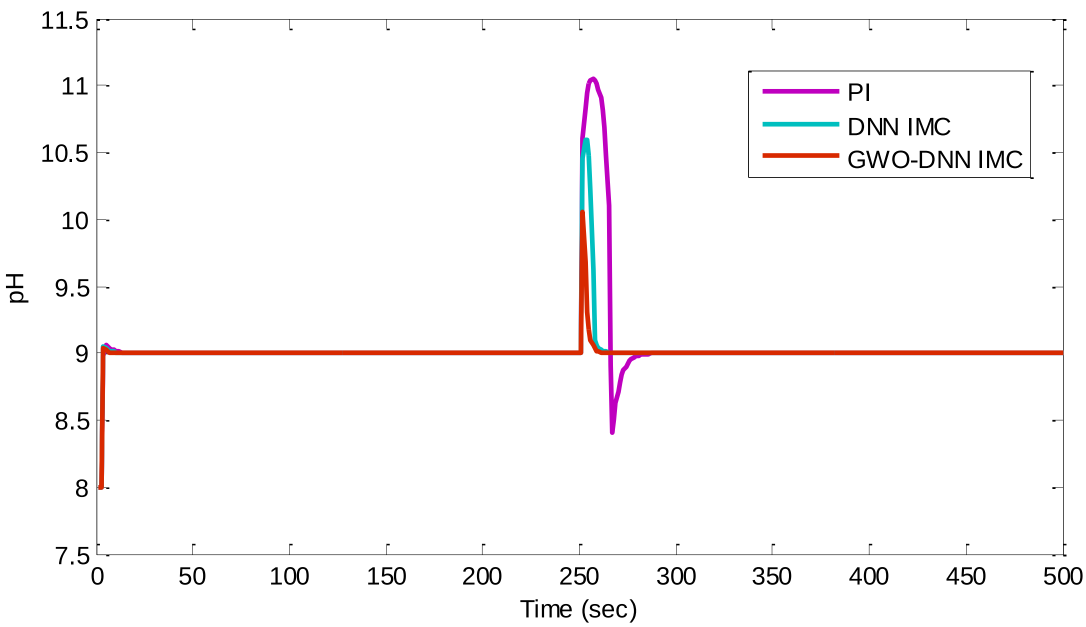

Figure.7. Simulated regulatory response of pH process with PI, DNN IMC and GWO-DNN IMC at the Operating Point of 9 (10% Load Change in base flow rate applied at 250th Second)

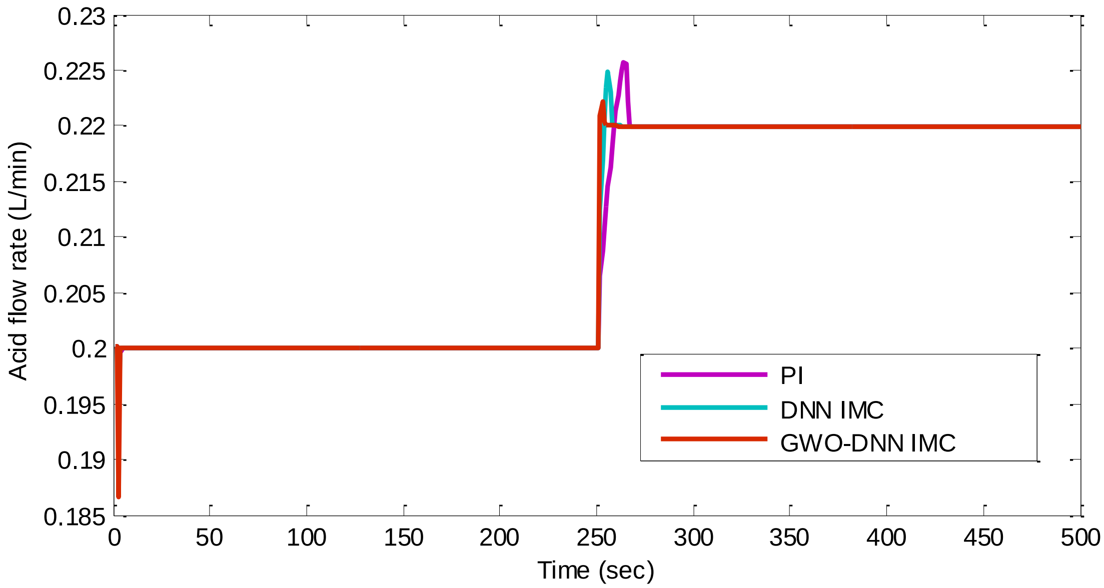

Figure.8. Controller output of pH process with PI, DNN IMC and GWO-DNN IMC at the Operating Point of 9 (10% load change in base flow rate applied at 250th Second).

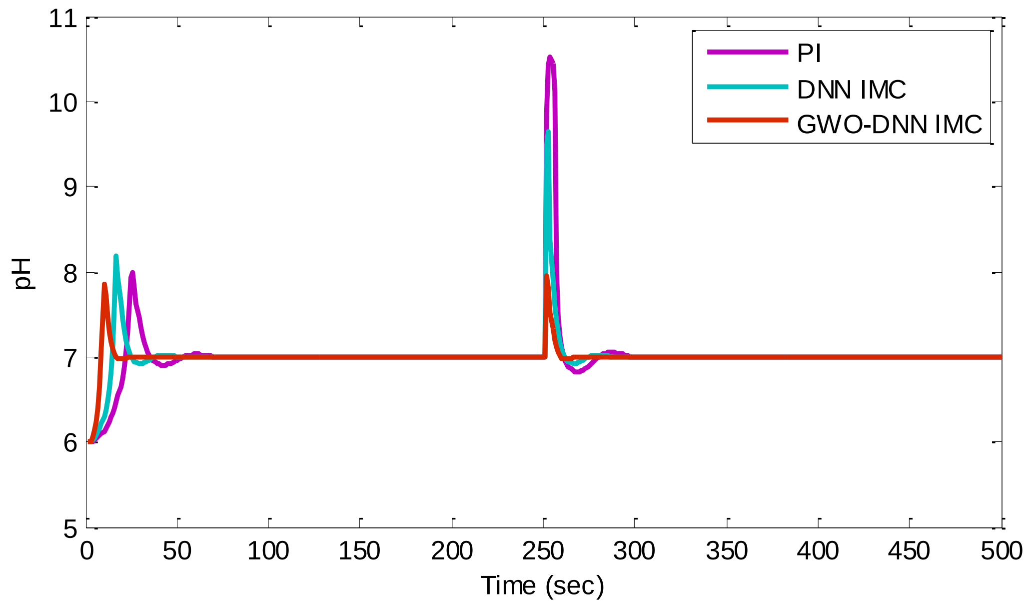

Figure.9. Simulated regulatory response of pH process with PI, DNN IMC and GWO-DNN IMC at the Operating Point of 7 (10% Load Change in base flow rate applied at 250th Second)

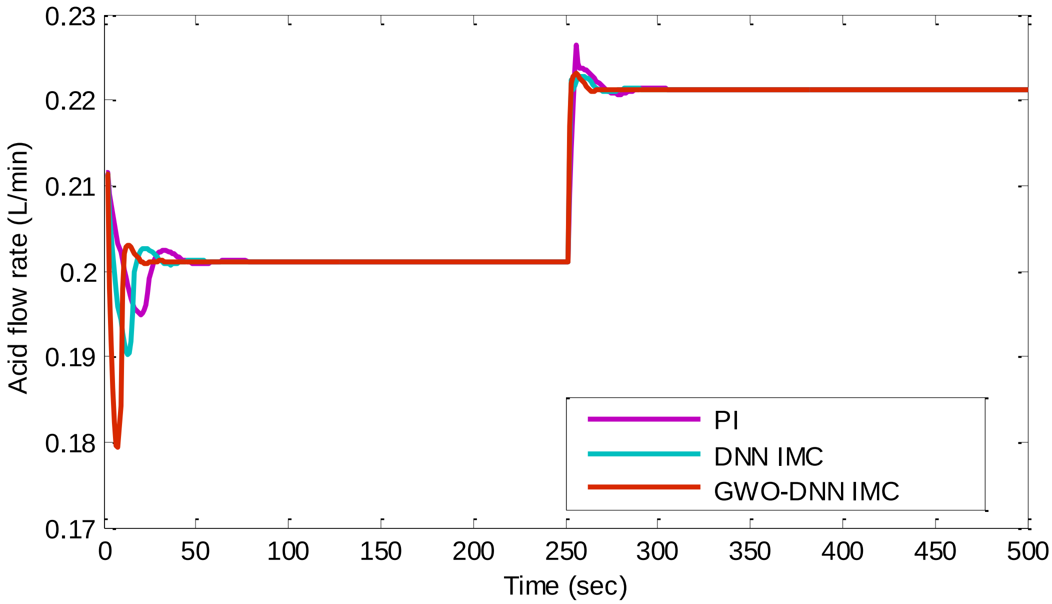

Fig.10. Controller Output of pH process with PI, DNN IMC and GWO-DNN IMC at the operating point of 7 (10% Load Change in Base Flow Rate applied at 250th Second).

Table 3 Performance Measures of PI, DNN IMC and GWO-DNN IMC Controller for load disturbance in base flow rate.

Operating Point	Percentage of Load Change in Base Flow Rate	ISE			Settling Time (Seconds)		
		PI	ANFIS IMC	BFALOLIMOT IMC	PI	ANFIS IMC	BFALOLIMOT IMC
pH 7	+10	54	15.1	2	52	34	16
pH 9	+10	44	14.7	2.1	22	15	12

7.Conclusion

This work discussed the design procedure of PI controller using pole placement technique. Also the Grey Wolf Optimization based DNN IMC scheme is created and applied. The servo response of the pH process at different operating points reveals that the GWO-DNN IMC outperforms when compared with those of DNN IMC and PI controller in terms of performance metrics. The superiority of the proposed GWO-DNN IMC was proved by the regulatory response of the pH process at the operation conditions of pH 7 and 9 in terms of ISE and settling time.

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