Design and Implementation of Adaptive Fuzzy Knowledge Based Control of pH for Strong Acid-Strong Base Neutralization Process

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ABSTRACT

pH control is a benchmark for control of nonlinear processes because of its importance in a number of industrial process applications. Fuzzy Knowledge Based Control (FKBC) of such nonlinear processes incorporates the method for constructing nonlinear controllers using heuristic experience. This paper describes design and implementation of adaptive FKBC for a pH neutralization process consisting of strong acid (Hydrochloric acid, HCl) and strong base (Sodium Hydroxide, NaOH) streams in the multifunctional Process Control Teaching System (PCT40) with Process Vessel accessory (PCT41) and pH Probe accessory (PCT42) of Armfield® Ltd., United Kingdom. The adaptive FKBC modifies fuzzy universe of discourse by using adaptive gain matrix based on error and change in error. The adaptive FKBC has been tested for servo as well as regulatory operation, and it proves itself to be simple, fast, and providing satisfactory performance evaluated in terms of Integral of Squared Errors (ISE). Results of adaptive FKBC for servo and regulatory operations have been compared with optimized fuzzy logic control schemes using Genetic Algorithm (GA), Differential Evolution (DE), and Particle Swarm Optimization (PSO) techniques. The pH neutralization system is interfaced with Laboratory Virtual Instrumentation Engineering Workbench (LabVIEW®) for experimental validation of results.

Keywords: strong acid-strong base neutralization process; nonlinear process; pH control; fuzzy knowledge based control; adaptive control; intelligent control.

INTRODUCTION

Intense global competition, profit based business strategies, rapidly changing socioeconomic conditions, demands of better quality control, increased safety concerns, and stringent environmental norms are prompting many process industries to automate their operations using accurate, robust, reliable, efficient, optimal, adaptive, and intelligent advanced control system. Control system design is greatly influenced by the amount of nonlinearities present within process. Classical controllers such as Proportional-Integral-Derivative (PID) or Proportional-Integral (PI) are adequate if the nonlinearity encountered is very mild. In presence of appreciable amount of nonlinearities, however, such linear models are ineffective since even small disturbances can force process away from the operating point. A good way to compensate processes with known nonlinearities and operating condition variations is use of adaptive control techniques. An adaptive control system automatically adjusts its parameter using feedforward, feedback, or both strategies to compensate for corresponding variations in the properties of the process [Shinskey, 1979; Cohen & Friedmann, 1974; Åström & Wittenmark, 2008]. Nonlinear dynamics of pH neutralization process lead to development of many variants of adaptive control, with popular ones being Gain-scheduling, Model Reference Adaptive Control (MRAC), and Self-Tuning Regulator (STR). Gain-scheduling is based on determination of process operating conditions and then accordingly changes the controller parameters in order to compensate process variations [Lin & Yu, 1993; Chan & Yu, 1995; Klatt & Engell, 1996]. MRAC uses a reference model of the process that tells how the process output should ideally respond to the command signal [Palancar et al., 1996]. Although MRAC is a good alternative to PID, it has to be tuned for each particular process and the tuning depends on the presence of lag, delay, and other factors. For non-well-known processes, the controller must be tuned experimentally, and it could be a disadvantage from a commercial or business point of view. STRs are intended to control systems with unknown but either constant or slowly varying parameters. STRs are generally composed of three parts: a parameter estimator, a linear controller, and a block that determines the controller parameters from the estimated parameters [Åström et al., 1977].

Fuzzy Knowledge Based Control (FKBC) utilizes fuzzy set theory proposed by Zadeh, which deals with an ambiguous and imprecise class of objects, called linguistic variables, and is characterized by membership functions with membership degrees assigned between 0 and 1, fuzzy conditional statements, and Fuzzy Inference System (FIS) [Zadeh, 1965; Zadeh, 2008]. Mamdani type and Sugeno type fuzzy logic controllers are two generalized and popular FKBC schemes [Mamdani, 1974; Mamdani, 1977; King & Mamdani, 1977; Procyk & Mamdani, 1979; Takagi & Sugeno, 1985]. FKBC has been widely applied to realize PI, PD, and PID schemes for pH control of neutralization process [Palancar et al., 2007; Jiayu et al., 2009; Saji & Sasi, 2010; Karasakal et al., 2013; Heredia-Molinero et al., 2014; AlSabbah et al., 2015; Kannangot et al., 2015]. Further, many researchers have used FKBC in association with neural networks for pH control of neutralization process [Jang & Sun, 1995; Eikens et al., 1995; Chen & Chang, 1996; Alkamil et al., 2018]. Additionally, many variants of gain-scheduled and self-tuned FKBC techniques are also available in the literature [Adroer et al., 1999; Fuente et al., 2002; Fuente et al., 2006; Babuska et al., 2002; Venkateswarlu & Anuradha, 2004; Salehi et al., 2009; Nsengiyumva et al., 2018]. Finally, some recent research works on the design of adaptive controller for nonlinear systems using backstepping technology have also been reported in the literature [Yu et al., 2018; Zhou et al., 2017; Xiang et al., 2017; Nejati et al., 2012].

Over the last four decades, researchers have proposed many pH control schemes using different techniques such as adaptive and intelligent. However, there are still considerable challenges in control of pH neutralization process. First, control of pH for strong acid (HCl)-strong base (NaOH) neutralization process has not been investigated extensively. Second, many reported works are based on simulation studies only and their experimental validations are often lacking. Third, the optimized fuzzy controller parameter values need to be retuned if either operating condition or process parameters change, and therefore the performance of adaptive FKBC needs to be compared with evolutionary and swarm optimization techniques based optimized fuzzy controller [Singh et al., 2018].

Armfield® pH Neutralization System

Armfield® Process Control Teaching System (PCT40) with Process Vessel Accessory (PCT41) and pH Sensor Accessory (PCT42), shown in Figure 1, has been used as a pH neutralization system. Armfield pH neutralization system is provided with a software package to facilitate the device interfacing with computer through USB. The device driver is installed on 32-bit Microsoft Windows® XP operating system. The system 32 directory contained following device driver files: ARMUSB.INF, ARMFIELDLTDTHERMUSB.INF, THERMUSB.SYS, ARMUSB.SYS, and ArmIFD.DLL. The first two files tell the computer how to recognize the data acquisition card, also called Interface Device (IFD), installed within the base unit PCT40 when the neutralization system is plugged in the computer. The next two files are the IFD drivers for the USB interface. The last file is a Dynamic Link Library (DLL), which is used to pass data between the user program and the IFD driver through USB interface. Based on types of I/O data, i.e., analog and digital, user can access, i.e., read and write, data logger for the IFD driver through basic function calls to DLL file. Few important pin connections of PCT40 are given next:

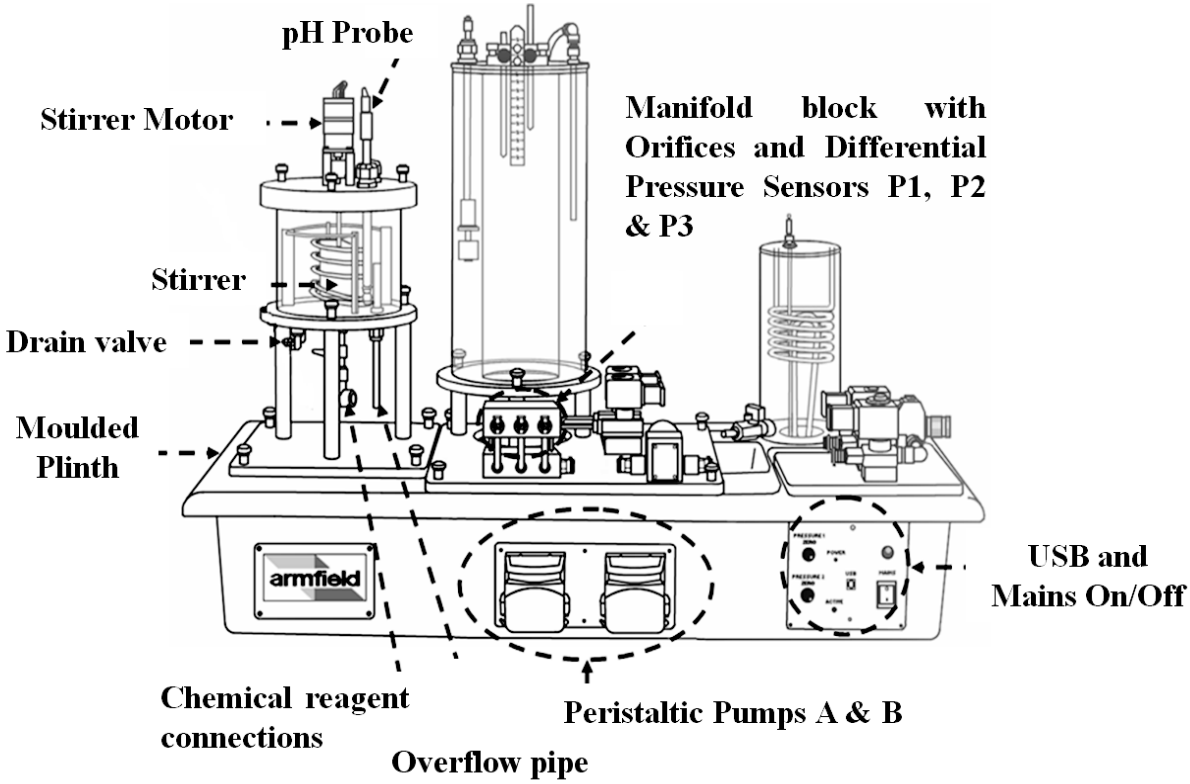

Figure 1. Armfield PCT40 with PCT41 and PCT42 schematic (*Courtesy: Armfield Ltd., UK*)

Pin 12: Analog input pin 12 corresponds to Channel 11 (Ch11), which gives PCT42 output on 0 to 5 V scale. The magnitude of 0 to 5 V is digitized into a 12-bit number. The interface passes a binary value between 000000000000 and 011111111111 to the computer.

Pins 22 and 24: Analog output pins 22 and 24 correspond to Digital to Analog Converters (DAC0 and DAC1), which give acid peristaltic pump A and base peristaltic pump B speeds, respectively, on 0 to 5 V scale. The magnitude of 0 to 5 V is taken from a 12-bit number. Here, the computer passes a decimal value between 0 and 2047 to the interface.

Pin 46: Digital output pin 46 corresponds to PCT41 stirrer ON/OFF condition. Here, the computer passes either logic 0 or logic 1 to the interface.

Interfacing software LabVIEW® 12.0 communicates with the Armfield pH neutralization system by accessing appropriate I/O data of the DLL file, using the following standard call library function node: ReadAnalog11ArmIFD.DLL (to read analog pH sensor value from Ch11), WriteAnalogsArmIFD.DLL (to write analog pump speed values to DAC0 and DAC1), and WriteDigitalsArmIFD.DLL (to write digital logic values to turn stirrer On/OFF).

To calibrate the flowrates F_a and F_b of pumps A and B, pump speeds S_a and S_b are varied from 0 to 100% in steps of 5%, respectively. Figure 2 shows the resulting linear calibration curve for pumps A and B flowrates. To calibrate the pH sensor voltage V_{pH}, the buffer solution having pH values 4, 7, and 9.2 is used. Figure 3 shows the resulting linear calibration curve for pH sensor. Table 1 summarizes important and selected specifications of Armfield pH neutralization system. It may be noted that specifications of Armfield PCT40 with PCT41 and PCT42 are comparable to parameters of the pH neutralization system available in the literature [Karasakal et al., 2013; Mészáros et al., 2009; Wan et al., 2006].

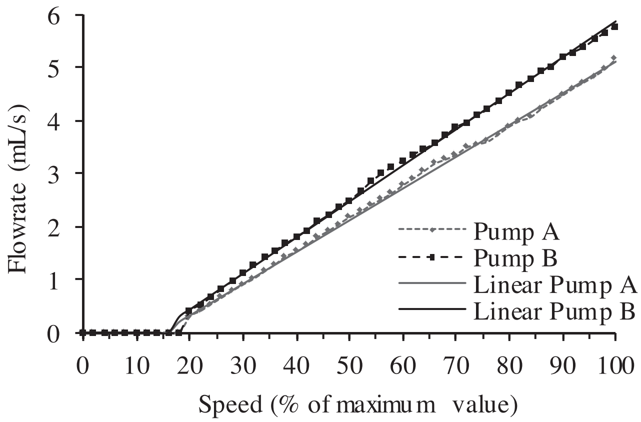

Figure 2. Peristaltic pumps flowrate calibration curve.

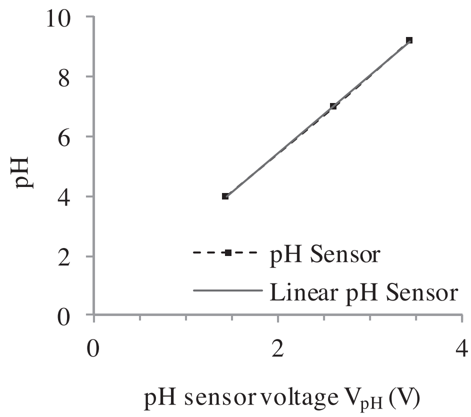

Figure 3. pH sensor calibration curve.

To obtain step responses of Armfield pH neutralization system for sampling duration of 300 seconds, the pH of the process is initially kept around the neutral point, i.e., pH = 7, with initial speeds of pumps A and B as S_{a0} = 35% and S_{b0} = 38.5%, respectively, and thereafter, by keeping pump A speed unchanged at S_{a0}, a step change in pump B speed ΔS_b is applied; i.e., the pump B speed is maintained at $S_{b0} + \Delta S_b$. Figure 4 shows the various plot of experimental output for S_{a0} = 35%, S_{b0} = 38.5%, and ΔS_b = 41.5%, 36.5%, 31.5%, 26.5%, 21.5%, 16.5%, 11.5%, 6.5%, 1.5%, -3.5%, -8.5%, -13.5%, and -18.5%. From experimental data, it is observed that the Armfield pH neutralization system is quite nonlinear in nature and it has a dead time of approximately three sampling instants, i.e., 3 seconds for all values of ΔS_b.

Table 1. Selected specifications of Armfield pH neutralization system.

Parameter	Specification
PCT41 process vessel volume	2000 mL
pH of raw water	6.7121
pH of HCl	1.75
pH of NaOH	12.1
Flowrate of pump A for Speed of pump A < 18%	0 mL/s
Flowrate of pump A for Speed of pump A = 18 to 100%	0.2021 to 5.1139 mL/s
Flowrate of pump B for Speed of pump B < 18%	0 mL/s
Flowrate of pump B for Speed of pump B = 18 to 100%	0.2989 to 5.8749 mL/s
Voltage of pH sensor	0 to 5 V
pH range	0.1868 to 13.2438
Sampling period	1000 ms

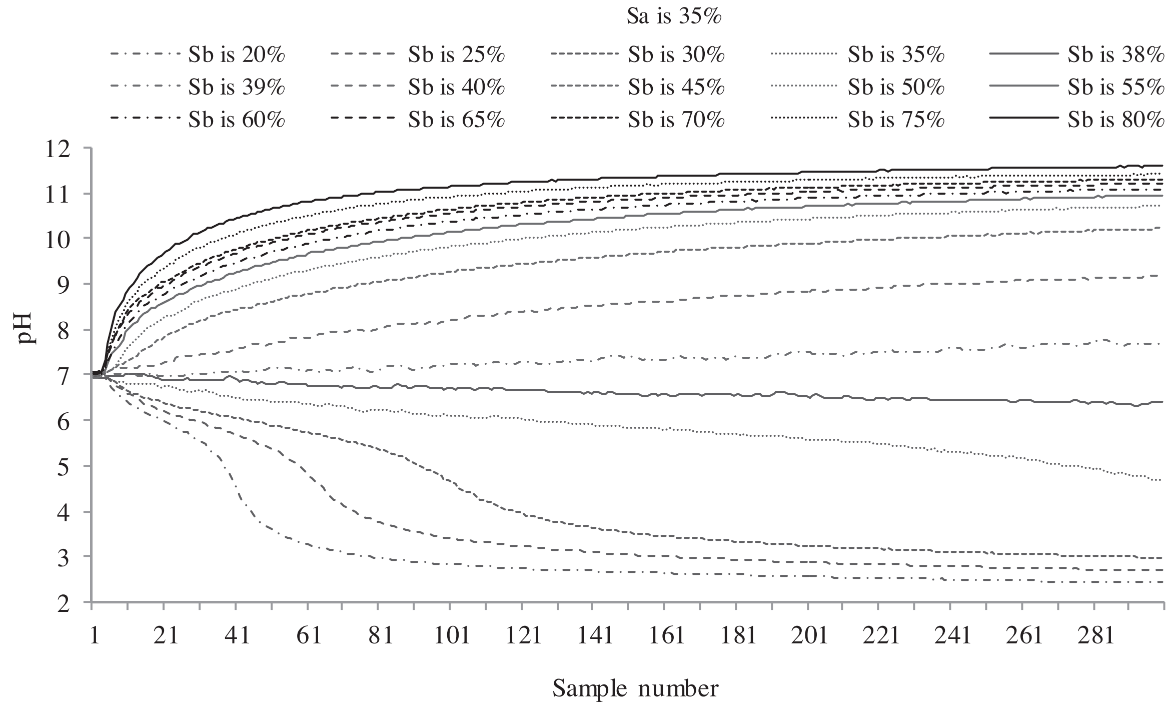

Figure 4. Step responses of pH neutralization system.

Adaptive FKBC

The adaptive FKBC structure is based on Mamdani Fuzzy Inference System (FIS), as shown in Figure 5. At k^{th} sampling instant, Mamdani FIS has linguistic input variables as normalized error $e^*(k) = e(k)/K_1$, in pH, and normalized change in error $ce^*(k) = ce(k)/K_2$, in pH, and linguistic output variable as normalized change in output $co^*_{FLC}(k) = co_{FLC}(k)/K_3$, in %, where K_1, K_2, and K_3 are scaling factors. Each linguistic variable can attain the following linguistic values: Negative Large (NL), Negative Medium (NM), Negative Small (NS), Zero (ZE), Positive Small (PS), Positive Medium (PM), and Positive Large (PL). The fuzzy membership functions of linguistic variables have been shown in Figure 6. Table 2 shows the fuzzy rule table with 49 fuzzy rules for pH control of neutralization process. Since fuzzy rules are culmination of experience and knowledge of an operator, the proposed fuzzy rules ensure the stability of fuzzy controller. The individual fuzzy rules FR_l, $l = 1$ to $l = r = 7{\times}7$, can be expressed using Eq. (1).

$$FR_l\text{: IF } e^* \text{ is } L_e \wp\ ce^* \text{ is } L_{ce}, \text{THEN } co^*_{FLC} \text{ is } L_{co} \tag{1}$$

where $\wp$ is fuzzy AND operator, and L_e, L_{ce} and L_{co} are the linguistic values of linguistic variables e^*, $ce^*$and co^*_{FLC} respectively.

Application of Mamdani based fuzzy implication to individual activated rules results in output fuzzy sets whose membership functions μ_{FR_l}, $l = 1$ to r, are given in Eq. (2).

$$\mu_{FR_l} = min\{\wp\left(\mu_{L_e}, \mu_{L_{ce}}\right), \mu_{L_{co}}\} \tag{2}$$

Using max-min fuzzy aggregation to the membership functions μ_{FR_l} results in an equivalent fuzzy set whose membership function μ_{FR} is given in Eq. (3).

$$\mu_{FR} = max\left[\mu_{FR_1}, \mu_{FR_2}, \mu_{FR_3}, \dots \mu_{FR_{r-1}}, \mu_{FR_r}\right] \quad (3)$$

The defuzzified output $\mathrm{co}^*_{\mathrm{FLC}}$ using Centre of Gravity (COG) method is given in Eq. (4).

$$\mathrm{co}^*_{\mathrm{FLC}} = \frac{\int\{(\mu_{FR})\mathrm{co}^*_{\mathrm{FLC}}\}d(\mathrm{co}^*_{\mathrm{FLC}})}{\int(\mu_{FR})d(\mathrm{co}^*_{\mathrm{FLC}})} \quad (4)$$

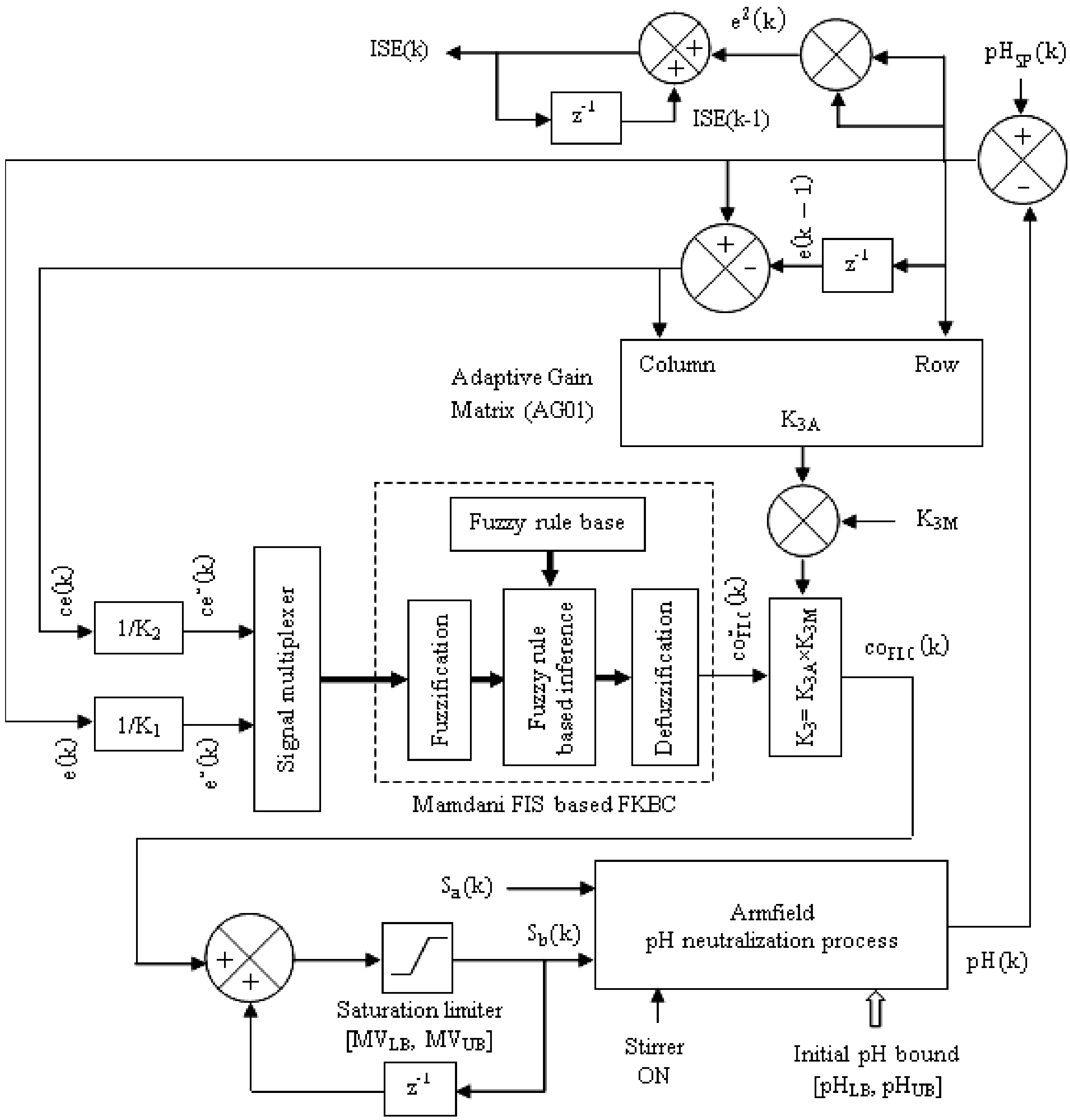

Figure 5. Schematic of adaptive FKBC of Armfield pH neutralization process.

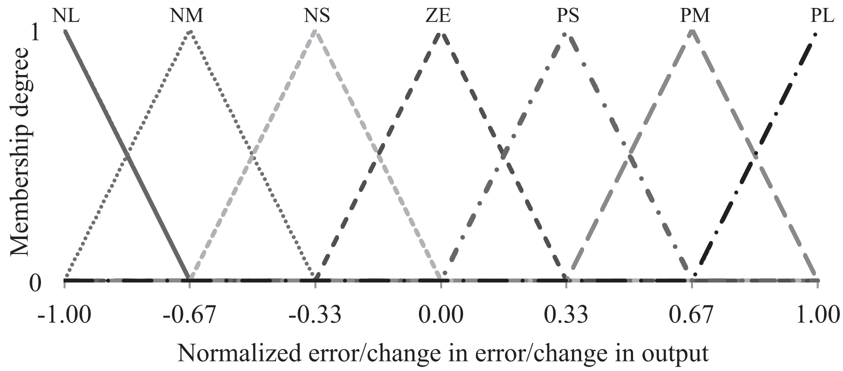

Figure 6. Fuzzy membership functions of normalized error/change in error/change in output.

Table 2. Fuzzy rule table.

		ce*						
		NL	NM	NS	ZE	PS	PM	PL
e*	NL	NL	NL	NL	NL	NM	NS	ZE
	NM	NL	NL	NL	NM	NS	ZE	PS
	NS	NL	NL	NM	NS	ZE	PS	PM
	ZE	NL	NM	NS	ZE	PS	PM	PL
	PS	NM	NS	ZE	PS	PM	PL	PL
	PM	NS	ZE	PS	PM	PL	PL	PL
	PL	ZE	PS	PM	PL	PL	PL	PL

Table 3. Adaptive gain matrix K_{3A}.

		ce						
		$ce\in[-6,-1)$	$ce\in[-1,-0.5)$	$ce\in[-0.5,-0.1)$	$ce\in[-0.1,0.1]$	$ce\in(0.1,0.5]$	$ce\in(0.5,1]$	$ce\in(1,6]$
e	$e\in[-6,-1)$	8	8	8	8	6	4	2
	$e\in[-1,-0.5)$	8	8	8	6	4	2	4
	$e\in[-0.5,-0.1)$	8	8	6	4	2	4	6
	$e\in[-0.1,0.1]$	8	6	4	2	4	6	8
	$e\in(0.1,0.5]$	6	4	2	4	6	8	8
	$e\in(0.5,1]$	4	2	4	6	8	8	8
	$e\in(1,6]$	2	4	6	8	8	8	8

In this work, we have used feedback control of Armfield pH neutralization process in which under nominal operating conditions Controlled Variable (CV), i.e., pH, is maintained at a set-point value (pH_{SP}) with zero error as input to the pH controller, and Manipulated Variable (MV), i.e., speed of base pump B (S_b), and Disturbance Variable (DV), i.e., speed of acid pump A (S_a), have values MV0 = 38.5% and DV0 = 35%, respectively. Manipulating variable is subjected to a saturation limiter in order to maintain $S_b(k)$ within bound [MV_{LB}, MV_{UB}], i.e., [18%, 80%]. To evaluate the performance of fuzzy logic based pH controller, fitness function ISE(k) is evaluated. Since we are considering a real, physical, and constantly stirred pH neutralization process, the initial pH range must be maintained within bound [pH_{LB}, pH_{UB}], i.e., [$(pH_{SP})_{initial}$ + 0.1, $(pH_{SP})_{initial}$ - 0.1], to ensure approximately the same initial conditions.

The basic idea of adaptive FKBC scheme is to assign various discrete values to scaling factor K_3 depending upon instantaneous values of variables $e(k)$ and $ce(k)$. Eq. (5) gives expression for scaling factor K_3 as follows:

$$K_3 = K_{3A} \times K_{3M} \quad (5)$$

where K_{3A} is the discrete component to be determined using adaptive gain matrix shown in Table 3 and K_{3M} is the multiplier.

Table 3 shows values of K_{3A} based on empirical knowledge of the process. To determine the values of K_{3A}, first appropriate region of e and ce needs to be identified. Basis of entries of Table 3 has been explained through following four cases involving first row of Table 3.

Case 1: If $e \in [-6, -1)$ and $ce \in [-6, 0.1]$ i.e., pH is far away from pH_{SP} and pH is moving either rapidly away from pH_{SP} or very slowly towards pH_{SP}, so pH controller needs to take very large corrective action. Thus, we assign K_{3A} equal to 8 for this case.

Case 2: If $e \in [-6, -1)$ and $ce \in (0.1, 0.5]$ i.e. pH is far away from pH_{SP} and pH is moving slowly toward pH_{SP}, so pH controller needs to take large corrective action. Thus, we assign K_{3A} equal to 6 for this case.

Case 3: If $e \in [-6, -1)$ and $ce \in (0.5, 1]$ i.e., pH is far away from pH_{SP} and moving moderately toward pH_{SP}, so pH controller needs to take small corrective action. Thus, we assign K_{3A} equal to 4 for this case.

Case 4: If $e \in [-6, -1)$ and $ce \in (1, 6]$ i.e., pH is far away from pH_{SP} and moving rapidly toward pH_{SP}, so pH controller needs to take least corrective action. Thus, we assign K_{3A} equal to 2 for this case.

From Table 3 it is evident that, in order to ensure reduced settling time, K_{3A} has been assigned large values, and in order to ensure steady-state response within settling band as error decreases, K_{3A} has been assigned small values. Figure 7 shows LabVIEW front panel appearance of adaptive FKBC of pH neutralization process. The LabVIEW block diagram for Mamdani FIS based adaptive FKBC structure (AFL01) is shown in Figure 8.

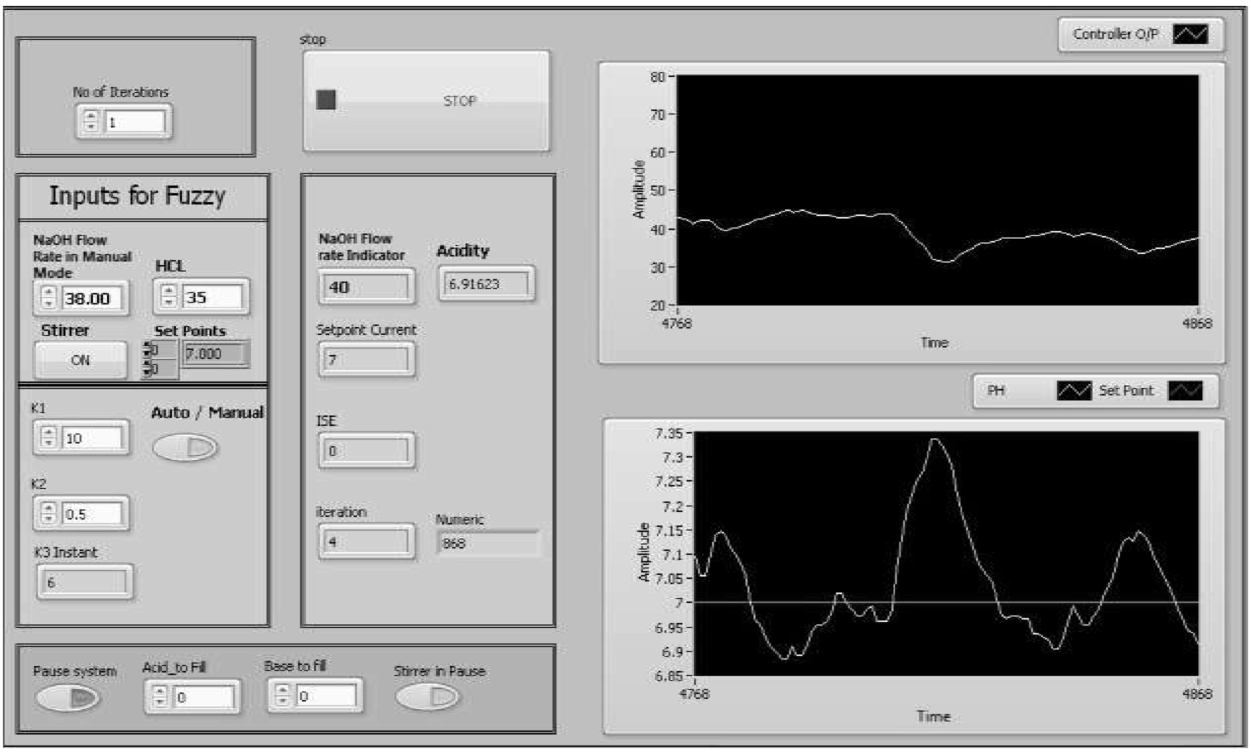

Figure 7. LabVIEW front panel of adaptive FKBC.

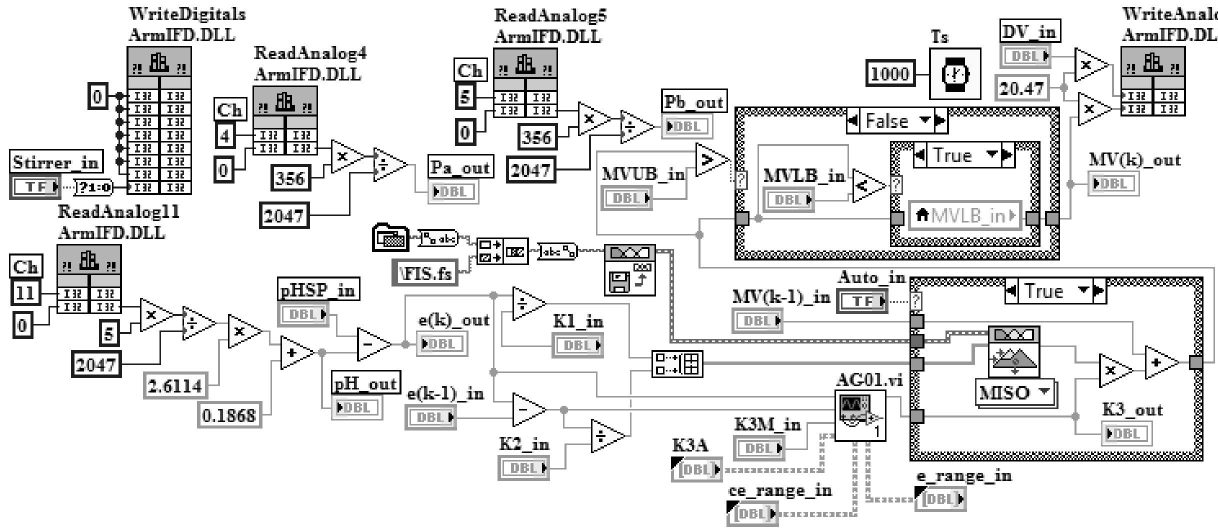

Figure 8. LabVIEW block diagram of Mamdani FIS based adaptive FKBC (AFL01).

RESULTS AND DISCUSSION

In order to evaluate the performance of adaptive FKBC for servoregulatory (SR) operations in pH neutralization process, SR operations have been divided into six cases, namely, SR1, SR2, SR3, SR4, SR5, and SR6, to cover dynamic pH range from 6 to 9. For servooperations, step changes in setpoint, from $(pH_{SP})_{initial}$ to $(pH_{SP})_{final}$, i.e., 6 to 7, 7 to 8, 8 to 9, 9 to 8, 8 to 7, and 7 to 6, are introduced for 200 seconds with nominal acid flow rate as S_a = DV0, i.e., 35%. For regulatory operations, step changes in disturbance variable, from $(DV)_{initial}$ to $(DV)_{final}$, i.e., 35% to 30%, 30% to 35%, 35% to 40%, and 40% to 35%, are introduced consecutively for 100 seconds at each setpoint $(pH_{SP})_{final}$, i.e., 7, 8, 9, 8, 7, and 6. Thus, SRi, where i = 1, 2, 3, 4, 5, and 6, involves servooperation of 200 seconds followed by regulatory operations of 400 seconds. Therefore, the entire duration for SR operations is 3600 seconds.

Figures 9(a) to 9(c) show pH response, pump speed variations, and K_3 for cases $K_1 = 10$, $K_2 = 0.5$, and $K_{3M} = 3$ and 4. Table 4 gives experimental performance summary of adaptive FKBC for servoregulatory operations in pH neutralization process. Table 5 gives comparison of adaptive FKBC with optimized Fuzzy Logic Control (FLC) and piecewise optimized FLC schemes using Genetic Algorithm (GA), Differential Evolution (DE), and Particle Swarm Optimization (PSO) techniques.

The following observations can be made from the obtained results.

(i) The adaptive FKBC for SR operations with $K_1 = 10$, $K_2 = 0.5$, and $K_{3M} = 3$ gives total ISE as 96.0062 of which SR5 and SR1 contributions are 27.4581 and 17.6177, respectively.

(ii) The adaptive FKBC for SR operations with $K_1 = 10$, $K_2 = 0.5$, and $K_{3M} = 4$ gives total ISE as 79.8271 of which SR5 and SR1 contributions are 18.3122 and 17.5504, respectively. It is evident that fall time, maximum undershoot, and settling time reduced considerably for SR5 in this case.

(iii) Genetic Algorithm (GA), Differential Evolution (DE), and Particle Swarm Optimization (PSO) based optimized Fuzzy Logic Control (FLC) for SR operations give total ISE as 80.3776, 67.9637, and 67.9266, respectively [Singh et al., 2018].

(iv) GA, DE, and PSO based optimized piecewise FLC for SR operations give total ISE as 66.1221, 64.3561, and 64.8051, respectively [Singh et al., 2018].

From the above discussion, it is clear that the performance index ISE obtained in cases of optimized FLC and optimized piecewise FLC is better than that in case of adaptive FKBC scheme for SR operations. But optimization requires known operating conditions and it may happen that the optimized controller settings are not applicable to a new operating condition. On the other hand, the adaptive FKBC scheme has unique advantage of being independent of operating conditions and it works very well for unknown operating conditions.

Table 4. Experimental performance of adaptive FKBC for SR operations.

Parameters K_1, K_2, K_{3M}	Servo operation (200 samples)		Regulatory operation (100 samples)		Regulatory operation (100 samples)		Regulatory operation (100 samples)		Regulatory operation (100 samples)	
	$(pH_{SP})_{initial}$, $(pH_{SP})_{final}$, DV	ISE, maximum overshoot / undershoot	pH_{SP}, $(DV)_{initial}$, $(DV)_{final}$	ISE, maximum overshoot	pH_{SP}, $(DV)_{initial}$, $(DV)_{final}$	ISE, maximum undershoot	pH_{SP}, $(DV)_{initial}$, $(DV)_{final}$	ISE, maximum undershoot	pH_{SP}, $(DV)_{initial}$, $(DV)_{final}$	ISE, maximum overshoot
10, 0.5, 3	6, 7, 35	11.3593, -0.3240	7, 35, 30	1.2801, -0.3050	7, 30, 35	1.6775, 0.3070	7, 35, 40	2.5100, 0.3580	7, 40, 35	0.7908, -0.2480
10, 0.5, 4		11.3040, -0.2100		0.4747, -0.2100		0.6003, 0.1730		3.0686, 0.3330		2.1028, -0.4010
10, 0.5, 3	7, 8, 35	7.6813, -0.1090	8, 35, 30	0.7509, -0.2680	8, 30, 35	0.9747, 0.2040	8, 35, 40	0.7832, 0.2040	8, 40, 35	0.7255, -0.2300
10, 0.5, 4		6.2474, -0.0840		0.5960, -0.2750		0.6036, 0.1780		0.8839, 0.2670		0.4092, -0.1860
10, 0.5, 3	8, 9, 35	8.8530, -0.1170	9, 35, 30	0.4648, -0.1490	9, 30, 35	0.5276, 0.1770	9, 35, 40	0.5824, 0.1960	9, 40, 35	0.5040, -0.1680
10, 0.5, 4		9.5923, -0.0400		0.3008, -0.1610		0.3171, 0.1700		0.3469, 0.1570		0.3274, -0.1420
10, 0.5, 3	9, 8, 35	11.6065, 0.0890	8, 35, 30	0.4825, -0.1860	8, 30, 35	0.5388, 0.1780	8, 35, 40	0.7198, 0.1910	8, 40, 35	0.5510, -0.2430
10, 0.5, 4		9.7252, 0.0820		0.4366, -0.1980		0.3592, 0.1460		0.6448, 0.2350		0.4676, -0.2240
10, 0.5, 3	8, 7, 35	22.9464, 0.6770	7, 35, 30	0.5639, -0.1840	7, 30, 35	0.7934, 0.2240	7, 35, 40	1.8408, 0.2370	7, 40, 35	1.3136, -0.3370
10, 0.5, 4		14.7684, 0.4220		0.6536, -0.2030		0.8880, 0.2620		1.0729, 0.2620		0.9293, -0.2930
10, 0.5, 3	7, 6, 35	12.4186, 0.1870	6, 35, 30	0.6763, -0.2460	6, 30, 35	0.6551, 0.2000	6, 35, 40	0.6065, 0.2060	6, 40, 35	0.8280, -0.2020
10, 0.5, 4		10.3599, 0.0530		0.5604, -0.1700		0.4816, 0.1680		0.6032, 0.1430		0.7016, -0.1890

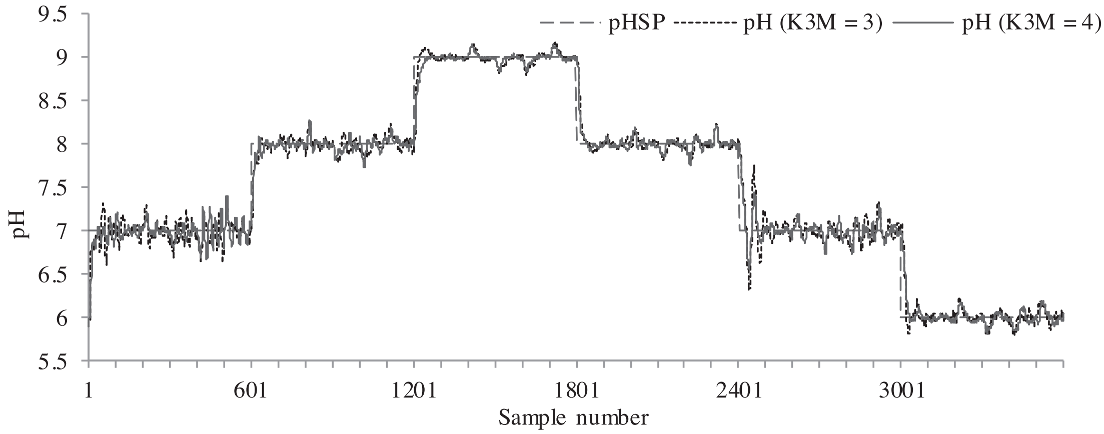

Figure 9(a). pH responses for $K_1 = 10$, $K_2 = 0.5$, $K_{3M} = 3$ and 4.

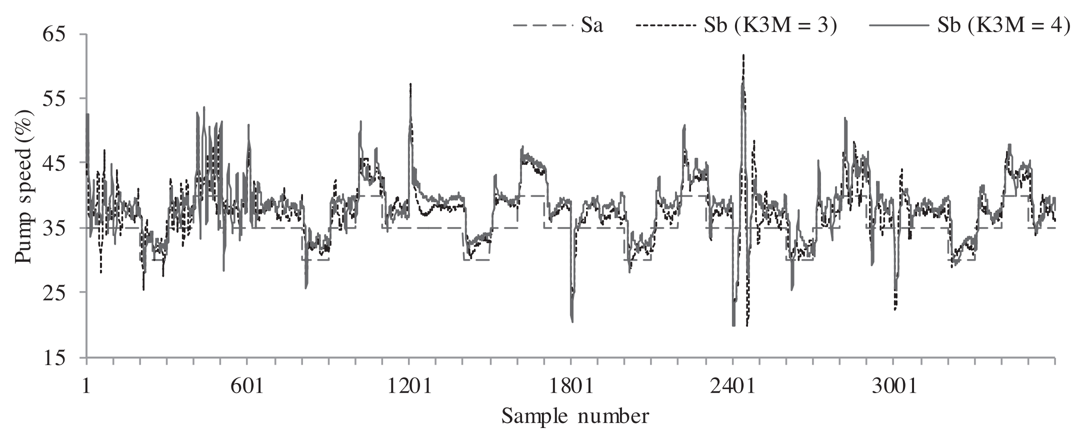

Figure 9(b). Pumps speed variations for $K_1 = 10$, $K_2 = 0.5$, $K_{3M} = 3$ and 4.

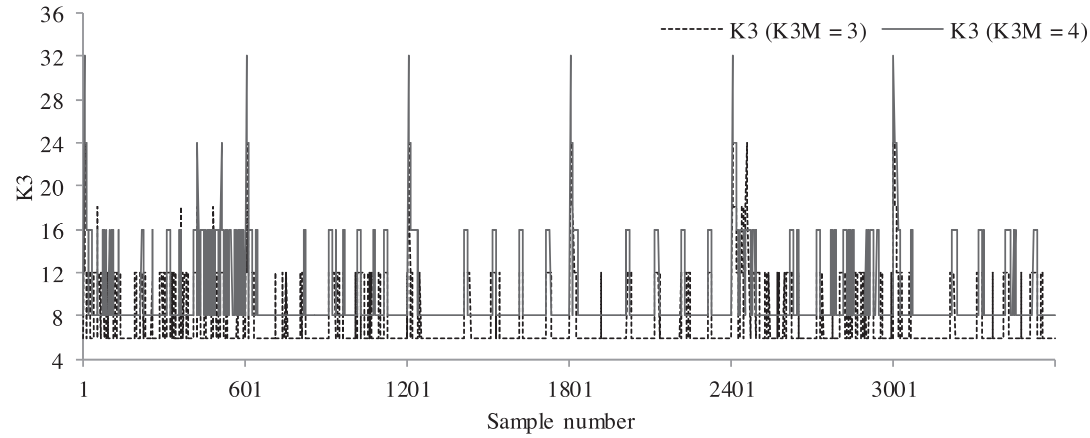

Figure 9(c). K_3 for $K_1 = 10$, $K_2 = 0.5$, $K_{3M} = 3$ and 4.

Table 5. Comparison of optimized and piecewise optimized FLC with adaptive FKBC for SR operation.

Control scheme	Method	Experimental ISE
Optimized FLC	GA	80.3776
	DE	67.9637
	PSO	67.9266
Piecewise Optimized FLC	GA	66.1221
	DE	64.3561
	PSO	64.8058
Adaptive FKBC	$K_{3M} = 3$	96.0062
	$K_{3M} = 4$	79.8271

CONCLUSION

In this paper, Mamdani FIS based adaptive FKBC scheme has been implemented on Armfield pH neutralization process. The adaptive FKBC uses input scaling factors K_1 and K_2, and output scaling factor K_3. Keeping K_1 and K_2 constant, adaptive mechanism actually determines the value of K_3, which consist of two components: K_{3A}, which has discrete values 2, 4, 6, and 8 based on present error and change in error values, and K_{3M}, which is a magnifier that can take integer values. Adaptive FKBC is used for servo- and regulatory (SR) operations in pH neutralization process, and its performance index ISE comes as 96.0062 for $K_{3M} = 3$, and 79.8271 for $K_{3M} = 4$. In comparison, GA, DE, and PSO based optimized FLC for SR operations give total ISE as 80.3776, 67.9637, and 67.9266, respectively. Also, GA, DE, and PSO based optimized piecewise FLC for SR operations give total ISE as 66.1221, 64.3561, and 64.8051, respectively. ISE of adaptive FKBC for SR operations is greater than that for optimized FLC and optimized piecewise FLC; however, adaptive FKBC has distinct advantages of reducing design complexity and execution time as compared with evolutionary and swarm optimization techniques based optimized fuzzy controller.

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