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Genetic Optimization based Adaptive Fuzzy Logic Control of a pH Neutralization Process

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Abstract

Presence of severe nonlinearity in pH neutralization process makes the problem of pH control a difficult and challenging one. Further, optimized control of such highly nonlinear system requires tuning of various parameters with a suitable evolutionary algorithm (EA). This paper presents genetic algorithm (GA) based unconstrained, continuous and single-objective optimization of conventional and adaptive nonlinear fuzzy logic control (FLC) of pH neutralization process for servo and regulatory operations. The GA optimized adaptive FLC scheme changes the universe of discourse of input-output membership functions based on the region of operation and amount of step change in set-point and load. The performance of controllers are evaluated using integral of squared errors (ISE) and tested for random step changes in set-point and load.

Keywords: *Fuzzy control; genetic algorithm; pH neutralization; nonlinear; adaptive; optimization*

1. Introduction

Highly nonlinear behavior and time varying parameters of pH process makes it a benchmark for modeling and control of nonlinear processes. pH control plays an important role in many industrial process applications such as wastewater treatment in paper and pulp plants, boiler feedwater treatment in thermal power plants, biopharmaceutical plants, food processing plants, and various other chemical processing plants. In recent years the increased complexity of the processes, stringent requirements of product quality and conformance with strict environmental and safety regulations has led to research efforts in design and development of "intelligent" pH control systems. Intelligent control can be described as a control approach that tries to imitate important characteristics of the human brain and human way of thinking and decision making. It is also a term that is commonly used to describe control schemes that are based on artificial intelligence (AI) techniques such as neural networks, fuzzy logic, genetic algorithm (GA), and their hybrid combinations.

Early works on pH control involved development of first-principle based dynamic pH process model and their use in feedback, feedforward and adaptive control techniques [1, 2], [3]. One of the approaches proposed use of material balances and electroneutrality relations on component ions for dynamic pH process model and time-optimal pH control [4, 5]. Because of its simplicity, this model has been used by many researchers as a platform to introduce AI based control techniques [6-8]. In addition, dynamic pH models based on reaction invariant and strong acid equivalent were designed for various nonlinear and adaptive control schemes [9-13].

Fuzzy logic is based on fuzzy set theory [14]. A fuzzy set deals with an ambiguous and imprecise class of objects which are characterized by membership functions with degrees

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assigned between 0 and 1. Fuzzy logic introduced concept of linguistic variables, fuzzy conditional statements and fuzzy inference system (FIS) to analyze an ill-defined complex systems and decision processes [15]. Though fuzzy logic brought an unconventional shift in nature of computing based on words and perceptions it faced however initial resistances from eminent but incredulous scientists and researchers [16]. Almost a decade later the synthesis of fuzzy logic control (FLC) schemes, famously known as Mamdani type FLC, for a small boiler steam engine combination could be realized [17, 18]. Self-organizing fuzzy controller having capability to modify its control rule base were also developed [19, 20]. Further an alternative and simpler Sugeno type FLC scheme were also applied for system identification and control [21]. Fuzzy logic has been extensively applied to obtain intelligent equivalent of the conventional counterpart such as proportional-integral (PI), proportional-integral-derivative (PID), sliding-mode and model predictive control techniques [22-25].

Evolutionary algorithms (EAs) are population based search techniques in which optimal solution is reached by a candidate on the basis of Darwin's theory of biological evolution. As per Darwinian theory, the principle of natural selection favors those species for survival and further evolution which are fittest. Over a number of years, various but independent types of EAs such as evolution strategies, evolutionary programming, GA, and genetic programming were invented and developed by many scientists and researchers with an aim of utilizing them for optimal solution of various engineering problems [26, 27]. However, GA conceived by Holland and its variants developed by his associated team members received wide attention [28], [29]. GAs contributed immensely to many scientific and engineering applications [30]. GA is also applied for parameters optimization of various controllers [31-35].

2. Dynamic Modeling of pH Neutralization Process

The pH neutralization process is assumed to take place in continuous stirred tank reactor (CSTR) with perfect mixing and a constant volume. The CSTR has two influent streams: the hydrochloric acid as titration stream (feed A) and the sodium hydroxide as process stream (feed B), and one effluent stream. Based on principle of material balances, the mass balance equation can be written as:

$$V(dx_a/dt) = F_a C_a - (F_a + F_b)x_a \tag{1}$$

$$V(dx_b/dt) = F_b C_b - (F_a + F_b)x_b \tag{2}$$

The definitions and numerical values of the variables and parameters used for simulating Eq. (1) and (2) are: V is the constant volume of the CSTR (1.9 L); $\mathrm{C_a}$ is the concentration (0.05 mol/L) and $\mathrm{F_a}$ is the flow rate (0 to 6.23 mL/s *i.e.*, 0 to 100%) of acidic stream A; $\mathrm{C_b}$ is the concentration (0.05 mol/L) and $\mathrm{F_b}$ is the flow rate (0 to 6.23 mL/s *i.e.*, 0 to 100%) of basic stream B; $(\mathrm{F_a} + \mathrm{F_b})$ is the flow rate of the effluent stream; $\mathrm{x_a}$ is the concentration of acid component (chloride ion, $\mathrm{Cl^-}$) in the effluent stream (in mol/L); $\mathrm{x_b}$ is the concentration of base component (sodium ion, $\mathrm{Na^+}$) in the effluent stream (in mol/L).

The equilibrium relationship for water is given as

$$\mathrm{K_w} = [\mathrm{H^+}]\,[\mathrm{OH^-}] \tag{3}$$

where $\mathrm{K_w}$ is the dissociation constant of water (10^{-14}).

From the electroneutrality condition, we have

From the electroneutrality condition, we have

$$[Na^+] + [H^+] = [Cl^-] + [OH^-] \tag{4}$$

All of the Cl^- ion comes from the HCl and all of the Na^+ ion comes from the NaOH. Using Eq. (3) and (4), we have

$$[H^+]^2 - (x_a - x_b)[H^+] - K_w = 0 \tag{5}$$

From the definition of $pH = -\log_{10}[H^+]$, the pH titration curve for a strong acid-strong base is given by

$$pH = -log_{10}\left(\frac{x}{2} + \sqrt{\frac{x^2}{4} + K_w}\right) \tag{6}$$

$$\text{where } x = (x_a - x_b) \tag{7}$$

3. Design of FLC

The fuzzy controller for pH neutralization process is based on Sugeno FIS. The FIS consists of an input fuzzification stage, a fuzzy rule processing stage, and an output defuzzification stage. The fuzzifier stage determines the degree (varying between 0 and 1) of belonging of input to different membership functions. Since the antecedent of rule has more than one part, the AND fuzzy algebraic product operator has been applied to obtain the firing strength for that rule. The output level of each rule is weighted by the above firing strength. The final defuzzified output of the FIS is the weighted average of all rules' outputs.

The input variables used for the Sugeno FIS are error e(k) = pH_{SP} – pH(k) *i.e.*, the difference between the desired setpoint for pH as pH_{SP} and measured values of pH at the k^{th} sampling instant as pH(k), and change in error ce(k) = e(k) – e(k-1) *i.e.*, the difference between the error at the k^{th} and $(k-1)^{th}$ sampling instants. The output variable for Sugeno FIS is controller output co(k). The change in manipulated variable is the change in acid flow rate i.e. co1(k) = F_a(k) – F_a(k-1). The input variables are expressed in pH and output variable is expressed in %. The membership functions for the input variables (e, ce), and output variable (co) are shown in Figures 1, 2, and 3 respectively.

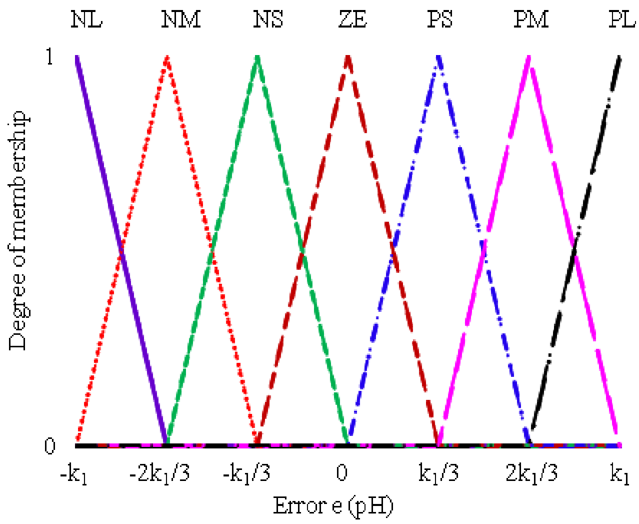

Figure 1. Membership Functions for Error

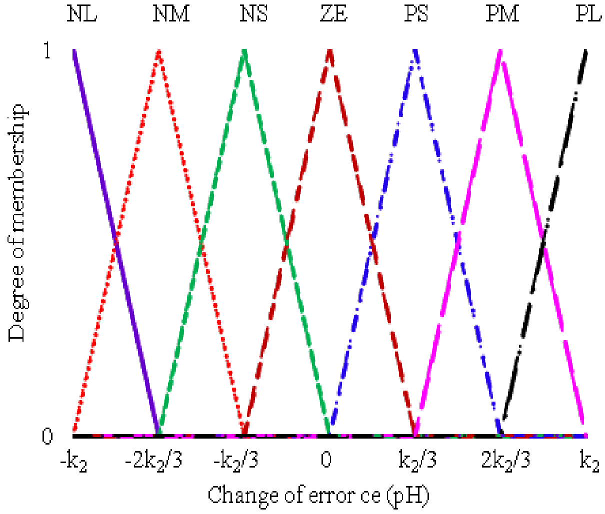

Figure 2. Membership Functions for Change of Error

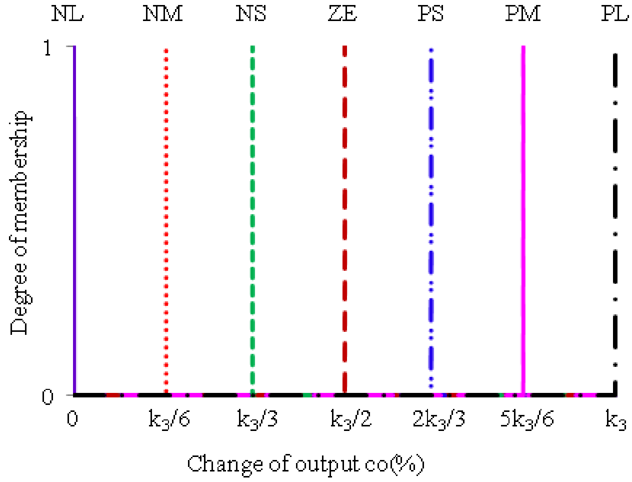

Figure 3. Membership Functions for Change of Output

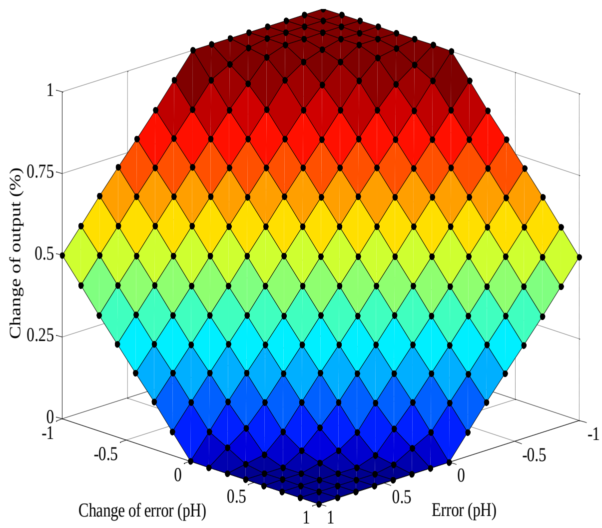

Figure 4. Normalized Fuzzy Controller Structure

Table 1. Fuzzy Rule Base

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

The variables k_1, k_2, and k_3 are positive scaling factors. The rule base for the input and output variables are shown in Table 1. For $k_1 = k_2 = k_3 = 1$, the normalized nonlinear output surface of the fuzzy controller is shown in Figure 4.

4. FIS Optimization Using GA

The flowchart for unconstrained and continuous GA optimization of FIS is shown in Figure 5. To optimize the FIS, the scaling factors k_1, k_2, and k_3 are chosen so that they proportionately scale the vertices of membership functions for variables e, ce, and co respectively. The range of e, ce, and co are $[-k_1\ k_1]$, $[-k_2\ k_2]$, and $[0\ k_3]$ respectively. GA optimization starts with an initial population of individuals of type 'double' and size 20, created randomly within the initial population range $[k_{1min}\ k_{2min}\ k_{3min};k_{1max}\ k_{2max}\ k_{3max}]$ where the subscripts 'min' and 'max' are representing minimum and maximum values respectively. We have $k_{1min} = k_{2min} = k_{3min} = 0$, $k_{1max} = k_{2max} = 4.5$, and $k_{3max} \in [2\ 60]$. Each individual in the population represents a potential solution to the optimization problem under consideration. The individuals evolve through successive iterations, called generations. During each generation, each individual in the population is evaluated using the fitness function. The evaluated fitness values of the individuals are ranked in an increasing order such that the best individual having minimum fitness value has the rank as 1, the next best individual has the rank as 2, and so on. The individuals with ranking 1 and 2 qualify for next generation population as elite children. The rank fitness scaling function is used to assign expectation values to the individuals which is inversely proportional to square root of their rank. Based on the assigned expectation values by the fitness scaling function, normalized expectation values for each individual in the population is calculated which is used by the selection function to select parents for next generation reproduction mechanism namely crossover and mutation. The stochastic uniform selection function is represented by a roulette wheel in which each individual corresponds to a section of the wheel equal to the normalized expectation value. A pointer then steps through the wheel in equal size steps, so as to cover the entire wheel in steps equals the required number of parents which is 32. At each step, the selection function creates a parent from the slot the pointer landed in. The GA uses selected parents to create next generation 14 crossover and 4 mutation children. The GA creates crossover children by combining a pair of parents whereas the mutation children are created by applying random changes to a single parent. The GA uses scattered crossover to create crossover children whereas the mutation children are created using Gaussian mutation. The procedure continues until the termination condition is satisfied. The GA uses maximum number of generations 100, stall generations 50, and fitness function tolerance 10^{-6} as the stopping criteria. Unless otherwise indicated, the values and procedure are true for both servo and regulatory operations of FLC.

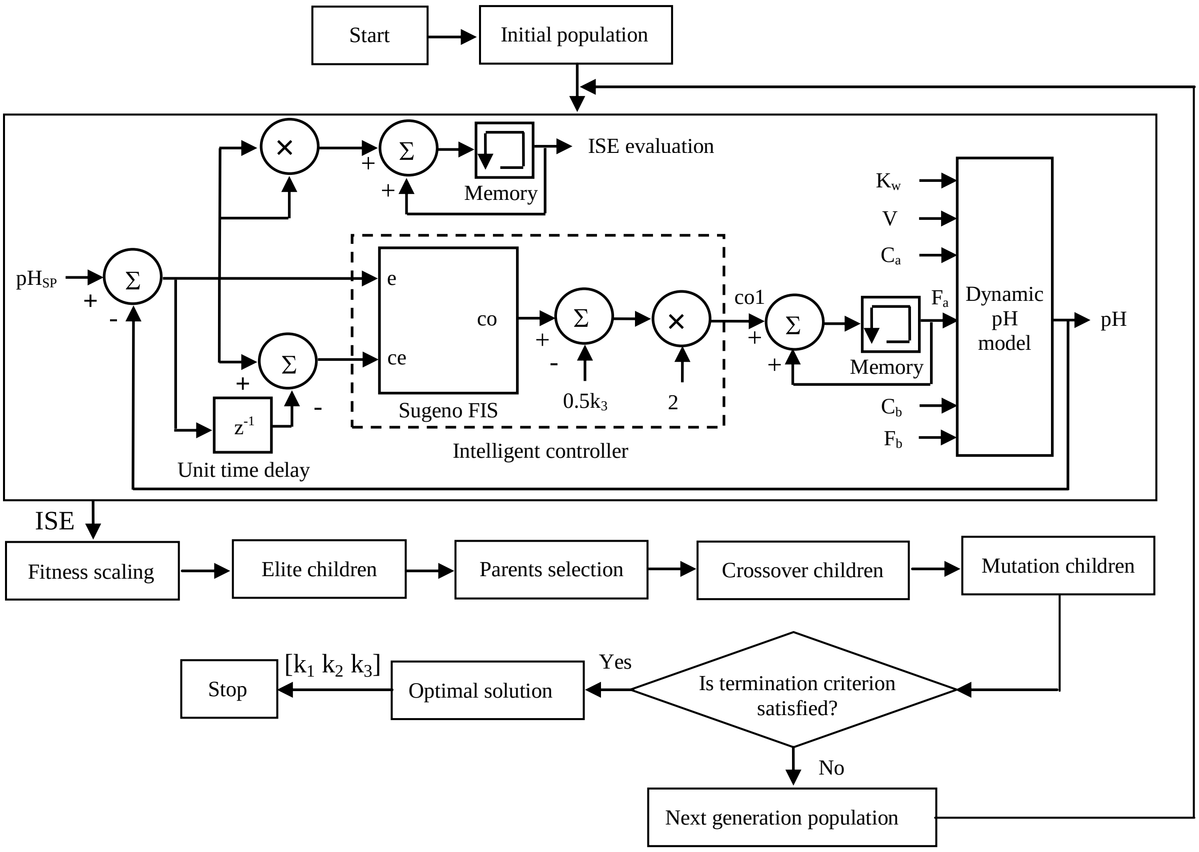

Figure 5. Unconstrained and Continuous GA Optimization Flowchart for Fuzzy Logic based pH Control

5. Simulation Results and Discussions

The performances of optimized conventional as well as adaptive controllers are compared for servo and regulatory control operations based on ISE, maximum overshoot and undershoot, and settling and rejection time (for ± 0.1 pH error band) using MATLAB simulation. To calculate ISE, all the errors with magnitude greater than or equal to 0.01 are considered since further smaller errors will have negligible contribution.

5.1. Servo Control

For servo control, the optimal conventional FLC scheme is designed based on fixed pH_{SP} variations of Case IA and tested for random pH_{SP} variations of Case IB, while F_b is kept constant at 1.75 mL/s. In Case IA, the pH_{SP} is subjected to unit step changes in sequence of 7, 8, 9, 10, 9, 8, and 7, and in Case IB, the pH_{SP} is subjected to random step variations in sequence of 7, 7.2, 7.6, 8.2, 9, 9.8, 9.7, 9.4, 8.9, 8.2, and 7.3, after every 4000 samples. The plot of best and mean values of ISE as a result of GA optimization for Case IA of conventional FLC is shown in Figure 6. The resulting best and mean ISE are 152.93 and 172.70 square pH respectively. The final mean fitness values are closer to best fitness values which indicate good GA convergence. The resulting optimal values of scaling factors are $k_1 = 4.4568$, $k_2 = 2.0409$, and $k_3 = 0.9108$. The variations of controlled and manipulated variables for Case IA of conventional FLC for selected sample duration are shown in Figures 8 and 9 respectively. For Case IA of optimal conventional FLC, the largest settling time of 500 samples occurs when $pH_{SP} = 9$ and $\Delta pH_{SP} = 1$, and the largest undershoot of 3.86 pH occurs when $pH_{SP} = 10$ and $\Delta pH_{SP} = -1$. Using optimized conventional FLC designed for Case IA, the controller performance is tested for Case IB.

The variations of controlled and manipulated variables for Case IB of conventional FLC for selected sample duration are shown in Figures 10 and 11 respectively. The resulting ISE is 37.49 square pH. For Case IB of conventional FLC, the largest settling time of 393 samples occurs when pH_{SP} = 9 and ΔpH_{SP} = 0.8, and the largest undershoot of 1.21 pH occurs when pH_{SP} = 8.9 and ΔpH_{SP} = -0.7.

For servo control, to design optimal adaptive FLC scheme, GA optimization is performed individually at pH_{SP} = 7, 7.25, 7.5, 7.75, 8, 8.25, 8.5, 8.75, 9, 9.25, 9.5, 9.75, 10 with F_b = 1.75 mL/s and change in set-point ΔpH_{SP} = 0, ±0.25, ±0.5, ±0.75, ±1 separately for $1 \leq k \leq 4000$ samples at each pH_{SP}. The plot for optimal ISE, k_1, k_2, and k_3 are shown in Figures 16, 17, 18, and 19 respectively. The variations of controlled and manipulated variables for Case IA of optimal adaptive FLC for selected duration are shown in Figures 24 and 25 respectively. For Case IA of optimal adaptive FLC, the ISE is 8.24, the settling time is 2 samples when pH_{SP} = 9 and ΔpH_{SP} = 1, and the undershoot is 0.08 pH when pH_{SP} = 10 and ΔpH_{SP} = -1. For Case IB of optimal adaptive FLC, the scaling factors k_1, k_2, and k_3 are chosen from the optimized adaptive set of readings of Case IA as shown in Table VI. The variations of controlled and manipulated variables for Case IB of optimal adaptive FLC for selected duration are shown in Figures 26 and 27 respectively. For Case IB of optimal adaptive FLC, the ISE is 4.64, the settling time is 2 samples when pH_{SP} = 9 and ΔpH_{SP} = 0.8, and the undershoot is 0.08 pH when pH_{SP} = 8.9 and ΔpH_{SP} = -0.7. The results are compared and summarized in Table II and Table III.

5.2. Regulatory Control

For regulatory control, the optimal conventional FLC scheme is designed based on fixed F_b variations of Case IIA and tested for random F_b variations of Case IIB, while pH_{SP} is kept constant at 7. In Case IIA, the F_b is subjected to step changes in sequence of 1.75, 1.8375, 1.75, 1.925, 1.75, 2.0125, 1.75, 2.1, and 1.75, and in Case IIB, the F_b is subjected random step variations in sequence of 1.75, 1.8025, 1.75, 1.89, 1.75, 1.9775, 1.75, 2.065, and 1.75, after every 4000 samples. The plot of best and mean values of ISE as a result of GA optimization for Case IIA of conventional FLC is shown in Figure 7. The resulting best and mean ISE are 457.55 and 515.70 square pH respectively. The final mean fitness values are closer to best fitness values which indicate good GA convergence. The resulting optimal values of scaling factors are k_1 = 2.8776, k_2 = 4.2777, and k_3 = 1.3243. The variations of controlled and manipulated variables for Case IIA of conventional FLC for selected sample duration are shown in Figures 12 and 13 respectively. For Case IIA of optimal conventional FLC, at pH_{SP} = 7, the largest settling time of 43 samples and the largest undershoot of 2.42 pH occurs when F_b = 2.1 and ΔF_b = -0.35 mL/s. Using optimized conventional FLC designed for Case IIA, the controller performance is tested for Case IIB. The variations of controlled and manipulated variables for Case IIB of conventional FLC for selected sample duration are shown in Figures 14 and 15 respectively. The resulting ISE is 511.48 square pH. For Case IIB of conventional FLC, at pH_{SP} = 7, the largest settling time of 49 samples and the largest undershoot of 2.35 pH occurs when F_b = 2.065 and ΔF_b = -0.315 mL/s.

For regulatory control, to design optimal adaptive FLC scheme, GA optimization is performed individually at pH_{SP} = 7, 7.25, 7.5, 7.75, 8, 8.25, 8.5, 8.75, 9, 9.25, 9.5, 9.75, 10 with F_b = 1.75 mL/s and change in base flow ΔF_b = 0, ±0.0875, ±0.175, ±0.2625, and ±0.35 mL/s separately for $1 \leq k \leq 4000$ samples at each pH_{SP}. The plot for optimal ISE, k_1, k_2, and k_3 are shown in Figures 20, 21, 22, and 23 respectively. The variations of controlled and manipulated variables for Case IIA for selected duration are shown in Figures 28 and 29 respectively. For Case IIA of optimal adaptive FLC, at pH_{SP} = 7, the ISE is 445.82, the settling time is 37 samples and the undershoot is 2.44 pH when F_b = 2.1 and ΔF_b = -0.35 mL/s. For Case IIB of optimal adaptive FLC, the scaling factors k_1, k_2, and k_3 are chosen from the optimized adaptive set of readings of Case IIA as shown in

Table VII. The variations of controlled and manipulated variables for Case IIB of optimal adaptive FLC for selected duration are shown in Figures 30 and 31 respectively. For Case IIB, at pH_{SP} = 7, the ISE is 366.15, the settling time is 35 samples and the undershoot is 2.36 pH when F_b = 2.065 and ΔF_b = -0.315 mL/s. The results are compared and summarized in Table IV and Table V.

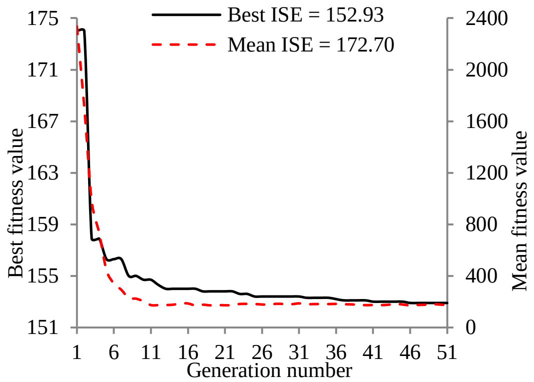

Figure 6. GA Optimization of Conventional FLC for Case IA

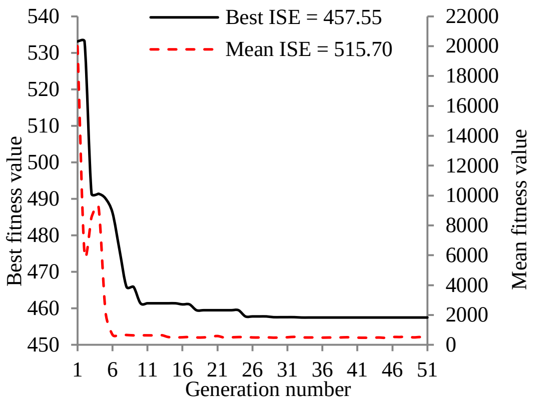

Figure 7. GA Optimization of Conventional for FLC for Case IIA

Table 2. Comparison of Servo FLC for Case IA

pH_{SP} (pH)		7	8	9	10	9	8
ΔpH_{SP} (pH)		1	1	1	-1	-1	-1
Maximum overshoot*/undershoot# (pH)	Optimal conventional	0.21	0.26	0.31	3.86	1.87	0.44
	Optimal adaptive	0.00	0.00	0.00	0.08	0.07	0.46
Settling time (samples) (±0.10 pH)	Optimal conventional	8	78	500	134	14	5
	Optimal adaptive	1	1	2	3	3	5
ISE	Optimal conventional	1.22	4.04	26.20	109.0	11.0	1.33
	Optimal adaptive	1	1	1.06	1.95	1.95	1.27

*For positive ΔpH_{SP} and ΔF_b. #For negative ΔpH_{SP} and ΔF_b.

Table 3. Comparison of Servo FLC for Case IB

pH_{SP} (pH)		7	7.2	7.6	8.2	9	9.8	9.7	9.4	8.9	8.2
ΔpH_{SP} (pH)		0.2	0.4	0.6	0.8	0.8	-0.1	-0.3	-0.5	-0.7	-0.9
Maximum overshoot*/undershoot# (pH)	Optimal conventional	0.21	0.14	0.15	0.24	0.29	0.09	0.37	0.83	1.21	0.70
	Optimal adaptive	0.04	0.13	0.01	0.00	0.01	0.00	0.05	0.05	0.09	0.32
Settling time (samples) (±0.10 pH)	Optimal conventional	2	3	11	76	393	1	131	72	14	7
	Optimal adaptive	1	4	1	1	1	1	1	2	3	13
ISE	Optimal conventional	0.10	0.20	0.54	3.25	15.4	0.65	4.90	6.64	4.14	1.70
	Optimal adaptive	0.05	0.23	0.36	0.64	0.64	0.01	0.10	0.30	0.84	1.47

Table 4. Comparison of Regulatory FLC for Case IIA

F_b (mL/s)		1.75	1.8375	1.75	1.925	1.75	2.0125	1.75	2.1
ΔF_b (mL/s)		0.0875	-0.0875	0.175	-0.175	0.2625	-0.2625	0.35	-0.35
Maximum overshoot*/undershoot# (pH)	Optimal conventional	1.46	1.46	1.92	1.92	2.21	2.21	2.42	2.42
	Optimal adaptive	1.48	1.44	1.92	1.92	2.23	2.23	2.44	2.44
Settling time (samples) (±0.10 pH)	Optimal conventional	11	11	22	22	32	31	42	43
	Optimal adaptive	9	10	17	18	26	26	44	37
ISE	Optimal conventional	10.92	10.92	32.08	32.08	66.49	66.51	120.5	118.0
	Optimal adaptive	8.99	8.26	30.67	30.70	67.51	67.53	115.7	116.5

Table 5. Comparison of Regulatory FLC for Case IIB

F_b (mL/s)		1.75	1.8025	1.75	1.89	1.75	1.9775	1.75	2.065
ΔF_b (mL/s)		0.0525	-0.0525	0.14	-0.14	0.2275	-0.2275	0.315	-0.315
Maximum overshoot*/undershoot# (pH)	Optimal conventional	1.14	1.14	1.76	1.76	2.11	2.11	2.35	2.35
	Optimal adaptive	1.15	1.14	1.77	1.77	2.13	2.13	2.36	2.36
Settling time (samples) (±0.10 pH)	Optimal conventional	7	7	14	14	38	37	49	49
	Optimal adaptive	12	10	18	20	25	25	34	35
ISE	Optimal conventional	4.45	4.45	20.35	20.36	79.70	82.57	149.8	149.8
	Optimal adaptive	3.98	4.53	22.97	22.58	54.79	54.78	100.5	100.1

Table 6. Adaptive Selection of Scaling Factors of FLC for Test Set Case IB Using Optimized Set of Case IA

Test set	pH_{SP} (pH)	7	7.2	7.6	8.2	9	9.8	9.7	9.4	8.9	8.2
	ΔpH_{SP} (pH)	0.2	0.4	0.6	0.8	0.8	-0.1	-0.3	-0.5	-0.7	-0.9
Optimized set	pH_{SP} (pH)	7	7.25	7.75	8.25	9	9.75	9.75	9.25	8.75	8.25
	ΔpH_{SP} (pH)	0.25	0.5	0.5	0.75	1	-0.25	-0.5	-0.5	-0.75	-1

Table 7. Adaptive Selection of Scaling Factors of FLC for Test Set of Case IIB using Optimized Set of Case IIA

Test set	F_b (mL/s)	1.75	1.8025	1.75	1.89	1.75	1.9775	1.75	2.065
	ΔF_b (mL/s)	0.0525	-0.0525	0.14	-0.14	0.2275	-0.2275	0.315	-0.315
Optimized set	F_b (mL/s)	1.75	1.75	1.75	1.75	1.75	1.75	1.75	1.75
	ΔF_b (mL/s)	0.0875	-0.0875	0.175	-0.175	0.2625	-0.2625	0.35	-0.35

*For positive ΔpH_{SP} and ΔF_b. #For negative ΔpH_{SP} and ΔF_b.

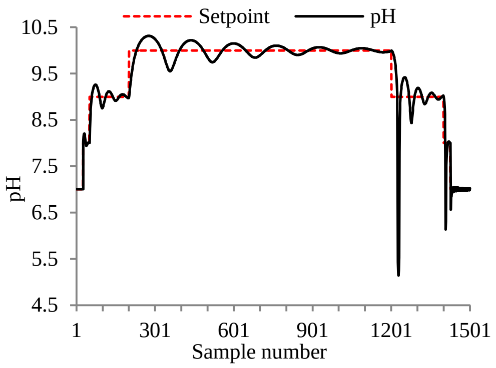

Figure 8. Controlled Variable Variations for Case IA

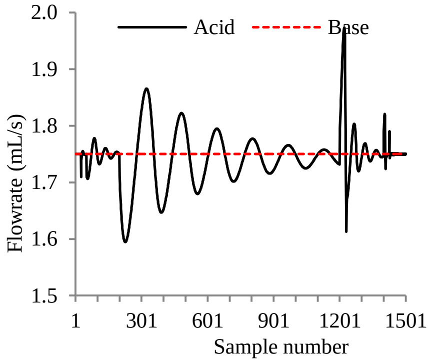

Figure 9. Manipulated Variable Variations for Case IA

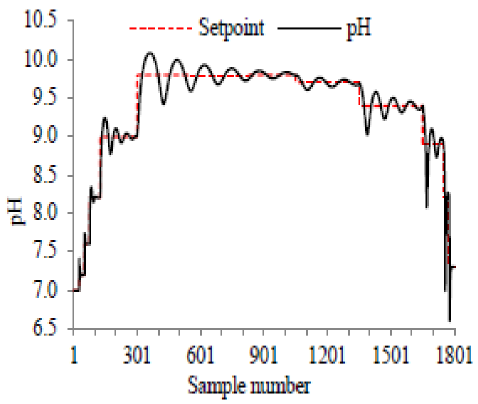

Figure 10. Controlled Variable Variations for Case IB

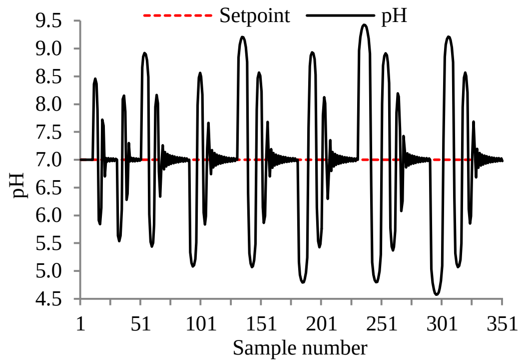

Figure 12. Controlled Variable Variations for Case IIA

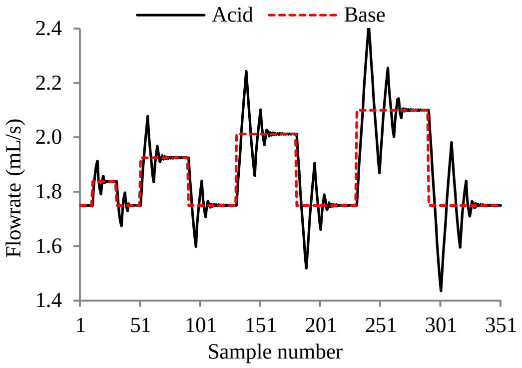

Figure 13. Manipulated Variable Variations for Case IIA

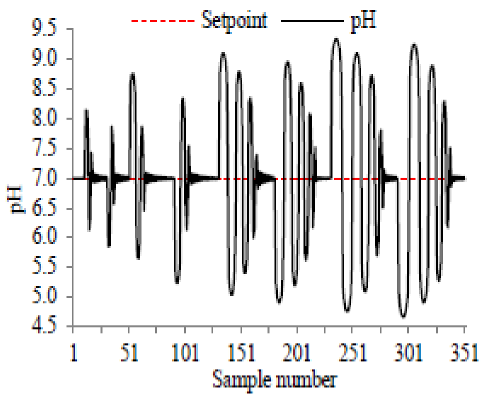

Figure 14. Controlled Variable Variations for Case IIB

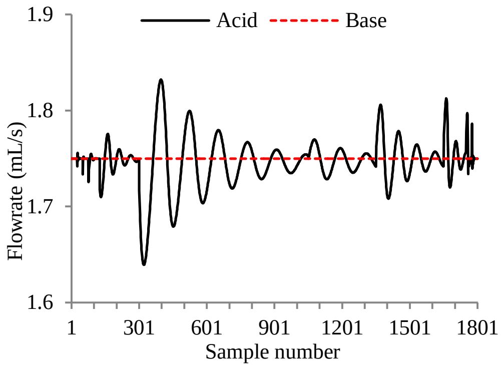

Figure 11. Manipulated variable for Case IB

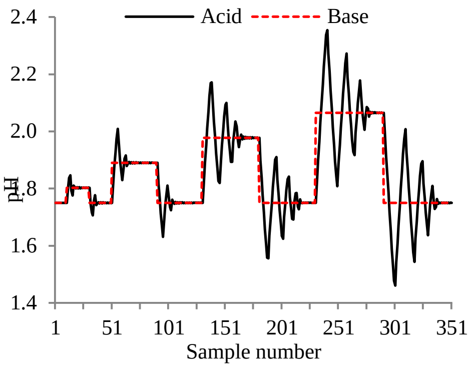

Figure 15. Manipulated Variations Variable Variations for Case IIB

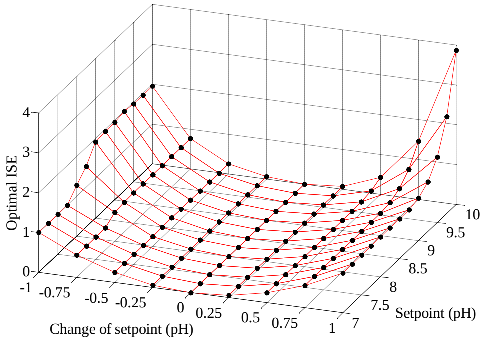

Figure 16. Optimal ISE for Adaptive   Adaptive Servo Control

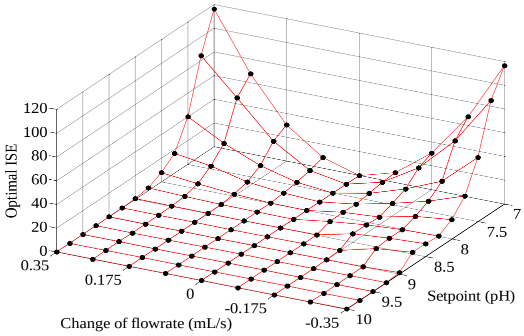

Figure 20. Optimal ISE for Regulatory Control

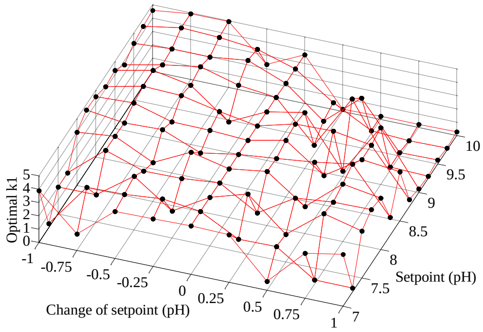

Figure 17. Optimal k_1 for Adaptive Servo Control

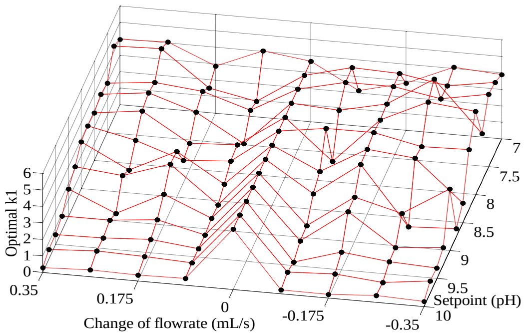

Figure 21. Optimal k_1 for Adaptive Regulatory Control

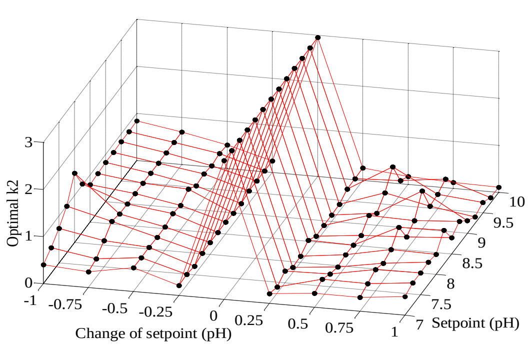

Figure 18. Optimal k_2 for Adaptive Servo Control

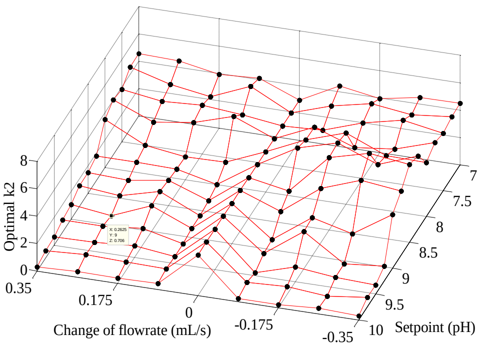

Figure 22. Optimal k_2 for Adaptive Regulatory Control

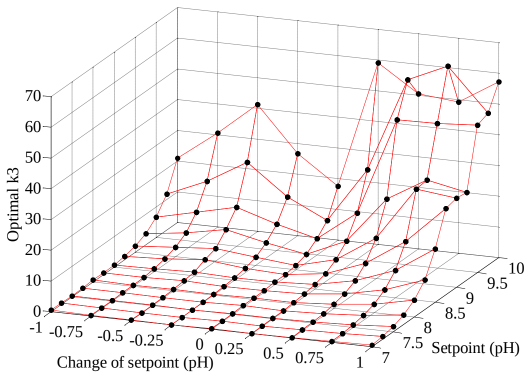

Figure 19. Optimal k_3 for Adaptive Servo Control

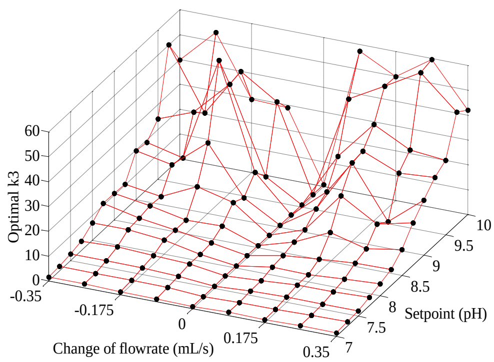

Figure 23. Optimal k_3 for Adaptive Regulatory Control

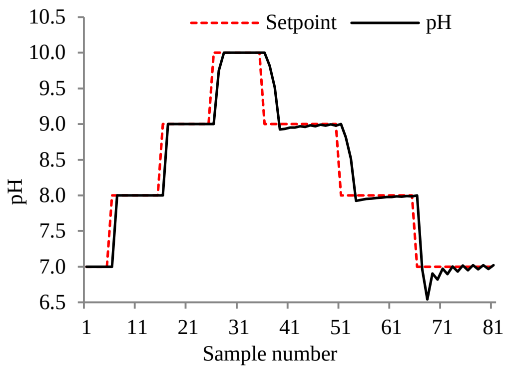

Figure 24. Controlled Variable Variations for Case IA

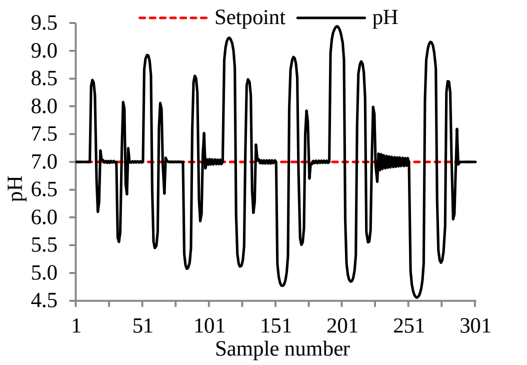

Figure 28. Controlled Variable Variations for Case IIA

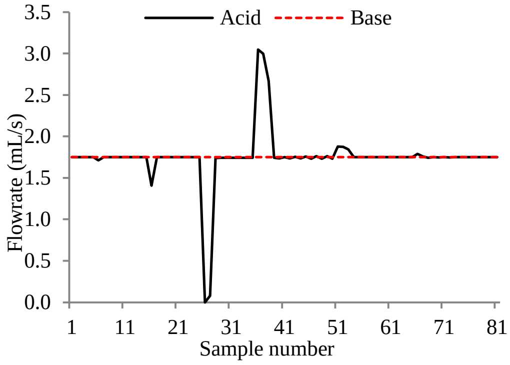

Figure 25. Manipulated Variable Variable Variations for Case IA

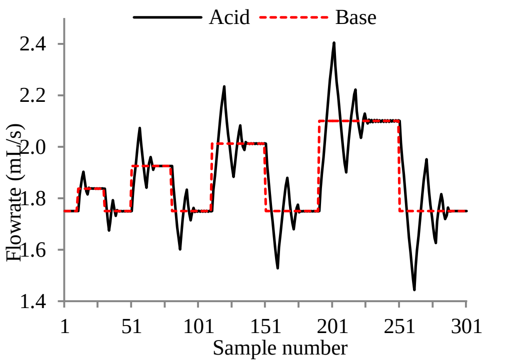

Figure 29. Manipulated Variations for Case IIA

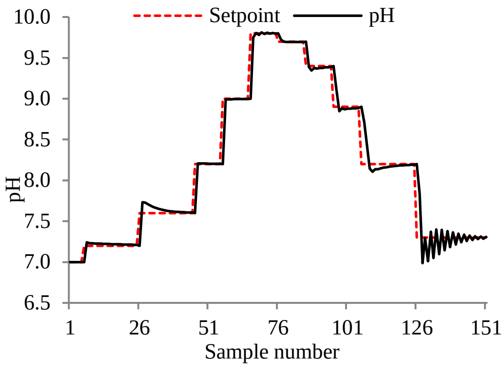

Figure 26. Controlled Variable Variations for Case IB

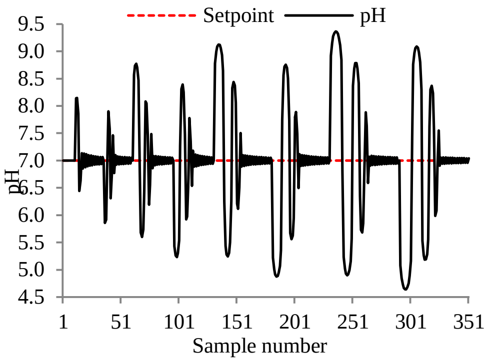

Figure 30. Controlled Variable Variations for Case IIB

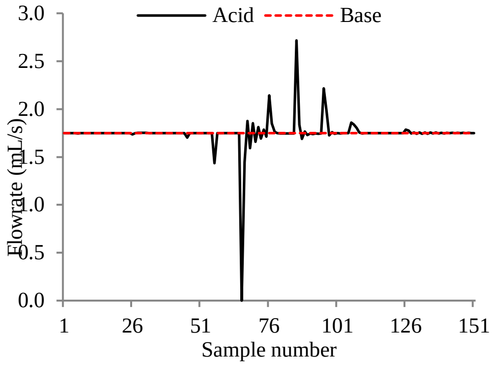

Figure 27. Manipulated Variable Variations for Case IB

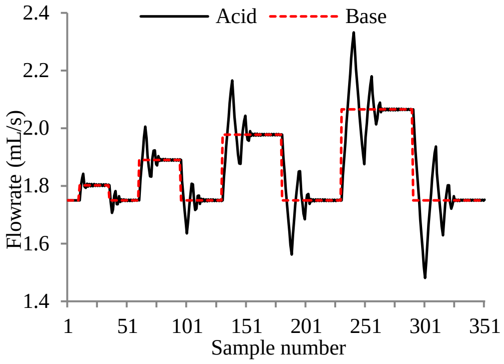

Figure 31. Manipulated Variable Variations for Case IIB

6. Conclusion

In this paper, an unconstrained, continuous and single-objective GA optimization based conventional FLC of pH neutralization process is developed for servo and regulatory control. To improve the controllers performance based on ISE, the adaptive FLC scheme is utilized to change the universe of discourse of input-output membership functions based on region of operation and amount of step change in set-point and load. For servo control design, the pH set-point is subjected to unit step changes in sequence as 7, 8, 9, 10, 9, 8, and 7, at constant base flow of 1.75 mL/s. The GA optimized conventional FLC scheme resulted in ISE of 152.93 whereas the GA optimized adaptive FLC scheme resulted in ISE of 8.24 only. Both the controllers are tested for random variations in set-point sequence of 7, 7.2, 7.6, 8.2, 9, 9.8, 9.7, 9.4, 8.9, 8.2, and 7.3 at constant base flow of 1.75 mL/s. For random set-point variations, the optimized conventional FLC scheme resulted in ISE of 37.49 whereas the optimized adaptive FLC scheme resulted in ISE of 4.64 only. Also significant improvement observed in settling time, overshoot, and undershoot in case of servo control, particularly for larger pH step change in set-point range of 8 to 10 pH. For regulatory control design, the base flow of 1.75 mL/s is subjected to ±0.0875, ±0.175, ±0.2625, and ±0.35 mL/s step changes at constant pH of 7. The optimized conventional FLC scheme resulted in ISE of 457.55 whereas the GA optimized adaptive FLC scheme resulted in ISE of 445.82. Both the controllers are tested for random variations in base flow sequence of 1.75, 1.8025, 1.75, 1.89, 1.75, 1.9775, 1.75, 2.065, and 1.75 mL/s at constant pH of 7. For random base flow variations the optimized conventional FLC scheme resulted in ISE of 511.48 and the optimized adaptive FLC scheme resulted in ISE of 366.15. Also significant improvement observed in settling time in case of regulatory control, particularly for larger magnitude of base flow variations such as ±0.3 mL/s.

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