Meta Heuristic Optimization based Model Based Controller for a Experimental pH Process

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ABSTRACT
Achieving high-performance and robust pH control can be challenging due to the nonlinear and time-varying characteristics of the process. The pH process can exhibit significant static nonlinear behavior because the process gain can vary greatly over the modest range of pH values. Additionally, the titration curve may change over time due to unmeasured variations in the buffering capacity. These nonlinearities make it difficult to control the pH process using conventional techniques. In this study, the titration curve of the pH process is obtained through both simulation and experimentation, using weak acid (CH3COOH) as the process stream and strong base (NaOH) as the titrating stream. A conventional PI controller is designed based on the obtained process parameters for different zones of the pH process. However, the designed PI controller may not provide satisfactory responses when the operating point changes from one zone to another. To address this issue, an optimized intelligent model-based controller is proposed for the non-linear pH process in real time.

Keywords: capacity, difficult, nonlinear, optimized.

1. INTRODUCTION

Mathematical modeling of the pH process is considered 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 using conventional techniques. In the modeling aspect, rigorous models from first principles involving the material balance and equilibrium equations were established by McAvoy [1] and was generalized to systems with an arbitrary number of acids and bases by Gustafsson, and Waller [2]. The model was derived from first principles, material balances and chemical equilibria and has become generally accepted in the literature.

In many practical pH processes time delays, time constants, gains and sensitivities change over a wide range occurs mainly due to varying flow and their chemical contents. A fixed model (off-line modeling) cannot adjust to variations in the process and an adaptive model (on-line modeling) has many practical problems. Unbiased and efficient model identification with in a control loop is difficult. The controlled signal can also be poor in many frequencies i.e. the system is not persistently exciting. From the control point of view, keeping the pH value constant at reference value is in many cases the objective of control whereas from the modeling point of view, system identification from practically constant signals is impossible or at least inefficient. Shinskey [3] developed an adaptive analogue controller that consisted of a conventional PID controller combined with a non-linear gain shaping element. The controller was commercially available and it was used in many practical applications.

In practice a fixed PID controller and its modifications are the most common controllers for pH control and that is hardly surprising because most of the practical pH processes are heavily buffered, approximately linear and very robust. However, there are a significant number of difficult, practical pH processes that can benefit from advanced control strategies. In addition to practical applications, there are also many pilot processes that are designed intentionally to be challenging for research purposes.

Pajunen [4] and Norquay et al.,[5] both used Wiener model assumption (linear dynamics and static nonlinearity) in their research. They used a linear ARX-model structure for the dynamic part and different approaches for the static nonlinearity. Pajunen used a piecewise linear approximation for the titration curve whereas Norquay modeled the nonlinearity with cubic splines. In both cases the inverse of the nonlinearity (corresponds to inverse titration curve) was used for pseudo-linearisation of the control loop. Pajunen used a model reference algorithm and Norquay used a model predictive algorithm as the actual controller. Arvind Kumar et. al., [6] developed the Wiener model based controller for the lab-scale pH setup. The performance of Wiener model based controller was compared with that of linear PI controller. An approach to the identification of time-varying, non-linear pH processes based on the Wiener model structure was reported by Kalafatis et. al.,[7]. The algorithm produces an on-line estimate of the titration curve, where the shape of this static nonlinearity changes as a result of changes in the weak-species concentration or composition of the process feed stream.

The Hammerstein model structure based model predictive control scheme was proposed for a pH process by Fruzzetti et.al, [8]. The wavenet based a Hammerstein model structure is shown to have potential for modeling strongly non-linear processes like the pH process. The systematic and sequential approach used for developing the Hammerstein model simplifies the problem of modeling the non-linear static nonlinearity and linear dynamics [9].

Jacobs and a group of researchers [10] and Proudfoot et.al., [11] did several industrial implementation of pH control. They used general model of first order dynamics with titration curve as the nonlinearity. They applied conventional and adaptive control strategies on a process that appeared to be a strong acid-strong base system with some minor buffering (due to carbon dioxide or the chemicalisation of municipal water).

Internal model control has been extensively applied to the pH process by sivaraman [12,13]. They estimated the weak acid concentration in the inflow and used the calculated concentration in the control law. In the research work of Subramani and Krishnaswamy [14] a fuzzy tuning was combined to the model. Hu et.al., [15] tested the augmented internal model controller with a laboratory scale pH pilot process (in this practical application buffering was added). In pilot experiments, the internal model controller outperformed the conventional PI-controller.

Neural network have not had a similar commercial breakthrough as fuzzy logic and practical application in pH control. Loh et.al., [16] viewed different approaches to neural network modeling and control in a pH process. Palancar et.al [17] developed a neural controller that consisted of two artificial neural networks, the first of which described the plant model and the second plant 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 neural networks learned plant on-line, i.e., the controller was adaptive. 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 [18].

Implementation of a neural network model-based predictive control scheme to a laboratory-scaled multivariable chemical reactor was described and three variables were controlled in the reactor - temperature, pH and dissolved oxygen [19]. Neural network to on-line updated PID controllers for pH process was reported by Chen and Huang (2004). Neural network approximation of non-linear model predictive controllers have been studied and illustrated for a simulated non-linear pH process. Simulation and real-time implementation of recurrent neural network for pH process has been addressed by Sivakumaran [20]. In this work an attempt is made to develop Grey Wolf Optimization based Deep Neural Network Internal Model controller for a real time pH process.

2. Mathematical Modeling of pH Process

The acid–base neutralization process is considered in this work. The process stream consists of a sodium hydroxide (NaOH) solution and the titrating stream consists of an acetic acid (CH_3COOH) solution. The cubic polynomial in hydrogen ion concentration $[H^+]$ with unknown ζ and ξ is expressed as

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

The reaction invariants, ζ and ξ are found from the following mass balances

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

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

where F_A is the acid flow rate (0-0.5 LPH), F_B is the base flow rate (0.4 LPH), C_A is the acid concentration (0.2 mol/L), C_B is the base concentration (0.1 mol/L), $[H^+]$ is the hydrogen ion concentration and V is the liquid volume (7.4 L^3). Finally the pH is calculated as

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

The steady-state titration curve for the acid-base neutralization process is obtained by solving the eqns. (1), (2), (3) and (4) in simulation using SIMULINK for change in the acid flow rate (F_A) from 0 – 0.5 L/min. The SIMULINK model of a pH process is shown in Figure 1. The titration curve is also obtained experimentally using ADAMS 5000 MATLAB interfacing card. The system is run experimentally in open-loop at different acid flow rates and at each acid flow rate, the pH values are measured after the system attained its steady state.

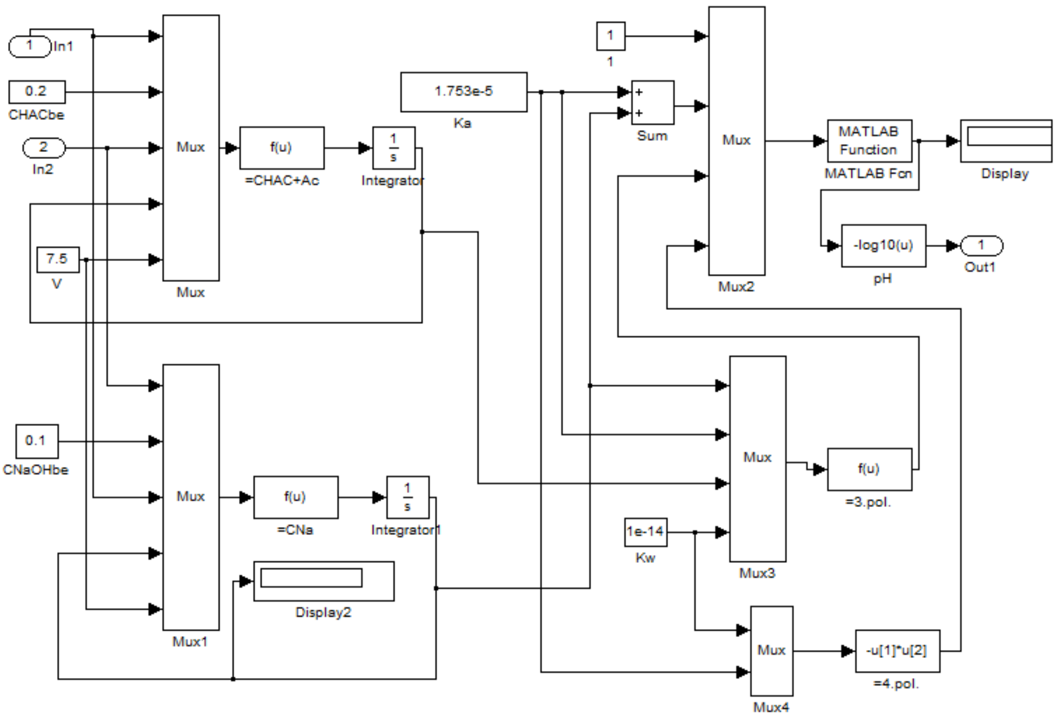

Fig 1

The acetic acid flow rate is varied from 0 to 0.5 LPH in small suitable steps and the corresponding variation in the pH process are recorded and presented in Table 1. The non-linear behavior of pH process clearly visible from Table 1. and Figure 2.

Table 1. Simulated input-output datas of pH process.

S.No	Acid Flow Rate (F_A)	pH	S.No	Acid Flow Rate (F_A)	pH
1	0	13	52	0.199995	8.86
2	0.1	12.6	53	0.199997	8.825
3	0.11	12.55	54	0.199998	8.814
4	0.12	12.49	55	0.2	8.79
5	0.13	12.42	56	0.2001	8.043
6	0.14	12.35	57	0.2002	7.753
7	0.15	12.26	58	0.2003	7.579
8	0.16	12.15	59	0.2004	7.454
9	0.17	12.02	60	0.2005	7.358
10	0.18	11.84	61	0.2006	7.279
11	0.185	11.71	62	0.2007	7.212
12	0.189	11.57	63	0.2008	7.154

13	0.19	11.53	64	0.2009	7.103
14	0.191	11.48	65	0.201	7.057
15	0.192	11.43	66	0.202	6.756
16	0.193	11.37	67	0.203	6.58
17	0.194	11.31	68	0.204	6.455
18	0.195	11.23	69	0.205	6.358
19	0.196	11.13	70	0.206	6.279
20	0.197	11	71	0.207	6.212
21	0.198	10.83	72	0.208	6.154
22	0.1981	10.8	73	0.209	6.103
23	0.1982	10.78	74	0.21	6.057
24	0.1983	10.75	75	0.22	5.756
25	0.1984	10.73	76	0.23	5.58
26	0.1985	10.7	77	0.24	5.455
27	0.1986	10.67	78	0.25	5.358
28	0.1987	10.64	79	0.26	5.279
29	0.1988	10.6	80	0.27	5.212
30	0.1989	10.57	81	0.28	5.154
31	0.19891	10.56	82	0.29	5.103
32	0.19892	10.56	83	0.3	5.057
33	0.19894	10.55	84	0.31	5.016
34	0.199	10.52	85	0.32	4.978
35	0.1991	10.48	86	0.33	4.944
36	0.1992	10.43	87	0.34	4.911
37	0.1995	10.22	88	0.35	4.881
38	0.1996	10.13	89	0.36	4.853
39	0.1997	10	90	0.37	4.827
40	0.1998	9.828	91	0.38	4.802
41	0.1999	9.537	92	0.39	4.779
42	0.19991	9.494	93	0.4	4.757
43	0.19994	9.337	94	0.41	4.735
44	0.19995	9.272	95	0.42	4.715
45	0.19996	9.197	96	0.43	4.696
46	0.19997	9.112	97	0.44	4.677
47	0.19998	9.015	98	0.45	4.66
48	0.19999	8.906	99	0.46	4.643
49	0.199991	8.895	100	0.47	4.626
50	0.199992	8.883	101	0.48	4.61
51	0.19999	8.872	102	0.49	4.595
			103	0.5	4.581

3. Experimental Setup of pH Process

The experimental setup of pH process is shown in Fig 2. It has two input streams, one containing acetic acid (CH_3COOH) as titrating stream and the other containing sodium hydroxide (NaOH) as process stream. Acid and base are stored in acid and base tank respectively. In this work, the acid flow rate is varying from 0-0.5 L/min and base flow rate is kept constant at 0.4 L/min. The dozed valveless metering pumps are used to pump the acetic acid and sodium hydroxide streams into the process tank with resolution of 0.72 ml/revolution. The flow of acid and base are not continuous but they are fed in dozed manner. The operating range of the pumps is 0-0.8 L/min. Stirrer is used to provide proper mixing to maintain uniform concentration throughout the process tank. The output variable is hydrogen ions present in the effluent stream, which is measured as pH using glass electrode based pH sensor in combination with pH transmitter (ABB make). The output from the pH transmitter is 4-20 mA. After the signal conditioning circuit voltage is fed into computer through ADC. Then the control algorithm calculates the error and generates the proper manipulated variable, which alters the acid flow rate into the process tank and maintains the desired pH value in closed-loop control. The comparison of simulated and experimental titration curves are shown in Fig.3. From this figure it can be concluded that the nonlinear model equations represent the static behavior of the system reasonably well.

Fig.2. Experimental setup of a pH process.

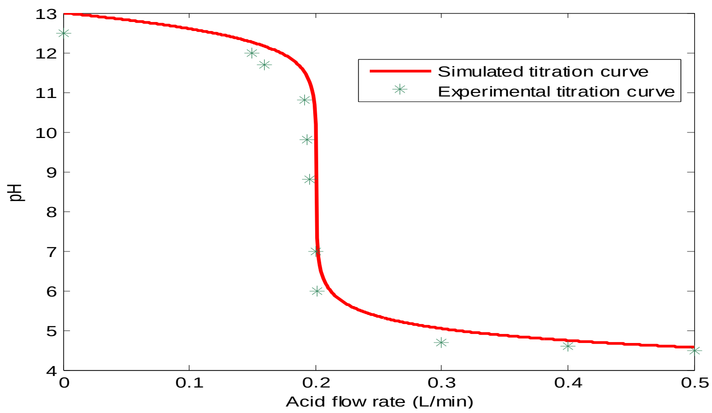

Fig.3. Comparison of simulated and experimental titration curves.

4. Interfacing Module

The ADAM-5000 series is a data acquisition and control system which can control, monitor and acquire data through multi-channel I/O modules. Encased in rugged industrial grade plastic bases, the system provides intelligent signal conditioning, analog I/O, digital I/O, RS-232 and RS-485 communication. The ADAM-5000 can handle up to any 4 combinations of I/O modules, while ADAM-5000E can handle up to 8 combinations of I/O modules.

Major features**:** The ADAM-5000 system consists of two major parts: the system kernel and I/O modules. The kernel includes a CPU card, power regulator, 4 slot base,8 slot base, built in RS-232 communication port, and a pair of built in RS-485 ports.

CPU- functions:

- Data acquisition and control of all I/O modules in the system.
- Alarm monitoring
- Data transformation
- Diagnosis (4 LEDs (PWR,RUN,TX,RX)to provide visual information of ADAM-5000 system, software diagnosis is also possible via RS-232)
- Calibration software and command set.

Components of ADAM 5000:

Processor: CPU- 80188, 16 bit microprocessor.

32 KB RAM, 128 KB ROM

Watchdog timer
Power consumption: 1.0 W (ADAM 5000)
Communication:
Speed: 1200 bps to 115.2 Kbps
Max distance: 4000 ft
Protocol: ASCII command
Communication error check: checksum
Asynchronous data format: 1 start bit, 8 data bit, 1 stop bit.
ADAM-5017, 8 channel analog input modules: The ADAM-5017 is a 16 bit, 8 channel analog differential input modules that provides programmable input ranges on all channels. It accepts mV inputs (±150 mV, ±500 mV), voltage inputs (±1V, ±5Vand ±10 V) and current input (±20 mA, requires resistor). The module provides data to the host computer in engineering units (mV, V or mA).
ADAM-5024, 4 channel analog output module: The ADAM-5024 is a 4 channel analog output module. It receives its digital input through the RS-485/232 interface of the ADAM-5000 system module from the host computer. It then uses the D/A converter controlled by the system module to convert the digital data into output signals.
The ADAM- 5000 series with input module (ADAM-5017) and output module (ADAM - 5024) used for interfacing the sensors and actuators of the process under study with the computer is shown in Fig.2. The module is configured at a baud rate of 9.6 Kbps and is supplied with ±24V for its operation. The input and output modules operate on current signal. The ADAMS interfacing module is shown in Figure 4.

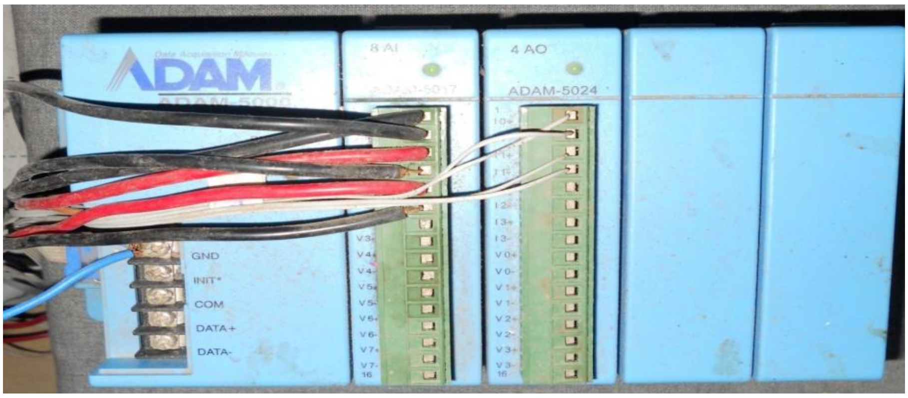

Fig.4. Real-time interfacing module (ADAMS-5000).

5. GWO based DNN Internal Model Controller

The general structure and description of GWO based DNN internal model controller for a experimental pH process is shown in Figure 5. It consists of an inverse model and the forward model, which is connected in parallel with the experimental pH process. Compared to conventional controllers, the IMC structure has only one tuning parameter λ and it is set to a value of 30 by repeated simulation studies. The experimental result for GWO based DNNIMC shows the good set point tracking comparable to the PI controller. The performance measures of the controllers are given in Table 1.

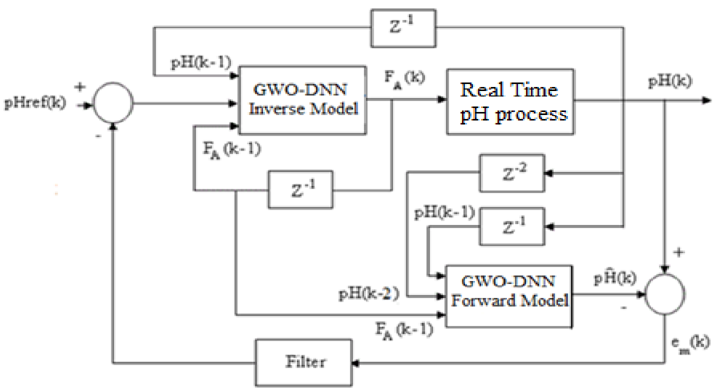

Fig.5. GWO based DNN Internal Model Controller

6. RESULTS AND DISCUSSION

The experimental result of pH process for the operating point of 7 and 8 by implementing PI controller and GWO based DNN IMC are shown in Figures 6 ,7,8 and 9 respectively along with controller output. The performance indices are given in Table 1. The results reveal that GWO based DNN IMC gives superior result in experimentation when compared to conventional PI controller.

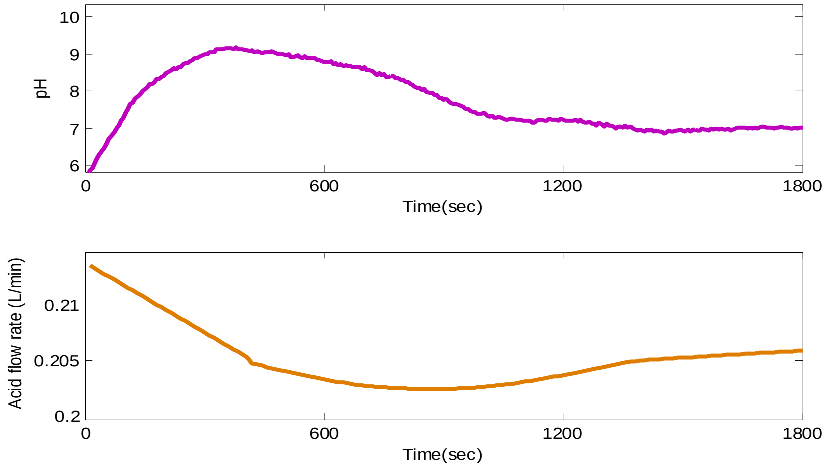

Fig. 6 Experimental servo response of a pH process with PI Controller (setpoint change from 6 to 7)

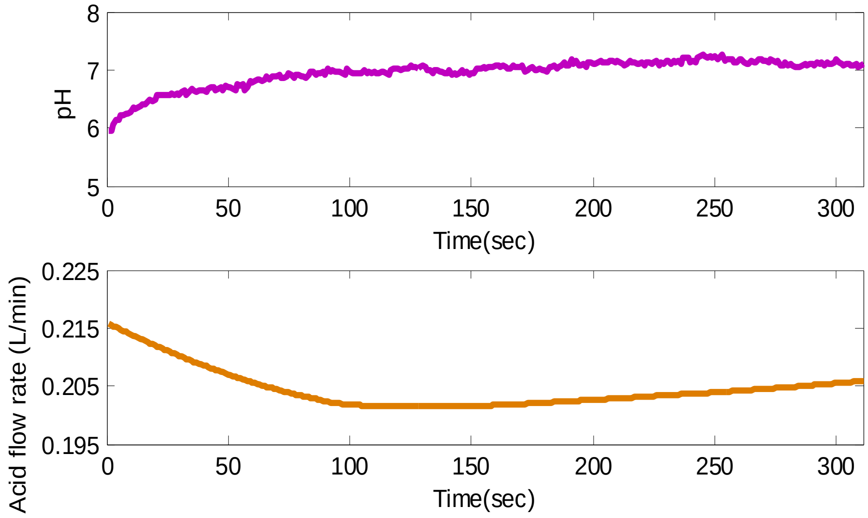

Fig.7 Experimental servo response of a pH process with GWO based DNN IMC (setpoint change from 6 to 7).

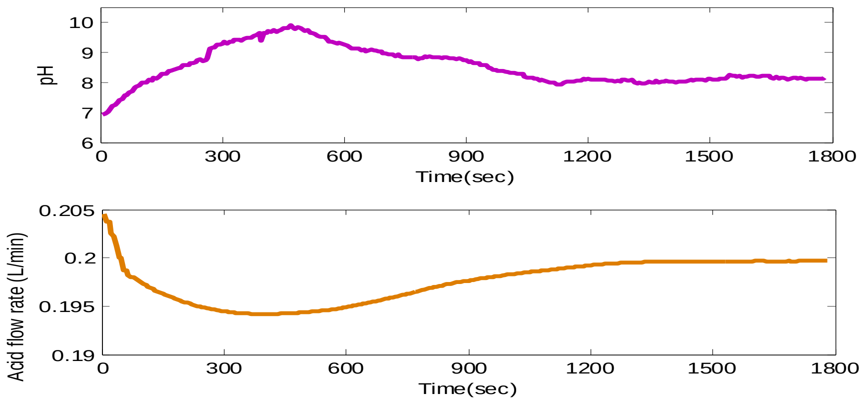

Fig.8 Experimental servo response of a pH process with PI controller (setpoint change from 7 to 8).

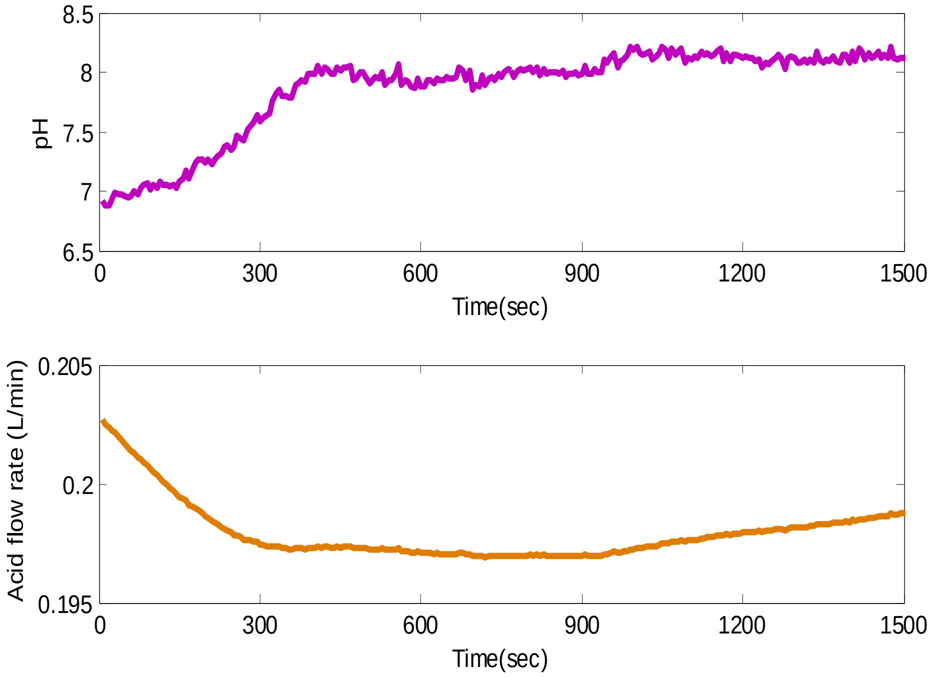

Fig.9 Experimental servo response of a pH process with GWO based DNN IMC (setpoint change from 7 to 8).

Table 1. Performance measures of experimental pH process with PI and GWO based DNN IMC

Setpoint Change	**ISE**		**IAE**		**Settling time (seconds)**	
	PI	**GWO based DNN IMC**	**PI**	**GWO based DNN IMC**	**PI**	**GWO based DNN IMC**
pH 6-7	6837	2423	3697	1529	1452	278
pH 7-8	7112	1654	3948	936	1526	956

CONCLUSION

In this work, the real time pH process experimental setup was developed and the obtained experimental titration curve was compared with that of simulated titration curve. The GWO based DNN IMC and PI controllers are were designed and implemented for a real time pH process. The servo response of pH process at various operating points shows that the GWO based DNN IMC produces better result when compared with that of PI controllers. The GWO based DNN IMC produces minimum values of ISE, IAE and settling time when compared with PI controller.

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