Optimal Fuzzy Logic Control of a pH Neutralization Process using Swarm and Evolutionary Algorithms

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Abstract: - pH control plays an important role in many modern industrial plants due to strict environment regulations. This paper presents performance comparison of optimal fuzzy logic based pH control scheme for neutralization process using swarm and evolutionary algorithms. Particle swarm optimization (PSO) and differential evolution (DE) used to optimize the input and output membership functions of fuzzy inference system. The fitness function for optimization is integral of squared errors (ISE). Performance of control scheme has been evaluated for servo and regulatory operations.

Key-Words: - pH neutralization process, fuzzy logic, nonlinear control, particle swarm optimization, differential evolution

1 Introduction

Over a number of years, pH control is recognized as benchmark for modelling and control of highly nonlinear industrial process units such as boiler feedwater treatment in thermal power plant, wastewater treatment in paper and pulp industry, biopharmaceutical manufacturing, and chemical processing. However, pH control has become more difficult and demanding because modern process industries require more accurate, robust and flexible control systems for efficient and reliable operations. To meet these demands, intelligent pH control strategies are increasingly being employed in modern process industries. Development of the first-principle based dynamic modelling of pH neutralization process involves material balance on selective ions, equilibrium constants and electroneutrality equation [1]. The associated model has been used by researchers as a platform for many subsequent investigations and forms the basis to introduce new and improved forms of dynamic modelling and pH control of neutralization process using the concept of reaction invariant and strong acid equivalent [2-3]. Many different and practical approaches for pH control based on feedforward and gain scheduling techniques have also been proposed in the literature [4-7].

The fuzzy set theory is the foundation of fuzzy logic based control [8]. The term "fuzzy" in fuzzy logic applies to the imprecision in the data and not in the logic [9]. The fuzzy logic based intelligent control methodology mimics human thinking and decision making mechanisms. Since its inception, considerable development of theoretical research and application of fuzzy logic has been done by both academic and industrial communities [10-11]. The application of fuzzy logic to conventional control techniques such as proportional-integral-derivative control, sliding mode control, and adaptive control, results in improved performance for the hybrid controller over their conventional counterparts [12-14].

Particle swarm optimization (PSO) is a population based stochastic search technique which simulates the movement of organisms such as bird flocking or fish schooling [15]. The main feature of PSO is the mutual and social cooperation of individual particles where they take a decision on the basis of current and previous exchanged information with their neighbouring particles in the population. Many researchers have extensively used particle swarm algorithm for optimization and control [16-18].

Differential evolution (DE) is a stochastic evolutionary algorithm in which optimization function parameters are represented as floating-point variables. The performance of DE in optimization of many real-valued, multi-modal functions is found to be superior in comparison with many other evolutionary optimization methods [19-21]. Also many DE variants have been developed for real-valued objective function optimization problems [22-23]. DE has also found its applications in industrial automation and control [24-25].

This research article is organized as follows. Section 2 describes the dynamic modeling of pH neutralization process. Section 3 introduces the design perspective of fuzzy logic control (FLC). Section 4 and 5 shows PSO and DE based optimization FIS, respectively. Section 6 presents result and discussion on performance FLC. Section 7 presents the conclusion.

2 Dynamic Neutralization Process Model

The pH neutralization process takes place in continuous stirred tank reactor (CSTR) with perfect mixing and constant maximum 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 outlet stream: the effluent stream. The flow characteristics of pump *A* and *B* are linear and identical. The dynamic model of pH neutralization process involves material balances on selective ions, equilibrium relationship, and electroneutrality equation. Based on principle of material balances the process mixing dynamics may be described as follows:

$$V_s \frac{dx_a}{dt} = F_a C_a - (F_a + F_b) x_a \qquad (1)$$

$$V_s \frac{dx_b}{dt} = F_b C_b - (F_a + F_b) x_b \qquad (2)$$

where V_s is the maximum volume of the CSTR (1.9 L); C_a is the concentration (0.05 mol/L) and F_a is the flow rate (0 to 6.23 mL/s i.e. 0 to 100%) of titration stream A; C_b is the concentration (0.05 mol/L) and F_b is the flow rate (0 to 6.23 mL/s i.e. 0 to 100%) of process stream B; $(F_a + F_b)$ is the flow rate of the effluent stream; x_a is the concentration of acid component (chloride ion, Cl^-) in the effluent stream (in mol/L); x_b is the concentration of base component (sodium ion, Na^+) in the effluent stream (in mol/L).

The equilibrium relationship for water is given as

$$K_w = [H^+][OH^-] \qquad (3)$$

where K_w is the water dissociation constant (10^{-14}). From the electroneutrality condition, we have

$$[Na^+] + [H^+] = [Cl^-] + [OH^-] \qquad (4)$$

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

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

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

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

where $x = (x_a - x_b) \qquad (7)$

3 Design of Fuzzy Logic based Controller

The fuzzy logic based controller for pH neutralization process is based on computationally efficient zero-order Sugeno fuzzy inference system (FIS). The input variables used for the fuzzy logic based controllers are error $e(k) = pH_{SP} - pH(k)$ i.e. the difference between the desired setpoint (pH_{SP}) and measured values of control variable $pH(k)$, and change in error $ce(k) = e(k) - e(k\text{-}1)$ i.e. the difference between the error at the present and previous instants. The fuzzy logic controller output $co(k) = F_a(k\text{-}1) - F_a(k)$ is used as the change in manipulated variable i.e. the change in acid flow rate of feed A. The normalized membership functions for the input variables (e^*, ce^*), and output variable (co^*) are shown in Fig. 1, and Fig. 2 respectively. The rule base for the input and output variables are shown in Table I.

The FIS consists of an input stage, a fuzzy rule processing stage, and an output stage. The input stage first determines the degree of membership (a number between 0 and 1) to which each input belong, and since the antecedent of rule has more than one part, the AND fuzzy algebraic product operator is applied to obtain one number that represents the firing strength for that rule. The output level of each rule is weighted by the above firing strength. The final output of the FIS is the weighted average of all rule outputs.

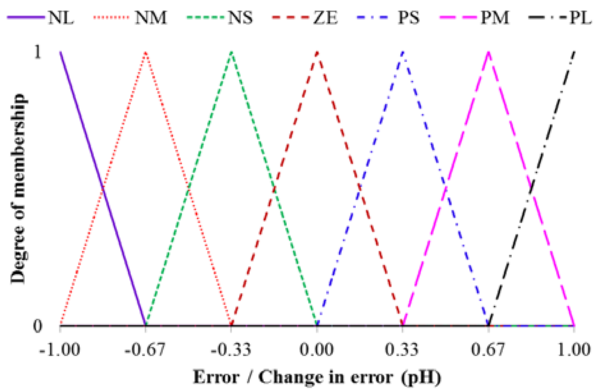

Fig. 1. Normalized membership functions for error and change in error

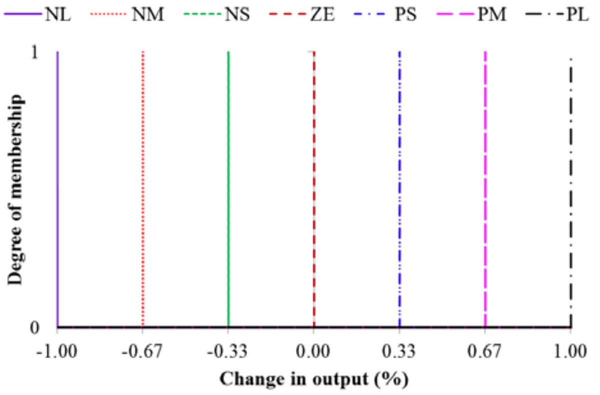

Fig. 2. Normalized membership functions for change in output

Table 1: Fuzzy Rule Base

e \ ce	NL	NM	NS	ZE	PS	PM	PL
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

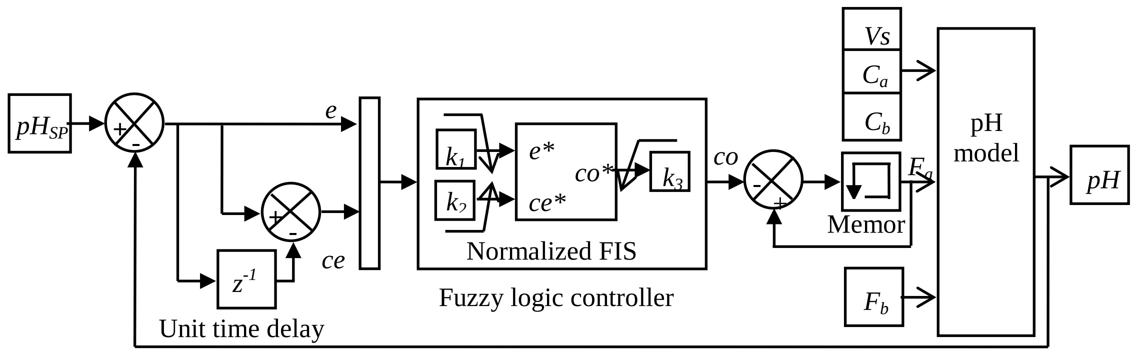

Fig. 3. Fuzzy logic based pH control

4 PSO based FIS

The schematic diagram of PSO based FIS for pH control is shown in Fig. 3. To optimize the FIS, the scaling factors k_1, k_2, and k_3 are chosen to proportionately scale the vertices of membership functions for normalized variables e^*, ce^*, and co^* respectively. The range of e, ce, and co are [-6 6], [-6 6], and [-1 1] respectively. The PSO flowchart is shown in Fig. 4. PSO starts with an initial population of particle positions (X) of type double and size 20, generated at random within the initial population range [0 0 0;4.5 4.5 2] representing minimum and maximum values for scaling factors k_1, k_2, and k_3 respectively. Also the velocity of the particles (V) are initially set to zero. Each individual particle position in the population represents a potential solution to the optimization problem under consideration. The moving particles evolve through successive iterations, called generations. During i-th generation, each particle in the population is evaluated using integral of squared errors (ISE) fitness function. The evaluated fitness values of the particles gives best global and best local fitness and position *fGbest, fLbest, xGbest* and *xLbest* respectively.

At the end of i-th generation, the velocity, the position and the inertia (C_0) of each particle is modified as per the following equation.

$$V \leftarrow C_0 V + C_1 R_1 \left(xLbest - X \right) + C_2 R_2 (xGbest - X) \tag{8}$$

$$X \leftarrow X + V \tag{9}$$

$$C_0 \leftarrow 0.9 - 0.4(i/G) \tag{10}$$

where the cognitive attraction (C_1) is 0.5, the social attraction (C_2) is 2, the total number of generations (G) is 100, and R_1 and R_2 are random numbers between 0 and 1. The procedure continues until the termination criteria is satisfied. The termination criteria for PSO are either reaching the maximum number of generations, or the stall generation limit (50), or the fitness limit (10^{-6}).

5 DE based FIS

The schematic diagram of DE based FIS for pH control is shown in Fig. 3. To optimize the FIS, the scaling factors k_1, k_2, and k_3 are chosen to proportionately scale the vertices of membership functions for normalized variables e^*, ce^*, and co^* respectively. The range of e, ce, and co are [$-k_1$ k_1],

[-k_2 k_2], and [-k_3 k_3] respectively. The DE flowchart is shown in Fig. 5. The DE starts with generation of an initial population vector of type double and size 20, randomly within the 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. The initial population range are chosen

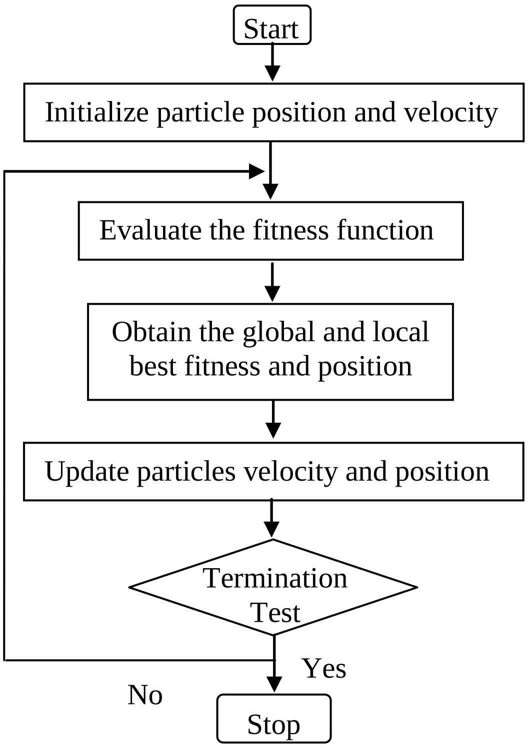

Fig. 4. PSO flowchart

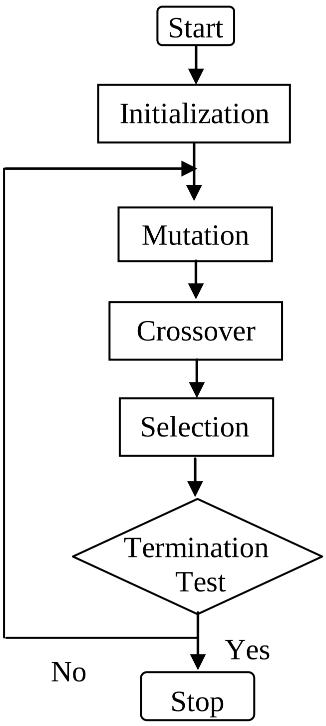

Fig. 5. DE flowchart

over narrow as well as wide search spaces such as [0 0 0;4.5 4.5 2] for *Case I*, [0 0 0;4.5 4.5 4] for *Case II*, [0 0 0;4.5 4.5 20] for *Case III*, and [0 0 0;4.5 4.5 40] for *Case IV*. Each individual in the population represents a potential solution to the optimization problem under consideration and evaluated using integral of squared errors (ISE) fitness function. The individuals evolve through successive generations. During each generation, DE population vector undergoes mutation, crossover and selection, until termination criterion are satisfied.

The mutation operation in DE expands the search space. For the 1×3 parameter vector $X_i(G)$, the mutation vector $V_i(G+1)$ is generated as

$$V_i(G+1) = X_p(G) + F\left[X_q(G) - X_r(G)\right] \tag{11}$$

where G = 1, 2, ..., 100 is the generation number; index i = 1, 2, ..., 20; random integer indexes $p \neq q \neq r \neq i \in \{1, 2, ..., 20\}$; F = 1 is the amplification factor.

The crossover operation in DE increases the diversity of perturbed parameter vectors. For the parameter vector $X_i(G)$ and the mutation vector $V_i(G+1)$, the trial vector is given by

$$U_i(G+1) = K_{1i}\, X_i(G) + K_{2i}\, V_i(G+1) \tag{12}$$

where K_{1i} and K_{2i} are logical constants. The logical constants K_{1i} and K_{2i} are inverse to each other such that

$$K_{1i} = \left(rand(1{,}3)\right)_i < CR \tag{13}$$

$$K_{2i} = K_{1i} < 0.5 \tag{14}$$

where $rand(1{,}3)$ is 1×3 uniformly distributed pseudorandom vector and CR = 0.8 is the crossover rate.

The selection operation in DE compares the values of the fitness function (f) for the parameter vector $X_i(G)$ and the trial vector $U_i(G+1)$ such that

$$X_i(G+1) = U_i(G+1)\ \ if\ f\left(U_i(G+1)\right) \leq f\left(X_i(G)\right) \tag{15}$$

$$X_i(G+1) = X_i(G)\ \ if\ f\left(U_i(G+1)\right) > f\left(X_i(G)\right) \tag{16}$$

The termination criteria for DE are either the maximum number of generations 100, or the minimum fitness function value (10^{-6}).

6 Results and Discussions

To evaluate the PSO and DE based FIS, servo and regulatory operations are carried out.

6.1 Servo Control of PSO based FIS

For servo operation, the variations in pH_{SP} is shown in Fig. 8. The local best and the mean fitness function values PSO based FIS for servo operation in individual generation are shown in Fig. 6. After 100 generations, the global best and the average mean fitness function values for PSO based FIS are 29.426 and 320.241 respectively. The optimized values of scaling factors for servo control are k_1 = 4.041, k_2 = 0.935, and k_3 = 0.457. The initial and final positions of the particles are shown in Fig. 7. The majority of the particles converges around the best particle. The variations of controlled and manipulated variables for servo response are shown in Fig. 8 and 9 respectively. For pH_{SP} variations of 9 to 8 and 5 to 6, we have maximum undershoot and overshoot of 1.244 pH unit respectively.

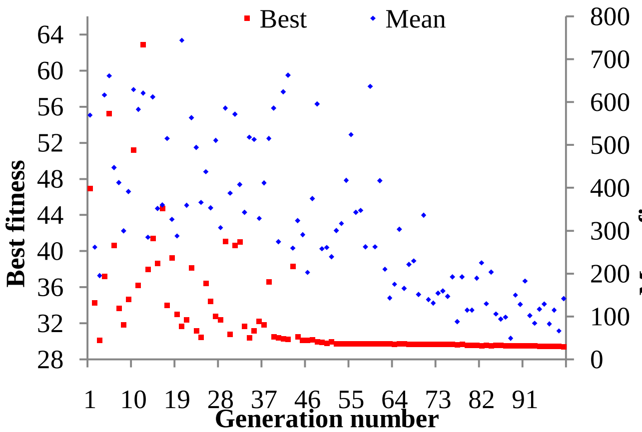

Fig. 6. Local best and mean fitness values for servo control

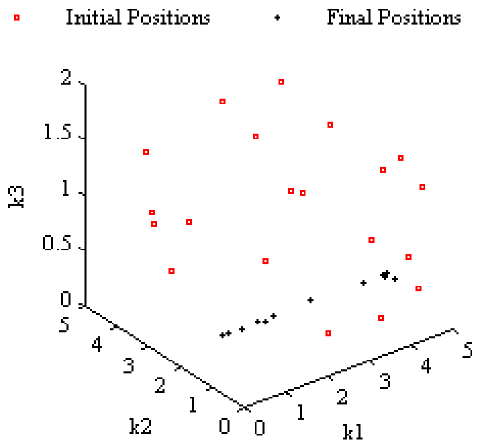

Fig. 7. Particle swarm initial and final positions for servo control

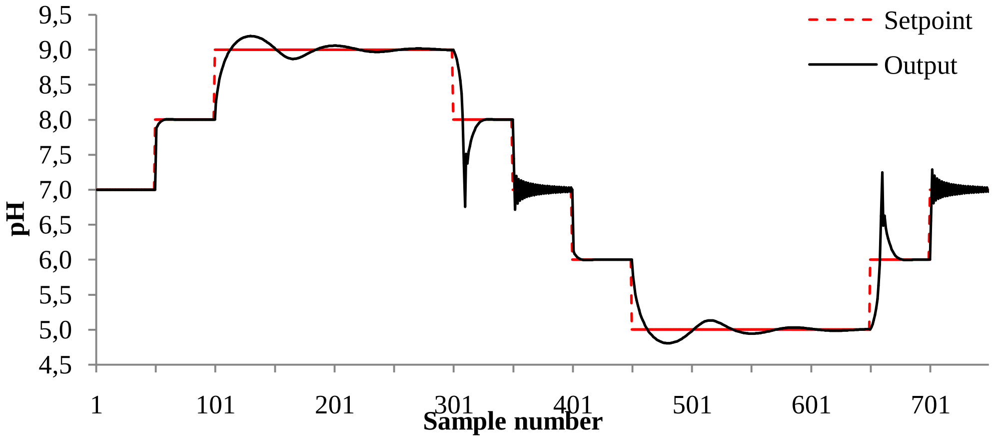

Fig. 8. Controlled variable variations for servo control

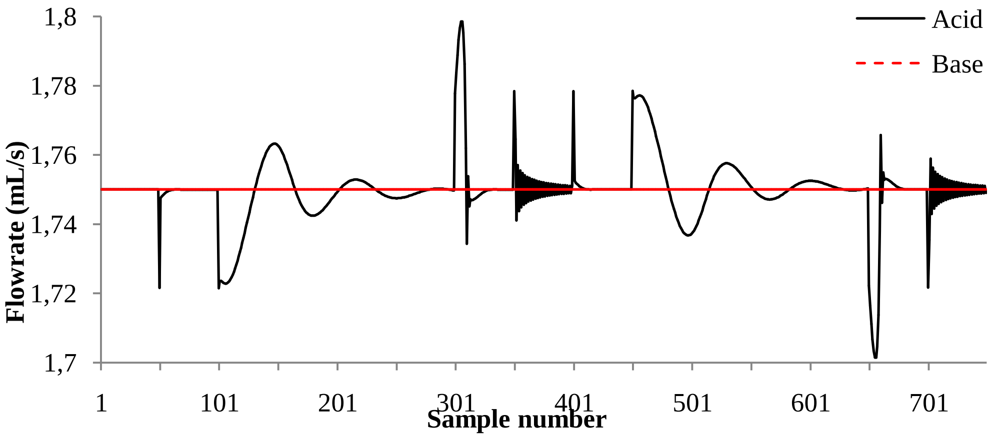

Fig. 9. Manipulated variable variations for servo control

6.2 Regulatory Response of PSO based FIS

For regulatory operation, the base flowrate (F_b) variation is shown in Fig. 13. The local best and the mean fitness function values PSO based FIS for regulatory operation in individual generation are shown in Fig. 10. After 100 generations, the global best and the average mean fitness function values for PSO based FIS are 164.502 and 2090.379 respectively. The optimized values of scaling factors for regulatory control are k_1 = 3.162, k_2 = 4.316, and k_3 = 1.396. The initial and final positions of the particle swarm are shown in Fig. 11. Here few particles converge around the best particle. The plots of controlled and manipulated variables for regulatory response are shown in Fig. 12 and 13 respectively. For F_b variations of 1.75 to 1.925 and 1.75 to 1.575 mL/s, we have maximum overshoot and undershoot of 1.921 pH unit respectively.

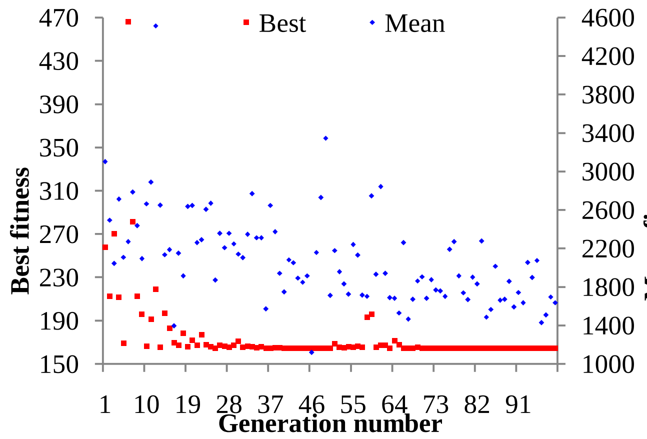

Fig. 10. Local best and mean fitness values for regulatory control

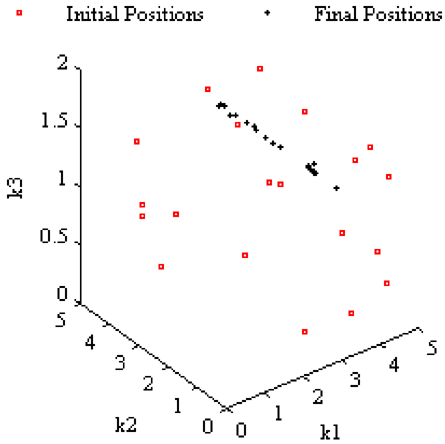

Fig. 11. Particle swarm initial and final positions for regulatory control

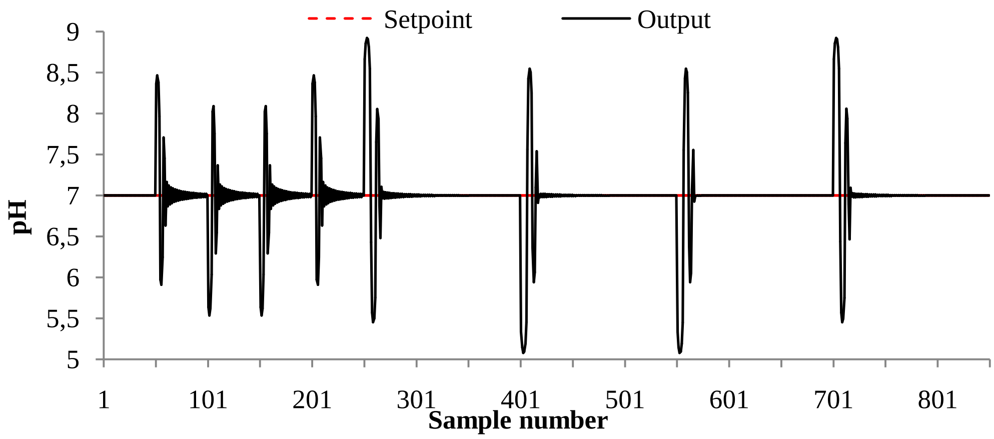

Fig. 12. Controlled variable variations for regulatory control

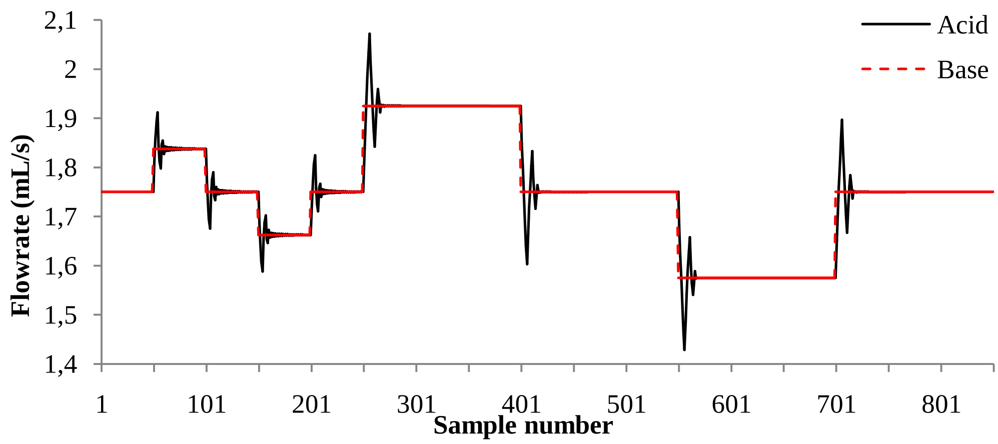

Fig. 13. Manipulated variable variations for regulatory control

6.3 Servo Control of DE based FIS

For servo operation, the pH setpoint (pH_{SP}) variations are shown in Fig. 16. The best and the mean fitness function values for various cases of initial population range are shown in Fig. 14 and 15 respectively. The DE converges in all the cases. After 100 generations, the best and mean ISE, the optimized k_1, k_2 and k_3 are 28.75, 28.76, 4.50, 0.98, 0.48 for *Case I*; 28.74, 28.78, 4.50, 0.98, 0.48 for *Case II*; 28.76, 28.86, 4.50, 0.98, 0.48 for *Case III*; and 28.76, 28.86, 4.48, 0.98, 0.48 for *Case IV* respectively. Using the *Case I* optimization values, the variations of controlled and manipulated variables for servo response are shown in Fig. 16 and 17 respectively. For pH_{SP} variations of 9 to 8 and 5 to 6, we have maximum undershoot and overshoot of 1.18 pH unit respectively.

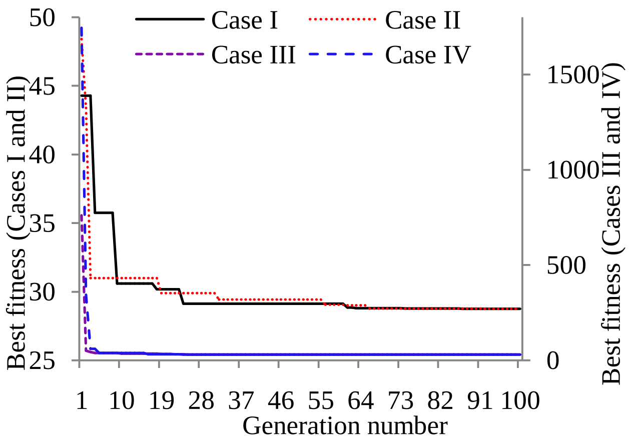

Fig. 14. Best fitness values for various cases (servo control)

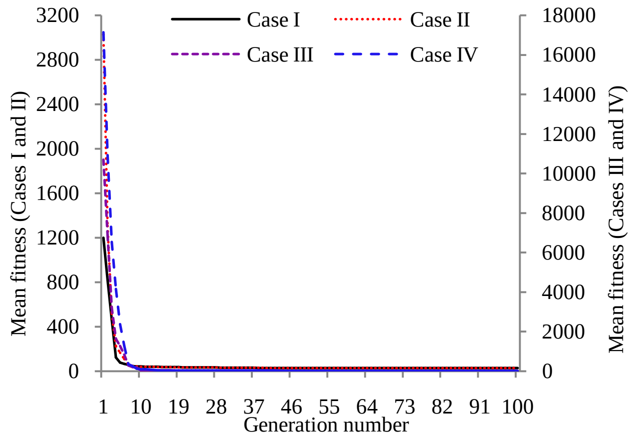

Fig. 15. Mean fitness values for various cases (servo control)

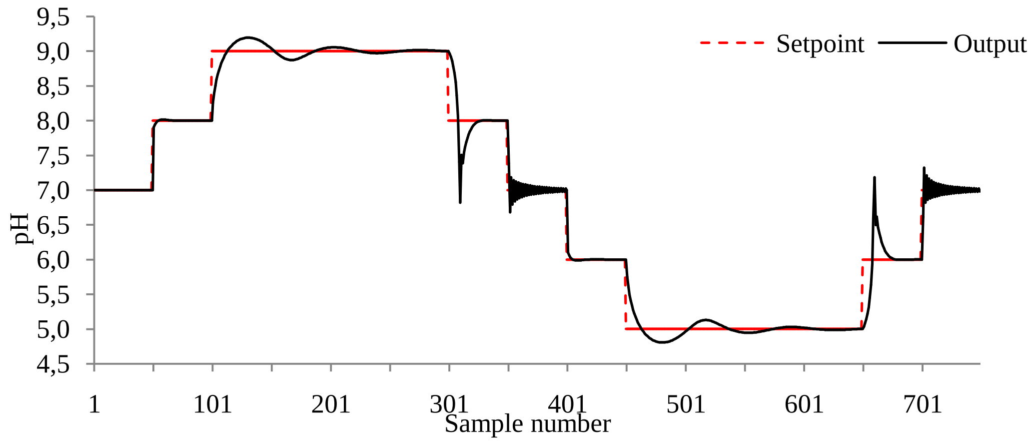

Fig. 16. Controlled variable variations for servo control (Case I)

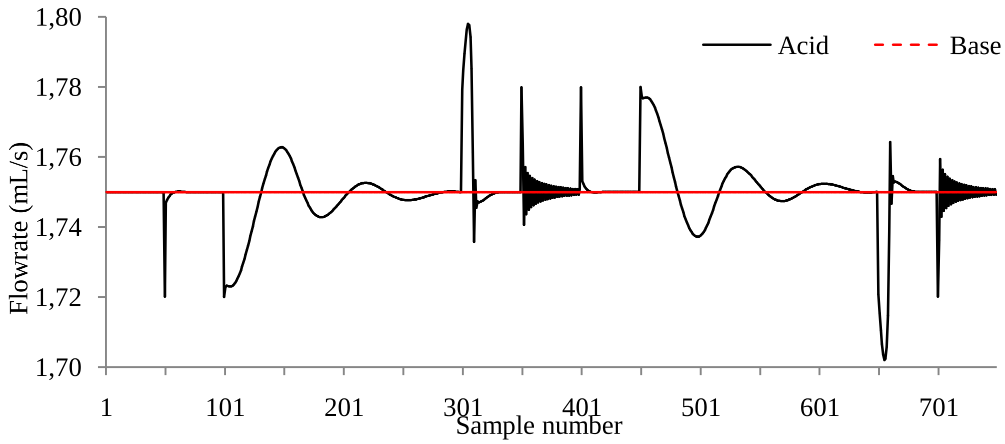

Fig. 17. Manipulated variable variations for servo control (Case I)

6.4 Regulatory Control of DE based FIS

For regulatory operation, the base flowrate (F_b) variations are shown in Fig. 21. The best and the mean fitness function values for various cases of initial population range are shown in Fig. 18 and 19 respectively. The DE converges in all the cases. After 100 generations, the best and mean ISE, the optimized k_1, k_2 and k_3 are 163.44, 163.58, 3.40, 4.50, 1.48 for *Case I*; 163.74, 164.54, 3.36, 4.44, 1.47 for *Case II*; 163.52, 164.57, 3.38, 4.50, 1.47 for *Case III*; and 163.60, 164.00, 3.41, 4.48, 1.48 for *Case IV* respectively. Using the *Case I* optimization values, the plots of controlled and manipulated variables for regulatory response are shown in Fig. 20 and 21 respectively. For F_b variations of 1.75 to 1.925 and 1.75 to 1.575 mL/s, we have maximum overshoot and undershoot of 1.92 pH unit respectively.

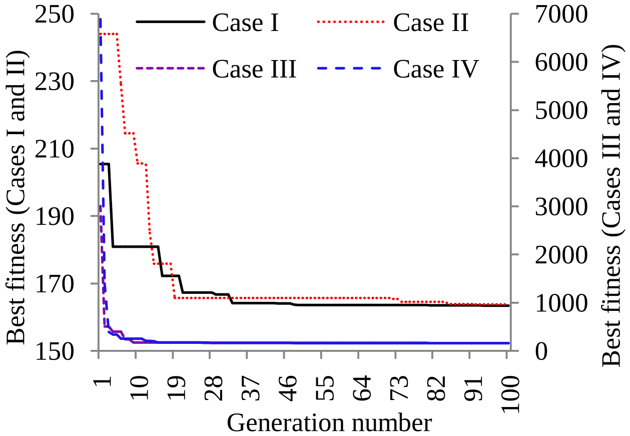

Fig. 18. Best fitness values for various cases (regulatory control)

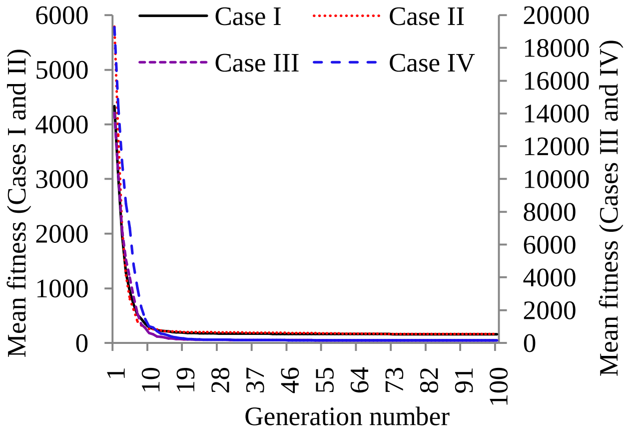

Fig. 19. Mean fitness values for various cases (regulatory control)

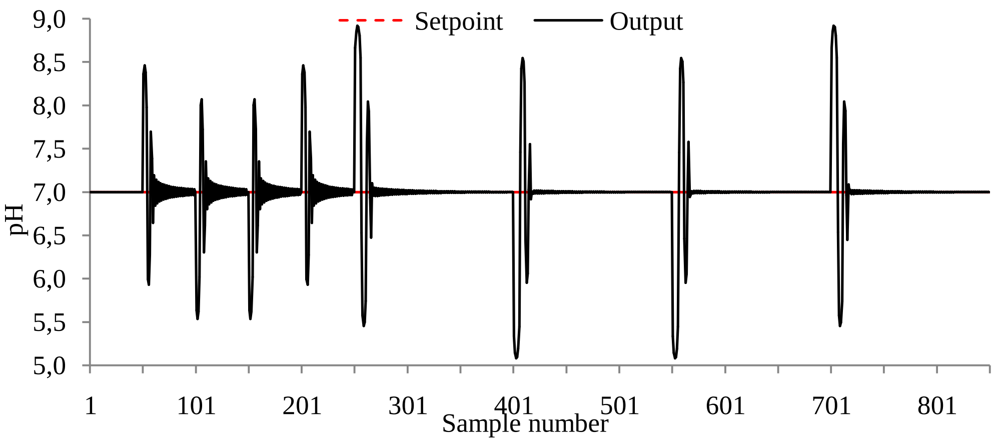

Fig. 20. Controlled variable variations for regulatory control (Case I)

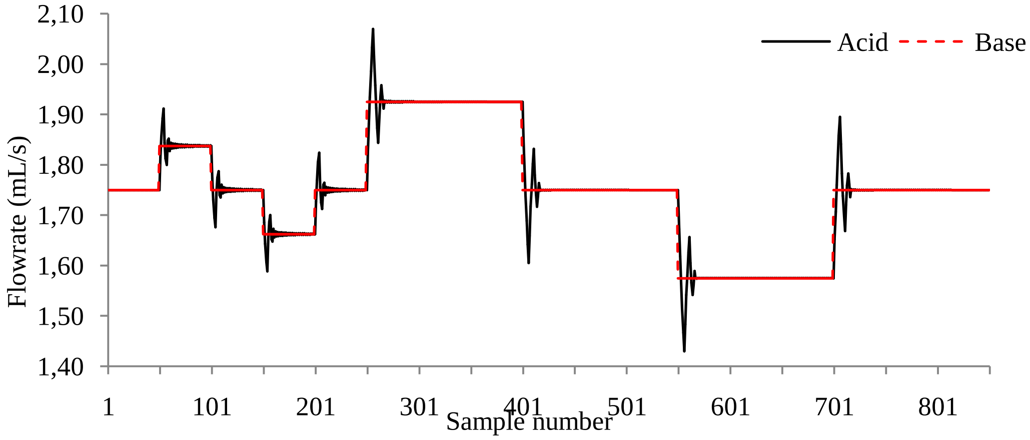

Fig. 21. Manipulated variable variations for regulatory control (Case I)

7 Conclusion

Using particle swarm optimization based fuzzy inference system, the pH controller is designed for both servo and regulatory operations. The pH controller is able to track and reject the variations in the setpoint and the base flowrate for servo and regulatory operations respectively. The particles in the swarm are able to converge from widely and randomly spread initial positions to a limited region of final position. However the rate of convergence is slower.

Using DE, optimal FIS is designed for pH control of a neutralization process. The DE is able to locate consistently the global optimal solution for narrow as well as wide search spaces. The DE rate of convergence is also faster. The pH controller is able to track and reject the variations in the setpoint and the base flowrate for servo and regulatory operations respectively.

We thus conclude that performance of DE is superior to PSO for optimization of FLC of a pH neutralization process.

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