# Design and Implementation of Intelligent Control Schemes for a pH Neutralization Process

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*Abstract:* - This paper describes, with extensive experimentation and simulation, three aspects of strong acid (Hydrochloric acid, HCl) and strong base (Sodium Hydroxide, NaOH) based pH neutralization process: (i) dynamic modeling, (ii) control, and (iii) optimization. Dynamic pH model based on Artificial Neural Network (ANN) has been used for various simulation studies involving servo and regulatory operations in Fuzzy Logic Control (FLC) scheme, and in optimization of pH controller parameters. This paper compares performance variables, such as Integral of Squared Errors (ISE), and maximum overshoot or undershoots, of optimized fuzzy control technique for servo and regulatory operations. The present work also describes finding optimum parameter settings of the pH controller using various search and optimization techniques such as Genetic Algorithm (GA), Differential Evolution (DE), and Particle Swarm Optimization (PSO), and the convergence of optimization techniques.

*Key-Words:* - pH neutralization process, artificial neural network, system identification, fuzzy logic, nonlinear control, genetic algorithm, particle swarm optimization, differential evolution

## 1 Introduction

In recent years, there is a major spurt in modernization of industrial plants through process automation since the new competitive business strategy is based on pricing, production, scheduling and delivery-time [1]. Process automation is essential for economical plant operation through efficient techniques for energy utilization and waste minimization, and compliance to laws concerning increased safety levels and reduction in environmental pollution. The far-reaching applications of pH measurement and control in modern commerce and industry necessitated development of controllers that permit pH processes to be regulated automatically. To deal with severe nonlinearities and address concerns of varying operating conditions and parameter variations in pH measurement and control applications, rigorous dynamic pH model are developed using first principle and system identification methods [2-8]. However, first principle based models do not represent true and realistic behavior of process, and system identification based block-structured models developed using experimental data and some insight into the system are limited by choice of suitable nonlinear structure and inability to accurately estimate model parameter. System identification technique based on input-output behavior of the system and without any knowledge of system configuration, such as Artificial Neural Network (ANN), has been very popular and successful, over last two decade, with wide range of nonlinear system applications. ANN based modeling is inspired by biological neural networks and it comprises a set of interconnected nonlinear processing element known as artificial neuron. ANN has an excellent ability to learn nonlinear dynamics of a complex process because of its inherent parallel and distributed configuration. ANN based model predictive control techniques have been extensively developed for pH neutralization process [9-13].

The focus of advanced control methodologies now a day is to develop intelligent control algorithm based on computational intelligence paradigms e.g. ANN, fuzzy logic, evolutionary computation such as Genetic Algorithm (GA) and Differential Evolution (DE), swarm intelligence such as Particle Swarm Optimization (PSO). 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, and brought an unconventional shift in nature of computing based on words and perceptions [14-17]. Zadeh discussed about unconventional perspectives of fuzzy logic, namely graduation, granulation, precisiation and the concept of a generalized constraint, and summarized that in large measure, the real-world is a fuzzy world and to deal with fuzzy reality we need fuzzy logic [18]. Fuzzy logic based pH control has been developed to obtain intelligent equivalent of the conventional counterpart such as PI, PD, PID and sliding-mode, and adaptive and model predictive control techniques [19-32].

Many researchers have utilized global optimization techniques based on evolutionary algorithms such as Genetic Algorithm (GA) and Differential Evolution (DE), and swarm algorithm such as Particle Swarm Optimization (PSO) for controller optimization. Evolutionary algorithms are population based search techniques in which optimal solution is reached on the basis of Darwin's theory of biological evolution. Over number of years, various but independent types of evolutionary algorithms were developed by many scientists and researchers with an aim of utilizing them for optimal solution of various engineering problems. However, GA conceived by Holland and its variants received wide attention [33-34]. GA is also applied for parameters optimization of various controllers [35-43]. Similarly, DE is a stochastic evolutionary algorithm in which optimization function parameters are represented as floating-point variables [44-46]. 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. DE has also found applications in industrial automation and control [47-49]. PSO, on the other hand, is a population based stochastic search technique which simulates the movement of organisms such as bird flocking or fish schooling [50]. The main feature of PSO is mutual and social cooperation of individual particles where they take a decision on basis of current and previous exchanged information with their neighboring particles in population. Many researchers have used particle swarm algorithm in optimization problems [51-56].

Although researchers have proposed many pH control schemes using different techniques such as conventional, adaptive and intelligent, however there are still few considerable challenges in dynamic modeling, control and optimization of pH neutralization process. First, HCl is an important and widely used chemical in steel pickling process in iron and steel industry, ore processing in mining industry, wastewater treatment in food processing, and neutralization reaction in chemical manufacturing, but strong acid-strong base neutralization has not been investigated extensively and many proposed dynamic pH models and subsequent control schemes are based on weak acid-strong base neutralization process. Second, first principle based model does not represent all the nonlinear dynamics of pH neutralization system, and the random variations in pH sensor values and process parameter variations cannot be accounted in first principle model. All these necessitates development of ANN based dynamic pH model using experimental values, which has capability to learn highly nonlinear behavior. Third, reported works in literature do not provide a comprehensive performance comparison of controller parameter optimization using GA, DE and PSO for pH control of strong acid-strong base neutralization process.

## 2 System description and identification

Armfield® Process Control Teaching System (PCT40) with Process Vessel Accessory (PCT41) having constant volume of $V_s$ = 2000 mL and pH Sensor Accessory (PCT42) with a voltage output of 0 to 5 V has been used as a pH neutralization system. Fig. 1(a) shows the schematic diagram of Armfield pH neutralization system consisting of important components pertaining to present work. The PCT40 has peristaltic pumps A and B which regulate flow of hydrochloric acid (HCl) and sodium hydroxide (NaOH) having concentrations $C_a$ (0.01778 mol/L) and $C_b$ (0.01259 mol/L) respectively. Eq. (1) and (2) gives linear regression based estimate for flowrates of pumps A and B, $F_a$ and $F_b$, for different values of speeds of pumps A and B, $S_a$ and $S_b$, with values of statistical coefficient $R^2$ as 0.9985 and 0.9984, respectively. The pH neutralization process takes place in PCT41 with perfect mixing and constant maximum volume ($V_s$). The pH probe PCT42 is calibrated against buffer pH solutions of 4, 7 and 9.2, and linear regression analysis is applied to obtain relationship between sensor voltage and equivalent pH, with statistical coefficient $R^2$ equals 0.9998, as shown in Eq. (3). Fig. 1(b) shows the dynamic response of pH sensor obtained by transferring the pH sensor from one standard buffer solution to another and then stirring it. There is negligible delay in pH sensor response since approximately two second time is elapsed on transferring the pH sensor from one buffer to another and then stirring it. Thus, we will consider entire process lag to be associated with its mixing dynamics.

$F_a = 0$ for $0 \leq S_a < 18$; $(0.0599\ S_a - 0.8761)$ for $18 \leq S_a \leq 100$ (1)

$F_b = 0$ for $0 \leq S_b < 18$; $(0.0680\ S_b - 0.9251)$ for $18 \leq S_b \leq 100$ (2)

$pH = 2.6114\ V_{pH} + 0.1868$ (3)

Using standard universal synchronous bus interface the PCT40 communicates with LabVIEW software installed on a personal computer having Windows operating system. The PCT40 interface device driver contains a dynamic link library (DLL) file which stores various input-output analog and digital control signal values. The analog signals between 0 V or 0% to 5 V or 100% are stored in 12-bit signed-magnitude representation as 000000000000 to 011111111111 in binary or 0 to 2047 in decimal whereas the digital signals either 0 V or 5 V are stored in 1-bit representation as 0 or 1 in binary, respectively. LabVIEW software accesses the DLL file for following functionality: read analog input, pH probe value from channel 11 (Ch11); write analog outputs, pump A and B speed values to digital-to-analog converters DAC0 and DAC1 respectively; write digital output, stirrer signal value to digital output line 7 (DO7).

Fig. 2(a) shows the speeds of pumps A and B at each sampling instants and Fig. 2(b) shows the corresponding pH response, where number of collected samples are 32750 at sampling instants of 1 second. We have used the tapped delay line approach, mainly due to its simplicity of implementation using established feedforward neural network architecture and supervised Levenberg–Marquardt (LM) training algorithm. The feedforward network uses current value of pumps speed, and past values of pH and pumps speed as the network inputs, to predict current value of pH as the network output. The resulting feedforward architecture is equivalent to nonlinear autoregressive network with external inputs (NARX) which can be described using Eq. (4).

$pH(i) = f(S_a(i-d),....,S_a(i),S_b(i-d),....,S_b(i),pH(i-d),....,pH(i-1))$ (4)

where 'i' is current sample number that varies from 11 to 32750, and number of delayed samples 'd' is 3. The LM training algorithm gives training MSE of $5.175\times10^{-4}$, validation MSE of $4.535\times10^{-4}$, and testing MSE of $4.671\times10^{-4}$, at $201^{th}$ epoch, and training stops after next 6 epochs. It is found that magnitude of error never exceeds 0.4 pH unit for entire data set of 32740 samples. Also more than 99% of those errors lie within magnitude range of 0.1 pH unit.

# 3 Optimized Fuzzy Logic based Control Schemes

The fuzzy logic controller structure is based on Mamdani Fuzzy Inference System (FIS) which uses ‘AND’ fuzzy operator, ‘Mamdani’ fuzzy implication, ‘max-min’ fuzzy aggregation, and ‘centre of gravity’ defuzzification. The input variables of fuzzy logic controller for pH neutralization process are error $\mathrm{e(k)}$ and change in error $\mathrm{ce(k)}$ at $k^{th}$ sampling instant. After dividing the input variables $\mathrm{e(k)}$ and $\mathrm{ce(k)}$ with scaling factors $K_1$ and $K_2$, we obtain normalized error and change in error, $\mathrm{e^*(k) = e(k)/K_1}$and $\mathrm{ce^*(k) = ce(k)/K_2}$, respectively. The signal multiplexer combines $\mathrm{e^*(k)}$ and $\mathrm{ce^*(k)}$ to give vector $[\mathrm{e^*(k), ce^*(k)}]$ as input to Mamdani FIS. The Universe of Discourse (UOD) of input linguistic variables $\mathrm{e^*(k)}$ and $\mathrm{ce^*(k)}$ are [-1, 1], in pH. After multiplying the normalized change in output $\mathrm{co^*(k)}$, which is defuzzified output of Mamdani FIS, by the scaling factor $K_3$, we obtain output variable $\mathrm{co(k) = co^*(k) \times K_3}$ of fuzzy logic controller. The UOD of output linguistic variable $\mathrm{co^*(k)}$ is [-1, 1], in %. The input and output linguistic variables of Mamdani FIS has seven linguistic values each, namely Negative Large (NL), Negative Medium (NM), Negative Small (NS), Zero (ZE), Positive Small (PS), Positive Medium (PM), and Positive Large (PL). The membership functions associated with linguistic values of $\mathrm{e^*}$, $\mathrm{ce^*}$, and $\mathrm{co^*}$are shown in Fig. 3. Since fuzzy rules are culmination of experience and knowledge of an operator, the proposed 49 fuzzy rules for pH control of neutralization process ensure the stability of fuzzy controller. The individual fuzzy rule can be represented using following structure shown in Eq. (5).

$FR_l$: IF $\mathrm{e^*}$ is $m$ AND $\mathrm{ce^*}$ is $n$, THEN $\mathrm{co^*}$ is $MF_{mn}$ (5)

where $l = 7m + n - 7$; $m$, $n$ = 1, 2, 3, 4, 5, 6, 7 represents NL, NM, NS, ZE, PS, PM, PM respectively; $MF_{11}$, $MF_{12}$, $MF_{13}$, $MF_{14}$, $MF_{21}$, $MF_{22}$, $MF_{23}$, $MF_{31}$, $MF_{32}$, $MF_{41}$ represents NL; $MF_{15}$, $MF_{24}$, $MF_{33}$, $MF_{42}$, $MF_{51}$ represents NM; $MF_{16}$, $MF_{25}$, $MF_{34}$, $MF_{43}$, $MF_{52}$, $MF_{61}$ represents NS; $MF_{17}$, $MF_{26}$, $MF_{35}$, $MF_{44}$, $MF_{53}$, $MF_{62}$, $MF_{71}$ represents ZE; $MF_{27}$, $MF_{36}$, $MF_{45}$, $MF_{54}$, $MF_{63}$, $MF_{72}$ represents PS; $MF_{37}$, $MF_{46}$, $MF_{55}$, $MF_{64}$, $MF_{73}$ represents PM; $MF_{47}$, $MF_{56}$, $MF_{57}$, $MF_{65}$, $MF_{66}$, $MF_{67}$, $MF_{74}$, $MF_{75}$, $MF_{76}$, $MF_{77}$ represents PL.

In this work, we have used feedback control of Armfield pH neutralization process in which pH is Controlled Variable (CV), speed of acid pump A ($S_a$) is Disturbance Variable (DV), and speed of

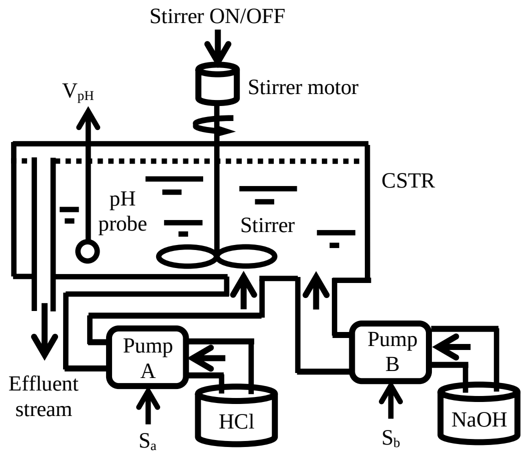



Fig. 1(a) Armfield pH neutralization system schematic

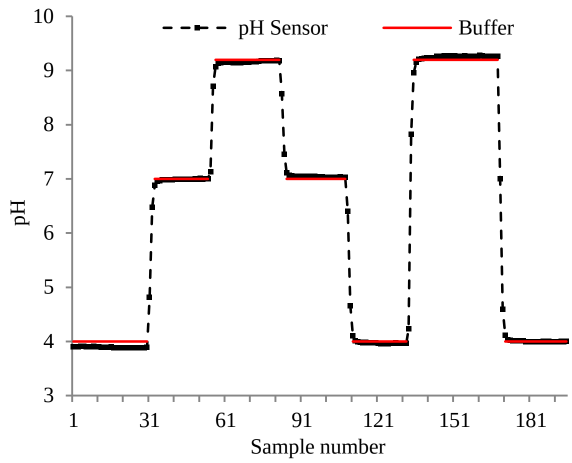



Fig. 1(b) Dynamic response of pH sensor

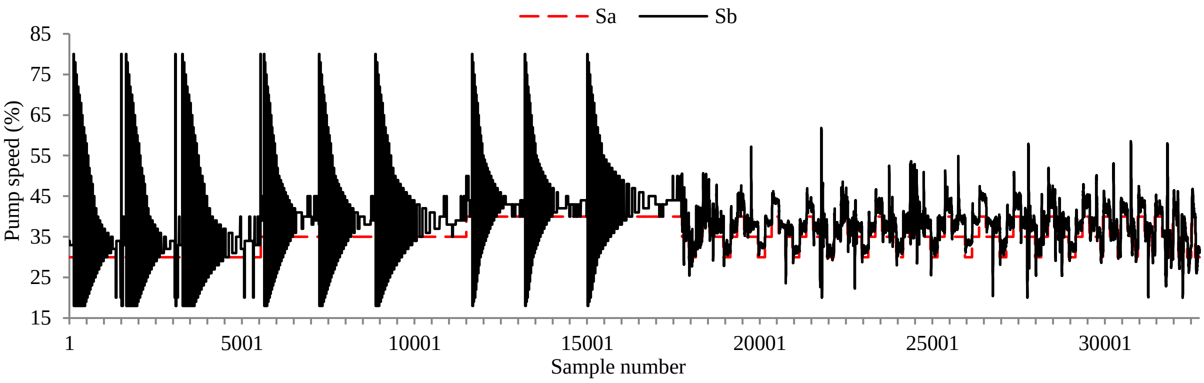



Fig. 2(a) Pumps speed at each sampling instants for system identification

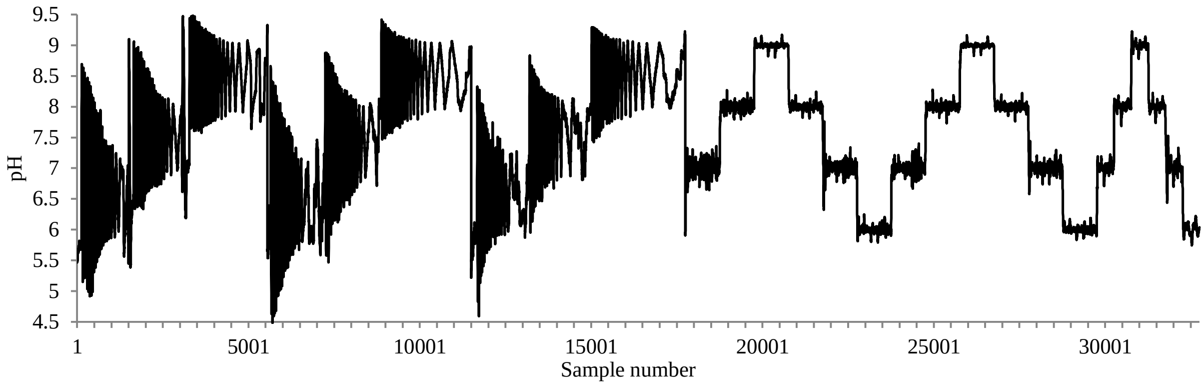



Fig. 2(b) pH response at each sampling instants for system identification

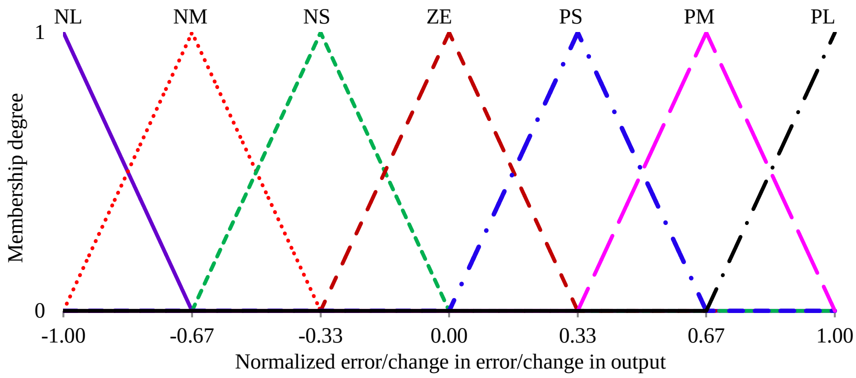
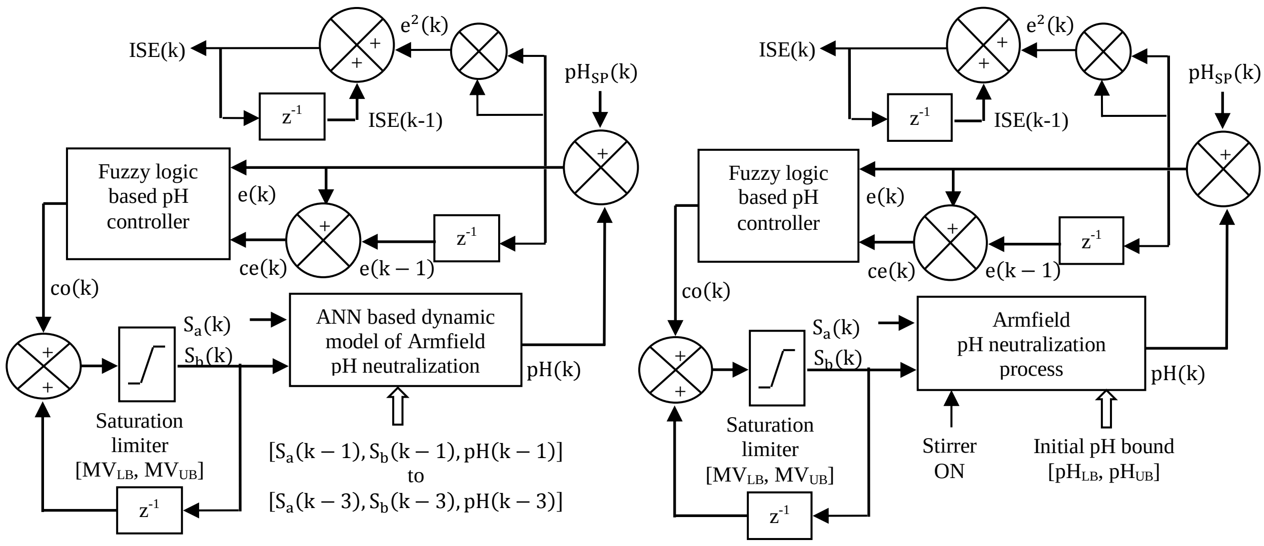



Fig. 3 Fuzzy membership functions of normalized error/change in error/change in output




(a) (b)

Fig. 4 Feedback control of pH neutralization process for (a) offline simulation on ANN based dynamic model of Armfield - pH00 (b) online experimental validation on Armfield - pH01

Table 1 Parameters for GA, DE, and PSO techniques based pH control system

| Technique | Parameters |
|---|---|
| Common GA, DE, and PSO parameters | No. of variables (n) = 3; No. of population members (L) = 20; No. of generations (G) = 50 for offline simulation and 5 for online validation; Range of population members (for GA and DE)/range of particles positions (for PSO) $[K_L;K_U]$ = $[K_{1L}, K_{2L}, K_{3L};K_{1U}, K_{2U}, K_{3U}]$ = [6 0.2 6;30 1 30]; Minimum ISE (ISE1); Minimum ISE desired (ISE1L) = 0; Absolute difference between minimum ISE for two successive generations (DISE1L) = 0; pH values range for online validation, $[pH_{LB}, pH_{UB}]$ where $pH_{UB} = (pH_{SP})_{initial} + 0.1$, $pH_{LB} = (pH_{SP})_{initial} - 0.1$; Nominal setting of manipulating variable (MV) for online validation, MV0 = 38.5; Nominal setting of disturbance variable (DV) for online validation, DV0 = 35; Saturation limiter for MV, $[MV_{LB}, MV_{UB}]$ = [18, 80]; Steady-state values at setpoint $(pH_{SP})_{initial}$ used as initial conditions for offline simulations, $[S_a(1), S_b(1), pH(1);S_a(2), S_b(2), pH(2);S_a(3), S_b(3), pH(3)]$ are [35, 39.59, 5.95;35, 39.34, 5.97;35, 39.56, 5.96] at $(pH_{SP})_{initial}$ = 6, [35, 38.29, 6.99;35, 37.99, 7.01;35, 37.99, 7.01] at $(pH_{SP})_{initial}$ = 7, [35, 39.97, 7.96;35, 39.72, 7.97;35, 39.60, 7.98] at $(pH_{SP})_{initial}$ = 8, [35, 39.42, 9.01;35, 39.24, 9.02;35, 39.22, 9.02] at $(pH_{SP})_{initial}$ = 9; Step changes in setpoint, from $(pH_{SP})_{initial}$ to $(pH_{SP})_{final}$, for servo operation with DV = DV0 are 6 to 7, 7 to 8, 8 to 9, 9 to 8, 8 to 7, 7 to 6; Step changes in disturbance variable, from $(DV)_{initial}$ to $(DV)_{final}$, for regulatory operation at each setpoint $(pH_{SP})_{final}$ = 6, 7, 8, 9 are 35 to 30, 30 to 35, 35 to 40, 40 to 35; Time duration for servo operation i.e. for each step change from $(pH_{SP})_{initial}$ to $(pH_{SP})_{final}$ = 200 seconds each for offline simulation and online validation; Time duration for regulatory operation i.e. for each step changes from $(DV)_{initial}$ to $(DV)_{final}$ = 100 seconds each for offline simulation and online validation |
| Additional GA parameters | Elite count (EC) = 2; Crossover rate (CR) = 0.8; Mutation scale (MSC) = 0.1; Mutation shrink (MSH) = 0.1; Population (Pop); Fitness function values (ISE); Normalized expectation (EN); Elite kids (EK); Crossover kids (CK); Mutation kids (MK); No. of crossover kids (NCK); No. of mutation kids (NMK); No. of crossover plus mutation parents (NCMP); Parents index for crossover and mutation (ICM); Starting parents index for mutation (IM) |
| Additional DE parameters | Weight factor (Weight) = 1; Crossover rate (CR) = 0.8; Number of random shuffling ($N_S$) = 5; Initial population (Pop0); Temporary population obtained using DE (PopT); Temporary fitness function values (ISET); Acceptable fitness function values after performance comparison (ISE) |
| Additional PSO parameters | Initial particle inertia ($C_0$) = 0.9; Lower and upper bounds for particle inertia $[C_{LB}, C_{UB}]$ = [0.4, 0.9]; Cognitive attraction ($C_1$) = 0.5; Social attraction ($C_2$) = 2; Initial particle velocity ($V_0$); Particle inertia (C); Particle velocity (V); Fitness function values (ISE); Local best position of last generation (LBX); Local best ISE of last generation (LBISE); Global best value (GBISE1); Array of global best values (GBISE); Global best member (GBK) |

For i = 1 to L
Initialize errors [e(1), e(2), e(3)], change in errors[ce(1), ce(2), ce(3)], and ISE $[ISE_i(1), ISE_i(2), ISE_i(3)]$
  For k = 4 to Duration for servo and regulatory operation (T)
    Read $pH_{SP}(k)$ and $S_a(k)$, and calculate e*(k), ce*(k), and co*(k)
    Update base flowrate $S_b(k) = S_b(k-1) + co(k)$, and limit base flowrate such that $MV_{LB} \le S_b(k) \le MV_{UB}$
    Estimate pH(k) using dynamic ANN model, and obtain fitness function value $ISE_i(k) = ISE_i(k-1) + e(k)\times e(k)$
  End
End
Obtain ISE = $[ISE_1; ISE_2; ISE_3; ...; ISE_L]$

Fig. 5(a) Pseudocode to evaluate fitness function for offline simulation (pH00)

For i = 1 to L
  Write in DLL to start stirrer, read from DLL to obtain pH sensor voltage, and estimate pH
  While initial pH is not within range [$pH_{LB}$, $pH_{UB}$] *% Start pH process initialization*
    If pH <$pH_{LB}$ = $(pH_{SP})_{initial}$ - 0.1, then write in DLL to set $S_a$ = DV0 = 35, $S_b$ = 35+5
    If pH >$pH_{UB}$ = $(pH_{SP})_{initial}$ + 0.1, then write in DLL to set $S_a$ = DV0 = 35, $S_b$ = 35+0
  End *% End pH process initialization*
  Initialize $S_a$ = DV0, $S_b$ = MV0, ISE = 0, $pH_{SP}$, DV
  For m = 1 to Number of Set points *% Begin pH control*
    For k = 1 to T*% For each servo and regulatory operations*
      Estimate pH(k), e*(k), ce*(k), and co*(k)
      Update base flowrate $S_b(k) = S_b(k-1) + co(k)$, and limit base flowrate such that $MV_{LB} \le S_b(k) \le MV_{UB}$
      Write in DLL to update $S_a$ and $S_b$, update fitness function value $ISE_i(k) = ISE_i(k-1) + (e(k))^2$
    End *% For each servo and regulatory operations*
  End *% End pH control*
End
Obtain ISE = [$ISE_1$; $ISE_2$; $ISE_3$; ...; $ISE_L$]

Fig. 5(b) Pseudocode to evaluate fitness function for online experimentation (pH01)

base pump B ($S_b$) is Manipulated Variable (MV). Under nominal operating conditions, CV is maintained at a set-point value ($pH_{SP}$) with zero error as input to the pH controller, and manipulated and disturbance variables have values MV0 and DV0 respectively. Fig. 4(a) shows block diagram of feedback control of pH neutralization process for simulation using fuzzy logic controller. Manipulating variable is subjected to a saturation limiter in order to maintain $S_b(k)$ within bound [$MV_{LB}$, $MV_{UB}$]. The simulated output pH(k) of ANN based dynamic pH model depends upon present inputs $[S_a(k),\ S_b(k)]$, and past three values of inputs-output $[S_a(k-1), S_b(k-1), pH(k-1)]$ to $[S_a(k-3),\ S_b(k-3), pH(k-3)]$. To evaluate performance of fuzzy logic based pH controller, fitness function ISE(k) is evaluated. Fig. 4(b) shows block diagram of feedback control of pH neutralization process for real-time experimental validation on Armfield pH neutralization system using LabVIEW. Since we are considering a real, physical, and constantly stirred pH neutralization process, the initial pH range must be maintained within bound [$pH_{LB}$, $pH_{UB}$] to ensure approximately same initial conditions. For satisfactory performance, pH controller parameters, namely [$K_1$, $K_2$, $K_3$], must be tuned for given operating conditions using global optimization techniques. In this work we have used Genetic Algorithm (GA) and Differential Evolution (DE) belonging to evolutionary algorithm, and Particle Swarm Optimization (PSO) of swarm algorithm, for offline tuning of fuzzy logic controller, and also for online tuning of fuzzy logic controller. The various parameters for GA, DE, and PSO techniques based pH control system are given in Table 1. Also, brief steps for implementation of GA, DE, and PSO techniques for pH control system are given in sections 3.1 to 3.3 respectively, and sections 4.1 to 4.3 give their performance comparison for servo-regulatory (SR) operations in pH neutralization process.

### 3.1 Genetic Algorithm (GA) based Optimized pH Controller

First step in GA optimization is to create initial population (GA01) of type ‘double’ and matrix size L × n where 'L' is the no. of individual population members and 'n' is the no. of variables in each population member. The randomly generated individuals are uniformly distributed over entire initial population range, [$K_{1L}$, $K_{2L}$, $K_{3L}$; $K_{1U}$, $K_{2U}$, $K_{3U}$] where the phrases 'L' and 'U' in subscripts represents the lower and upper respectively. Each individual member in the population represents a potential solution to the optimization problem under consideration. The individual population members evolve through successive iterations called generations. In order to evaluate fitness function, pH00 for offline and pH01 for online operations as given in Fig. 5(a) and Fig. 5(b) respectively, during each generation, overall ISE is calculated for each individual member of the population. To rank and scale evaluated fitness values, and determine elite kids ‘EK’ (GA02), the fitness values of the individuals are ranked between 1 and L such that the elitist individual member having minimum fitness value (ISE1) has the rank as 1, the next elite individual member with next lowest fitness value has the rank as 2, and similarly, the individual member with highest fitness values has the rank as L. The ranked individual members are assigned scaled values inversely proportional to square root of their rank. The assigned scaled values are used to select parents for crossover and mutation (GA03) operations so that offspring kids can be produced for next generation. In GA03, the stochastic uniform selection operator is represented by a roulette-wheel in which each parent corresponds to a portion of the wheel proportional to its scaled value. The GA moves along the wheel in steps of equal size and, at each step GA allocates a parent to the portion of roulette-wheel it occupies. To create crossover kids 'CK' (GA04), GA uses scattered crossover operator to combine a pair of parents from allocated parents for crossover operation. To create temporary mutation kids (GA05), GA uses Gaussian mutation operator to apply random changes to a single parent from allocated parents for mutation operation using parameters namely mutation scale, mutation shrink, current generation, and total generation. Since there is a possibility that mutation kids may go out of initial population range, it is required to check boundary conditions for mutation kids 'MK' (GA06). In case any mutation kid variable is out of range, the concerned variable is regenerated using process similar to GA01. For continuation of GA, it is required to check termination criteria (GA07). If any criteria are satisfied, then elitist kid with least ISE is saved as global optimal solution and process is stopped. Otherwise, elite kids, crossover kids, and mutation kids are combined to create the next generation population, and the complete procedure of fitness function evaluation to next generation population creation is again repeated. Fig. 6(a), Fig. 6(b), and Fig. 6(c) shows LabVIEW block diagrams for online implementation of GA based pH controller parameters optimization, fitness function evaluation, and Mamdani based FLC respectively.

### 3.2 Differential Evolution (DE) based Optimized pH Controller

Similar to GA01, first step in DE optimization is to create initial population (DE01) of type 'double' and matrix size L × n, and the individual population members evolve through successive generations. Also, during each generation, in order to evaluate fitness function (pH00 for offline and pH01 for online operations), overall ISE is calculated for each individual member of the population. To select competitive population members for current generation (DE02), ISE of individual members in present generation are compared with corresponding ISE in the last generation, and the evolved individual member is accepted only in case its fitness value is improved. The most important step in DE is differential mutation in which weighted difference of two population members are added to third one. In order to keep the three population members distinct, it is necessary to subject current population members with random shuffling (DE03). To create trial population with differential mutation and crossover (DE04), the resulting differential mutation quantities and last population members are subjected to crossover. The crossover operation in DE increases the diversity of differential mutation operation. It is required to check boundary conditions for trial population (DE05), and in case any variable is out of range, then new variable value is regenerated using DE01. Similar to GA07, we need to check termination criteria (DE06). On termination, the best member with minimum ISE is saved as global optimal solution. Fig. 7 shows LabVIEW block diagrams for online implementation of DE based pH controller parameters optimization.

### 3.3 Particle Swarm Optimization (PSO) based Optimized pH Controller

First step in PSO is to create initial particles position (PS01) of type 'double' and matrix size L × n, similar to GA01. The particles are assigned an initial velocity with magnitude same as corresponding particle position, and an initial inertia whose magnitude is same for all particles. Over successive generations, the particles update their velocity to reach the global optimal position based on their global and local best positions which are decided on the basis of fitness function values. In order to evaluate fitness function (pH00 for offline and pH01 for online operations) during each generation, overall ISE is calculated for each individual particle of the population. To determine global and local best particles positions and fitness function values (PS02), it is required for algorithm to compare present fitness function values with past values. In a particular generation, a particle is regarded as global best if it has lowest ever ISE, and local best if it has ISE less than that of corresponding particle in immediate preceding generation. For next generation, it is required to update particles velocity, position and inertia (PS03). To update individual particle velocity following three terms are added: First - current inertia multiplied with current velocity; Second - local best position minus current position is multiplied with a random number and a cognitive attraction constant; Third - global best position minus current position is multiplied with a random number and a social attraction constant. The current position is added with updated velocity in order to obtain updated individual particle position. The particle inertia is reduced with successive generations till it reaches lowest bound value. It is required to check boundary conditions for particles position (PS04), and in case any variable is out of range, then new variable value is regenerated using PS01. Similar to GA07, we need to check

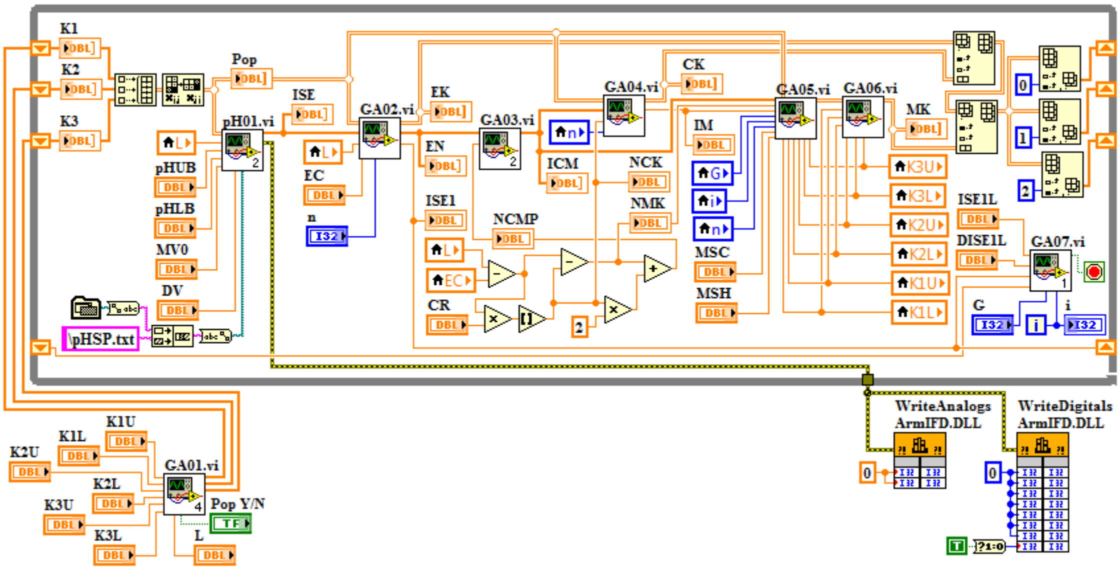


Fig. 6(a) LabVIEW block diagram implementation of GA optimization for fuzzy logic based pH controller

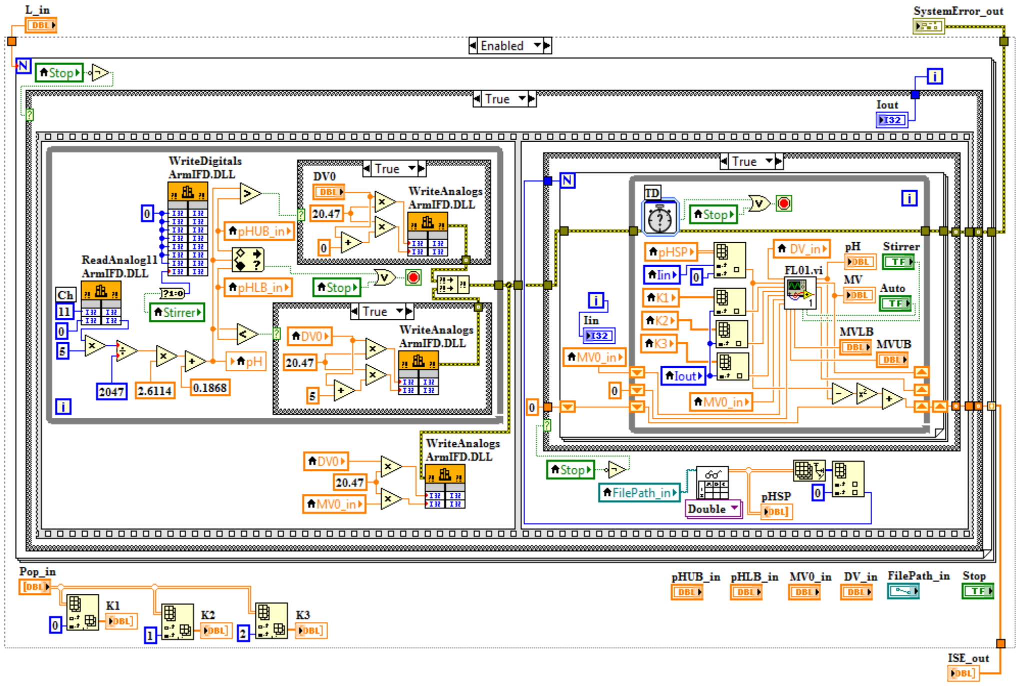


Fig. 6(b) LabVIEW block diagram to evaluate fitness function (pH01 for online)

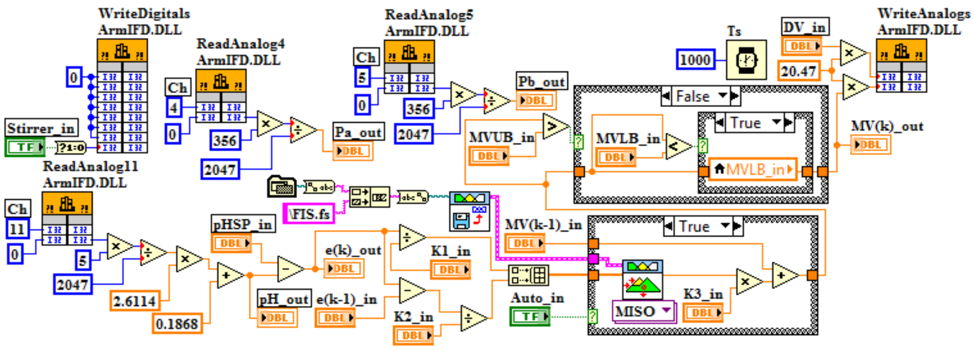


Fig. 6(c) LabVIEW block diagram for Mamdani FIS based fuzzy logic controller (FL01)

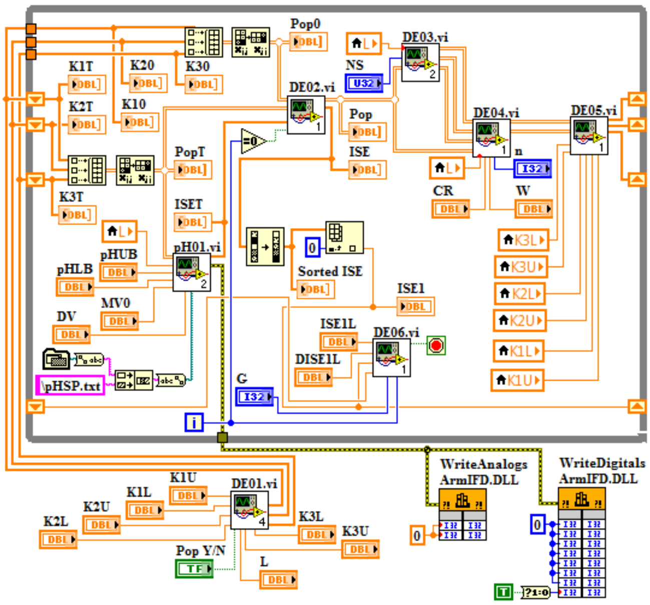


Fig. 7 Flowchart for DE based pH controller parameters optimization

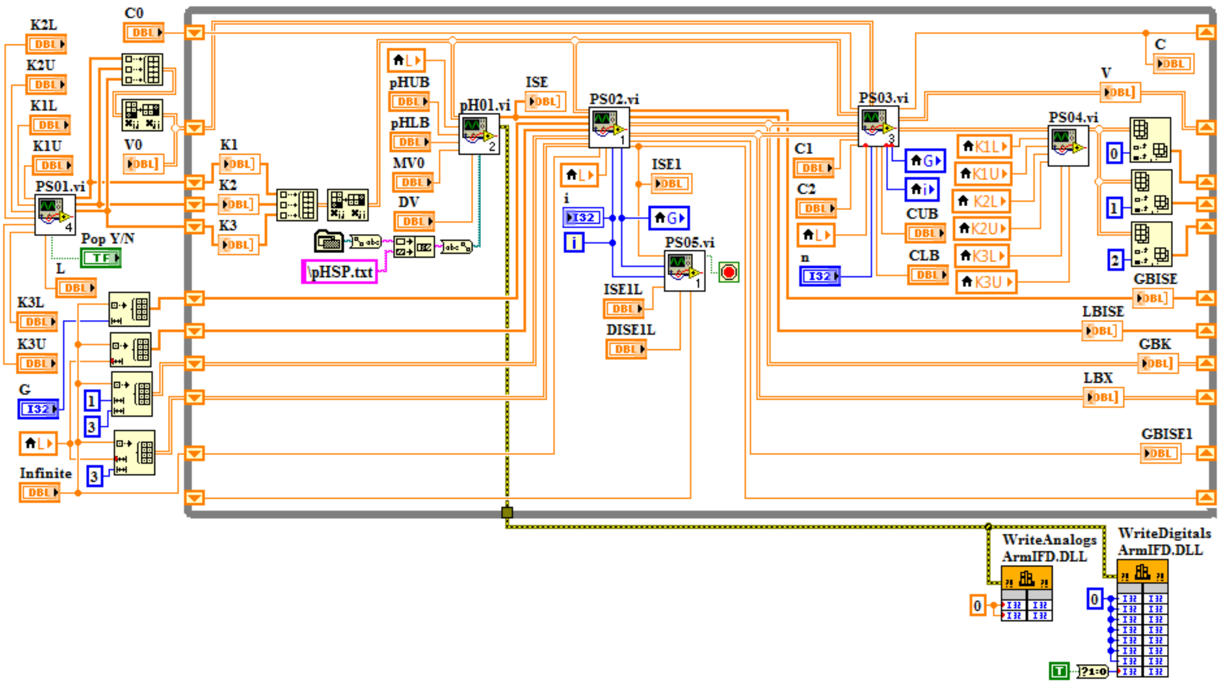


Fig. 8 Flowchart for PSO based pH controller parameters optimization

termination criteria (PS05). On termination, the global best particle position with minimum ISE is saved as global optimal solution. Fig. 8 shows LabVIEW block diagrams for online implementation of PSO based pH controller parameters optimization.

## 4 Simulation and Experimental Results and Discussions

To evaluate optimized FLC scheme based on Servo and Regulatory (SR) operations, the SR operations has been divided in six cases, namely SR1, SR2, SR3, SR4, SR5, and SR6, to cover dynamic pH range from 6 to 9. For servo operations, 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 servo operation of 200 seconds followed by regulatory operations of 400 seconds. Therefore, entire duration for SR operations is 3600 seconds.

### 4.1 Offline Optimized FLC Schemes for Servo and Regulatory Operations

Offline optimization of fuzzy logic controller is carried out using MATLAB software in order to obtain optimal values of $K_1$, $K_2$, and $K_3$. The performance of offline optimized fuzzy logic controller is evaluated on Armfiled pH neutralization process using LabVIEW software. Fig. 9(a) shows the best and mean values, and Fig. 9(b) shows initial and final population members, for offline GA, DE, and PSO optimization. Fig. 10(a) and Fig. 10(b) shows simulated as well as experimental pH response and pump speed variations respectively, using offline GA, DE, and PSO optimized fuzzy logic controller. Table 2 gives performance summary of simulated and experimental responses of offline GA, DE, and PSO optimized fuzzy logic controller for SR operations on the basis of ISE and maximum overshoot or undershoot. Following observations are made for offline optimized fuzzy logic controller.

(i) Offline GA optimization gives best simulated ISE as 73.88 and optimized parameters as $[K_1, K_2, K_3]$ = [25.22, 0.65, 14.15]. Experimental validation gives total ISE as 80.38 of which nearly 55% is accounted together for SR1, SR5, and SR6 operations.

(ii) Offline DE optimization gives best simulated ISE as 71.98 and optimized parameters as $[K_1, K_2, K_3]$ = [29.98, 0.75, 16.16]. Experimental validation gives total ISE as 67.96 of which nearly 54% is accounted together for SR1, SR5, and SR6 operations.

(iii) Offline PSO gives best simulated ISE as 72.26 and optimized parameters as $[K_1, K_2, K_3]$ = [29.34, 0.73, 15.75]. Experimental validation gives total ISE as 67.93 of which nearly 50% is accounted together for SR1, SR5, and SR6 operations.

The offline optimization of fuzzy logic controller uses ANN based dynamic model which has its own limitation in representing actual real-time dynamics of the pH neutralization process. The nonlinear fuzzy logic controller uses membership functions whose degree varies with error and change in error. The variation in membership degree and choice of appropriate rules based on error and change in error allows variation in fuzzy logic controller output and makes fuzzy logic controller as intelligent.

### 4.2 Offline Optimized Piecewise FLC Schemes for Servo and Regulatory Operations

Offline optimization of piecewise FLC for pH neutralization process is carried out using MATLAB software in order to obtain optimal values of $K_1$, $K_2$, and $K_3$ for SR1, SR2, SR3, SR4, SR5, and SR6 operations. The performance of optimized piecewise fuzzy logic controller is evaluated on Armfiled pH neutralization process using LabVIEW software. Fig. 11(a) shows the best and mean values, and Fig. 11(b) shows initial and final population members, for offline GA, DE, and PSO optimization. Fig. 12(a) and Fig. 12(b) shows simulated as well as experimental pH response and pump speed variations respectively, using offline GA, DE, and PSO optimized piecewise fuzzy logic controller. Table 3 gives performance summary of simulated and experimental responses of offline GA, DE, and PSO optimized piecewise fuzzy logic controller for SR operations on the basis of ISE and maximum overshoot or undershoot. Following observations are made for offline optimized piecewise fuzzy logic controller.

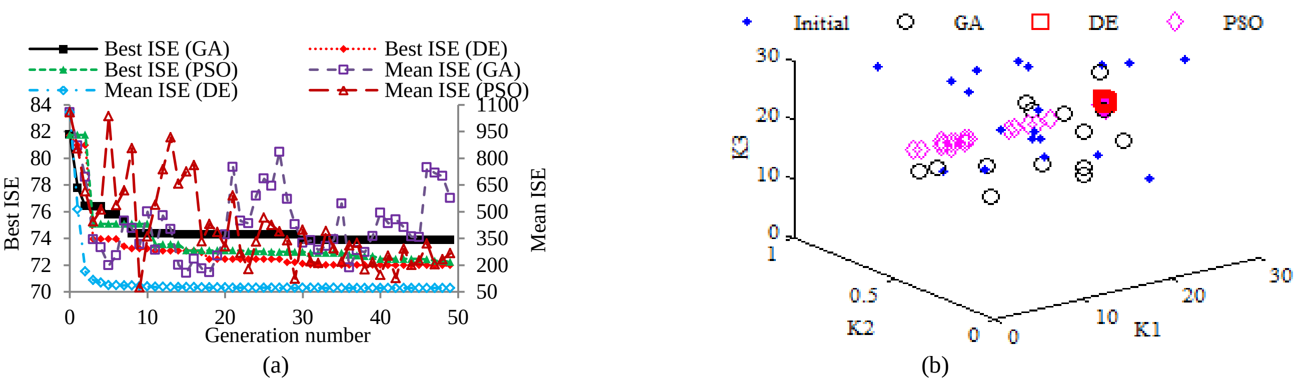



Fig. 9 Offline GA, DE, and PSO based FLC optimization for SR operations (a) best and mean values, (b) initial and final population members

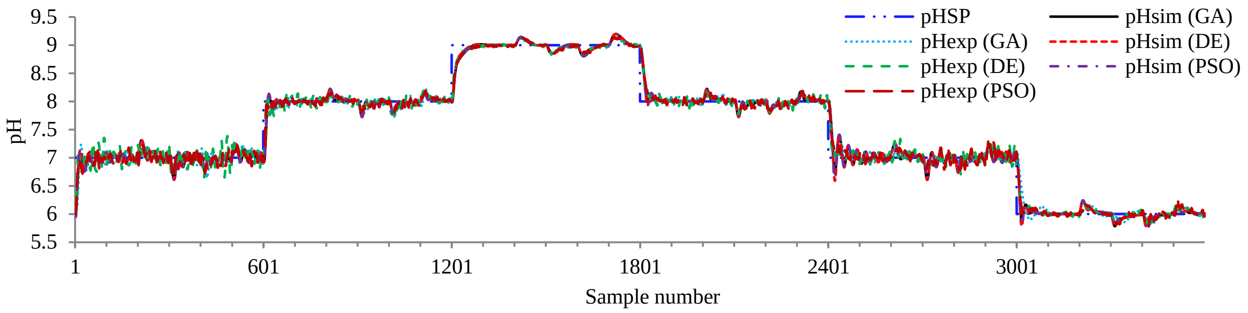



Fig. 10(a) Simulated and experimental pH responses of offline GA, DE, and PSO based FLC optimization for SR operations

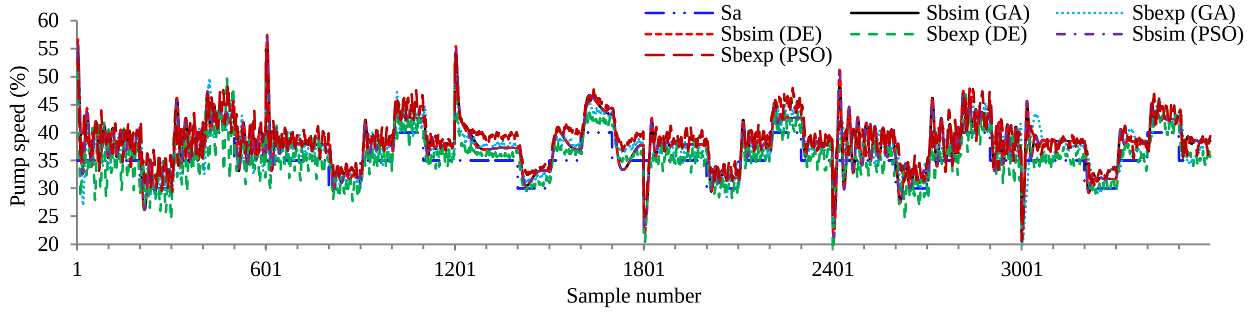



Fig. 10(b) Simulated and experimental pumps speed variations of offline GA, DE, and PSO based FLC optimization for SR operations

Table 2 Simulation results/ Experimental performance of offline GA, DE, and PSO based FLC for SR operations

| Optimization methods | Optimized parameters $[K_1,K_2,K_3]$ | 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 (Simulation / Experiment) | $pH_{SP}$, $(DV)_{initial}$, $(DV)_{final}$ | ISE, maximum overshoot (Simulation / Experiment) | $pH_{SP}$, $(DV)_{initial}$, $(DV)_{final}$ | ISE, maximum undershoot (Simulation / Experiment) | $pH_{SP}$, $(DV)_{initial}$, $(DV)_{final}$ | ISE, maximum undershoot (Simulation / Experiment) | $pH_{SP}$, $(DV)_{initial}$, $(DV)_{final}$ | ISE, maximum overshoot (Simulation / Experiment) |
| GA | For GA: [25.22, 0.65, 14.15] For DE: [29.98, 0.75, 16.16] For PSO: [29.34, 0.73, 15.75] | 6, 7, 35 | 7.69,-0.09 | 7, 35, 30 | 1.35,-0.31 | 7, 30, 35 | 1.91,0.39 | 7, 35, 40 | 0.60,0.26 | 7, 40, 35 | 0.10,-0.24 |
| | | | 10.35,-0.24 | | 1.22,-0.31 | | 1.15,0.29 | | 1.66,0.36 | | 1.41,-0.26 |
| DE | | | 7.38,-0.13 | | 1.41,-0.32 | | 1.87,0.39 | | 0.64,0.26 | | 0.99,-0.25 |
| | | | 8.56,-0.35 | | 1.41,-0.25 | | 1.84,0.34 | | 3.12,0.35 | | 1.38,-0.26 |
| PSO | | | 7.39,-0.11 | | 1.39,-0.31 | | 1.86,0.39 | | 0.65,0.27 | | 0.98,-0.25 |
| | | | 7.09,-0.19 | | 0.96,-0.23 | | 1.59,0.37 | | 1.25,0.28 | | 0.78,-0.22 |
| GA | | 7, 8, 35 | 8.28,-0.08 | 8, 35, 30 | 0.66,-0.22 | 8, 30, 35 | 0.81,0.28 | 8, 35, 40 | 0.55,0.21 | 8, 40, 35 | 0.38,-0.17 |
| | | | 6.87,-0.09 | | 0.50,-0.20 | | 0.84,0.24 | | 0.98,0.30 | | 0.83,-0.24 |
| DE | | | 7.87,-0.14 | | 0.67,-0.22 | | 0.80,0.28 | | 0.56,0.21 | | 0.38,-0.17 |
| | | | 6.44,-0.17 | | 0.55,-0.21 | | 0.72,0.21 | | 1.12,0.29 | | 0.66,-0.19 |
| PSO | | | 7.92,-0.12 | | 0.67,-0.22 | | 0.81,0.28 | | 0.56,0.21 | | 0.38,-0.17 |
| | | | 6.19,-0.11 | | 0.53,-0.16 | | 0.72,0.19 | | 0.82,0.21 | | 0.55,-0.19 |
| GA | | 8, 9, 35 | 10.21,-0.01 | 9, 35, 30 | 0.47,-0.14 | 9, 30, 35 | 0.50,0.15 | 9, 35, 40 | 0.98,0.20 | 9, 40, 35 | 1.11,-0.20 |
| | | | 9.89,-0.02 | | 0.46,-0.14 | | 0.62,0.17 | | 0.64,0.18 | | 0.48,-0.15 |
| DE | | | 9.28,-0.01 | | 0.48,-0.15 | | 0.52,0.15 | | 1.01,0.20 | | 1.16,-0.20 |
| | | | 7.30,-0.02 | | 0.42,-0.14 | | 0.54,0.17 | | 0.60,0.18 | | 0.48,-0.15 |
| PSO | | | 9.48,-0.01 | | 0.48,-0.15 | | 0.52,0.15 | | 1.02,0.20 | | 1.17,-0.20 |
| | | | 9.77,-0.02 | | 0.48,-0.13 | | 0.72,0.16 | | 0.60,0.15 | | 0.51,-0.14 |
| GA | | 9, 8, 35 | 9.49,0.01 | 8, 35, 30 | 0.66,-0.22 | 8, 30, 35 | 0.81,0.28 | 8, 35, 40 | 0.55,0.21 | 8, 40, 35 | 0.38,-0.17 |
| | | | 11.47,0.08 | | 0.50,-0.15 | | 0.71,0.22 | | 0.77,0.22 | | 0.45,-0.15 |
| DE | | | 8.88,0.07 | | 0.67,-0.22 | | 0.80,0.28 | | 0.56,0.21 | | 0.38,-0.17 |
| | | | 9.38,0.12 | | 0.53,-0.16 | | 0.67,0.22 | | 0.78,0.19 | | 0.77,-0.19 |
| PSO | | | 8.99,0.05 | | 0.68,-0.22 | | 0.81,0.28 | | 0.56,0.21 | | 0.38,-0.17 |
| | | | 10.28,0.06 | | 0.51,-0.15 | | 0.81,0.20 | | 0.80,0.17 | | 0.55,-0.19 |
| GA | | 8, 7, 35 | 11.45,0.28 | 7, 35, 30 | 0.93,-0.25 | 7, 30, 35 | 1.93,0.39 | 7, 35, 40 | 0.61,0.26 | 7, 40, 35 | 0.10,-0.24 |
| | | | 9.65,0.10 | | 0.59,-0.21 | | 0.63,0.18 | | 0.65,0.17 | | 0.76,-0.21 |
| DE | | | 11.92,0.41 | | 0.95,-0.25 | | 1.88,0.39 | | 0.65,0.27 | | 0.99,-0.25 |
| | | | 6.72,0.12 | | 1.47,-0.33 | | 1.07,0.28 | | 1.02,0.30 | | 1.44,-0.23 |
| PSO | | | 11.73,0.38 | | 0.96,-0.26 | | 1.87,0.39 | | 0.65,0.27 | | 0.98,-0.25 |
| | | | 7.75,0.11 | | 0.63,-0.18 | | 1.30,0.22 | | 1.17,0.22 | | 1.54,-0.35 |
| GA | | 7, 6, 35 | 7.16,0.12 | 6, 35, 30 | 0.87,-0.24 | 6, 30, 35 | 0.73,0.22 | 6, 35, 40 | 0.49,0.21 | 6, 40, 35 | 0.31,-0.16 |
| | | | 13.49,0.11 | | 0.67,-0.17 | | 0.66,0.16 | | 0.71,0.18 | | 0.79,-0.17 |
| DE | | | 6.84,0.22 | | 0.88,-0.24 | | 0.74,0.22 | | 0.50,0.21 | | 0.31,-0.16 |
| | | | 6.77,0.06 | | 0.47,-0.17 | | 0.60,0.15 | | 0.59,0.18 | | 0.55,-0.16 |
| PSO | | | 6.90,0.20 | | 0.89,-0.24 | | 0.75,0.22 | | 0.51,0.21 | | 0.31,-0.16 |
| | | | 7.22,0.05 | | 0.57,-0.18 | | 0.67,0.18 | | 0.83,0.22 | | 0.74,-0.27 |

(i) Offline GA optimization gives best simulated ISE as 64.73 and optimized parameters as [$K_1$, $K_2$, $K_3$] = [28.37, 0.84, 15.36] for SR1, [26.72, 0.80, 19.08] for SR2, [8.18, 0.50, 29.43] for SR3, [29.79, 0.95, 23.20] for SR4, [25.22, 0.59, 12.30] for SR5, [28.32, 0.93, 22.48] for SR6. Experimental validation gives total ISE as 66.12.
(ii) Offline DE optimization gives best simulated ISE as 64.3618 and optimized parameters as [$K_1$, $K_2$, $K_3$] = [30.00, 0.70, 15.00] for SR1, [30.00, 0.79, 20.38] for SR2, [9.07, 0.52, 30.00] for SR3, [30.00, 0.97, 23.78] for SR4, [29.96, 0.68, 13.92] for SR5, [28.80, 0.92, 22.39] for SR6. Experimental validation gives total ISE as 64.36.
(iii) Offline PSO gives best simulated ISE as 64.4981 and optimized parameters as [$K_1$, $K_2$, $K_3$] = [29.89, 0.69, 14.73] for SR1, [27.49, 0.79, 19.57] for SR2, [9.26, 0.50, 29.87] for SR3, [29.83, 0.95, 23.02] for SR4, [27.39, 0.63, 13.07] for SR5, [28.31, 0.94, 22.43] for SR6. Experimental validation gives total ISE as 64.81.
In comparison with offline optimized FLC for SR operations, use of offline optimized piecewise FLC for SR operations brings ISE values down by amount 14.26 for GA, 3.61 for DE, and 3.12 for PSO. Further it is evident from Table 3 that pH control for SR1 and SR5 cases is most challenging task.

### 4.3 Online Optimized piecewise FLC Schemes for Servo and Regulatory Operations

Online optimization of piecewise FLC for pH neutralization process is carried out using LabVIEW software in order to obtain optimal values of $K_1$, $K_2$, and $K_3$ for SR1 and SR5 operations. Fig. 13(a) and Fig. 15(a) shows the best and mean values, and Fig. 13(b) and Fig. 15(b) shows initial and final population members, for online GA, DE, and PSO optimization of SR1 and SR5 operations respectively. Fig. 14(a) and Fig. 16(a) shows pH response, and Fig. 14(b) and Fig. 16(b) shows pump speed variations obtained experimentally, using online GA, DE, and PSO optimized piecewise fuzzy logic controller for SR1 and SR5 operations respectively. Table 4 gives performance summary of experimental responses of online GA, DE, and PSO optimized piecewise fuzzy logic controller for SR1 and SR5 operations on the basis of ISE and maximum overshoot or undershoot. Following observations are made for online optimized piecewise fuzzy logic controller.

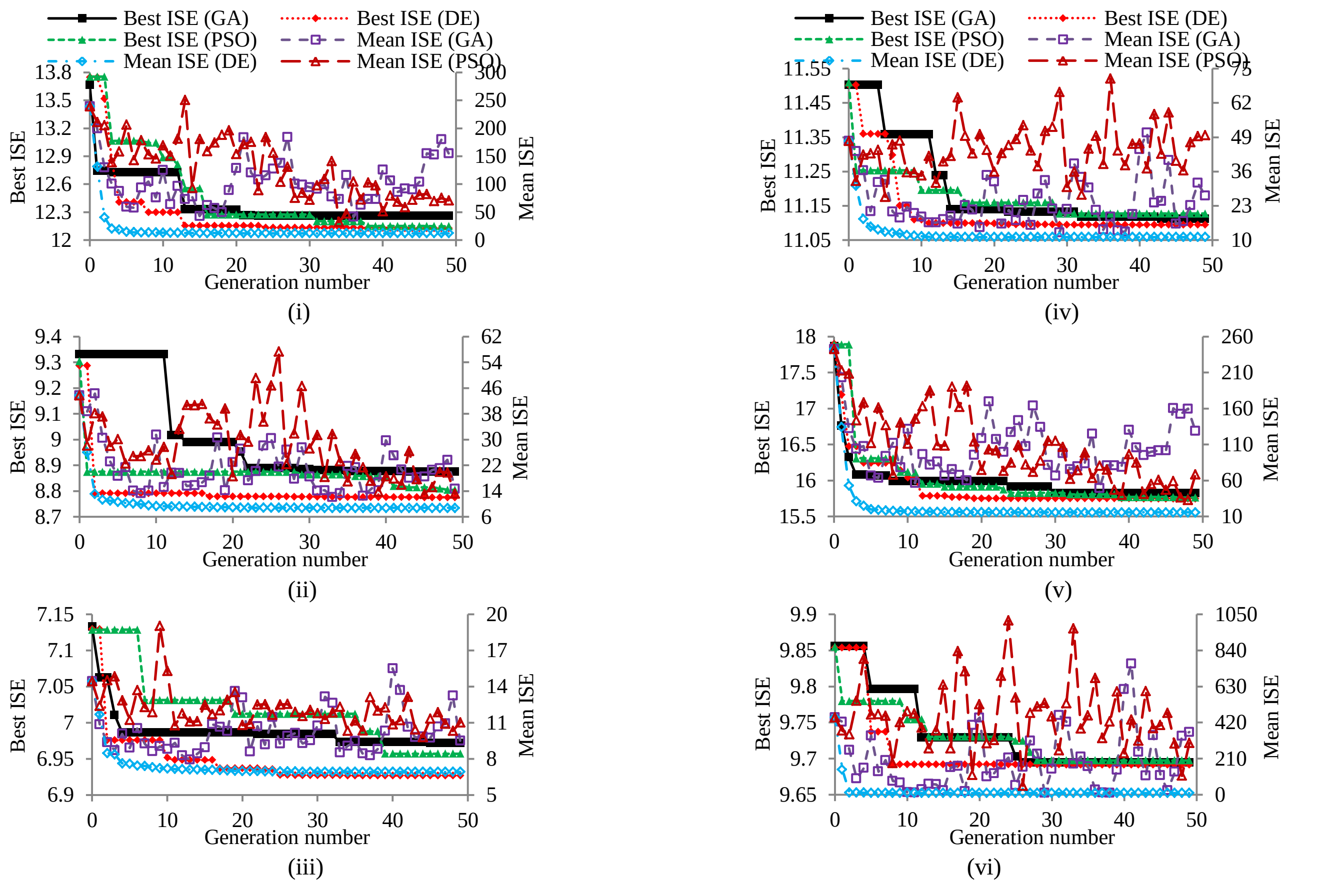



Fig. 11(a) Best and mean ISE values of offline GA, DE, and PSO based piecewise FLC optimization for SR operations (i) SR1 (ii) SR2 (iii) SR3 (iv) SR4 (v) SR5 (vi) SR6

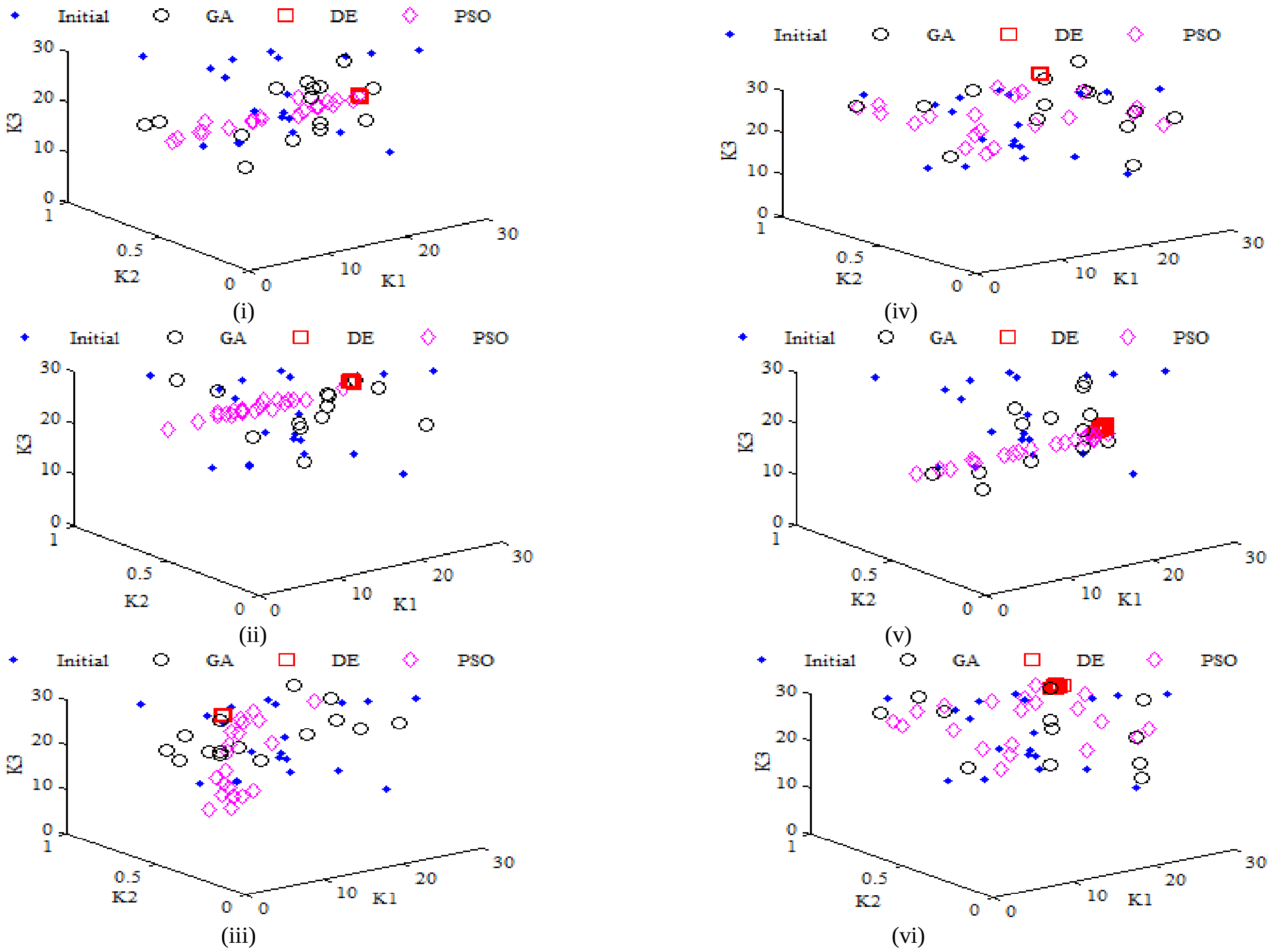


Fig. 11(b) Initial and final population members of offline GA, DE, and PSO based piecewise FLC optimization for SR operations (i) SR1 (ii) SR2 (iii) SR3 (iv) SR4 (v) SR5 (vi) SR6

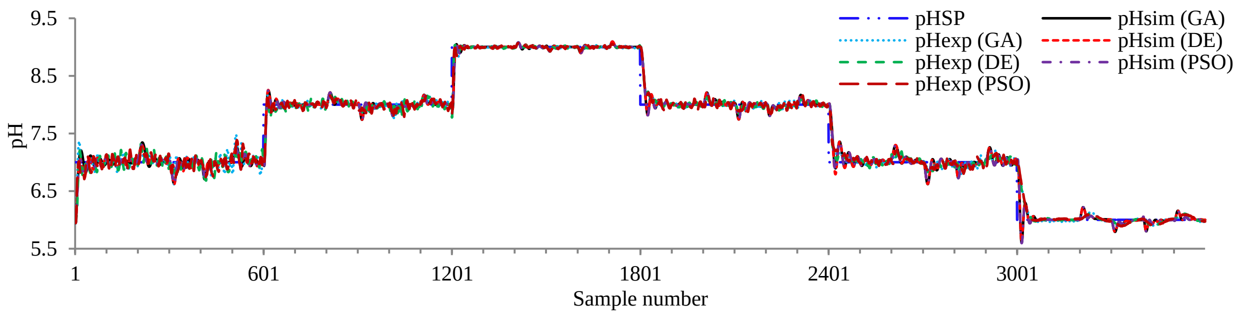


Fig. 12(a) Simulated and experimental pH responses of offline GA, DE, and PSO based piecewise FLC optimization for SR operations

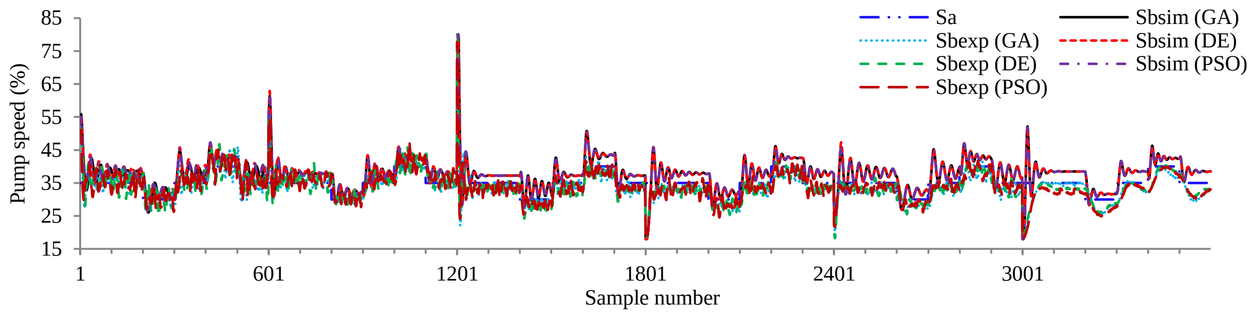


Fig. 12(b) Simulated and experimental pumps speed variations of offline GA, DE, and PSO based piecewise FLC optimization for SR operations

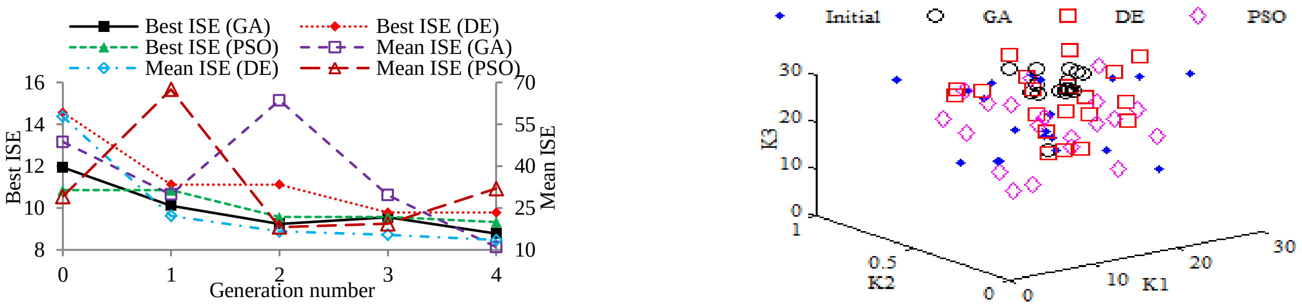
Table 3 Simulation results/Experimental performance of offline GA, DE, and PSO based piecewise FLC for SR operations

| Optimization methods | Optimized parameters [K1,K2,K3] | Servo operation (200 samples): $(pH_{SP})_{initial}$, $(pH_{SP})_{final}$, DV | Servo operation (200 samples): ISE, maximum overshoot / undershoot (Simulation / Experiment) | Regulatory operation (100 samples): $pH_{SP}$, $(DV)_{initial}$, $(DV)_{final}$ | Regulatory operation (100 samples): ISE, maximum overshoot (Simulation / Experiment) | Regulatory operation (100 samples): $pH_{SP}$, $(DV)_{initial}$, $(DV)_{final}$ | Regulatory operation (100 samples): ISE, maximum undershoot (Simulation / Experiment) | Regulatory operation (100 samples): $pH_{SP}$, $(DV)_{initial}$, $(DV)_{final}$ | Regulatory operation (100 samples): ISE, maximum undershoot (Simulation / Experiment) | Regulatory operation (100 samples): $pH_{SP}$, $(DV)_{initial}$, $(DV)_{final}$ | Regulatory operation (100 samples): ISE, maximum overshoot (Simulation / Experiment) |
|---|---|---|---|---|---|---|---|---|---|---|---|
| GA | [28.37, 0.84, 15.36] | 6, 7, 35 | 7.11,-0.20 | 7, 35, 30 | 1.68,-0.34 | 7, 30, 35 | 1.59,0.37 | 7, 35, 40 | 0.80,0.30 | 7, 40, 35 | 1.07,-0.28 |
| | | | 7.59,-0.37 | | 0.91,-0.29 | | 1.20,0.38 | | 1.77,0.31 | | 2.76,-0.48 |
| DE | [30.00, 0.70, 15.00] | | 7.39,-0.08 | | 1.29,-0.30 | | 1.80,0.39 | | 0.70,0.28 | | 0.94,-0.25 |
| | | | 9.18,-0.21 | | 1.69,-0.33 | | 0.95,0.22 | | 1.93,0.32 | | 0.91,-0.23 |
| PSO | [29.89, 0.69, 14.73] | | 7.41,-0.07 | | 1.31,-0.30 | | 1.77,0.38 | | 0.71,0.28 | | 0.94,-0.25 |
| | | | 7.61,-0.22 | | 1.04,-0.28 | | 1.06,0.25 | | 1.43,0.27 | | 1.95,-0.39 |
| GA | [26.72, 0.80, 19.08] | 7, 8, 35 | 6.96,-0.24 | 8, 35, 30 | 0.52,-0.21 | 8, 30, 35 | 0.69,0.26 | 8, 35, 40 | 0.39,0.20 | 8, 40, 35 | 0.32,-0.17 |
| | | | 6.78,-0.16 | | 0.33,-0.12 | | 0.46,0.16 | | 0.64,0.23 | | 0.41,-0.13 |
| DE | [30.00, 0.79, 20.38] | | 6.89,-0.25 | | 0.53,-0.21 | | 0.69,0.26 | | 0.36,0.19 | | 0.31,-0.16 |
| | | | 6.39,-0.12 | | 0.45,-0.19 | | 0.47,0.17 | | 0.74,0.19 | | 0.63,-0.15 |
| PSO | [27.49, 0.79, 19.57] | | 6.93,-0.25 | | 0.52,-0.21 | | 0.68,0.26 | | 0.37,0.20 | | 0.31,-0.17 |
| | | | 6.16,-0.12 | | 0.42,-0.16 | | 0.50,0.15 | | 0.74,0.25 | | 0.45,-0.15 |
| GA | [8.18, 0.50, 29.43] | 8, 9, 35 | 6.67,-0.05 | 9, 35, 30 | 0.08,-0.09 | 9, 30, 35 | 0.05,0.08 | 9, 35, 40 | 0.10,0.10 | 9, 40, 35 | 0.07,-0.09 |
| | | | 5.08,-0.05 | | 0.04,-0.06 | | 0.05,0.07 | | 0.06,0.09 | | 0.05,-0.07 |
| DE | [9.07, 0.52, 30.00] | | 6.63,-0.06 | | 0.07,-0.08 | | 0.05,0.07 | | 0.10,0.10 | | 0.08,-0.10 |
| | | | 5.52,-0.04 | | 0.05,-0.07 | | 0.06,0.08 | | 0.04,0.05 | | 0.04,-0.07 |
| PSO | [9.26, 0.50, 29.87] | | 6.67,-0.04 | | 0.07,-0.08 | | 0.05,0.07 | | 0.09,0.10 | | 0.08,-0.09 |
| | | | 5.08,-0.03 | | 0.04,-0.07 | | 0.05,0.07 | | 0.06,0.08 | | 0.03,-0.06 |
| GA | [29.79, 0.95, 23.20] | 9, 8, 35 | 9.29,0.18 | 8, 35, 30 | 0.51,-0.21 | 8, 30, 35 | 0.66,0.26 | 8, 35, 40 | 0.34,0.19 | 8, 40, 35 | 0.30,-0.17 |
| | | | 9.82,0.06 | | 0.29,-0.13 | | 0.38,0.14 | | 0.39,0.12 | | 0.23,-0.14 |
| DE | [30.00, 0.97, 23.78] | | 9.29,0.18 | | 0.50,-0.21 | | 0.66,0.26 | | 0.34,0.19 | | 0.30,-0.17 |
| | | | 9.90,0.05 | | 0.27,-0.13 | | 0.40,0.17 | | 0.39,0.19 | | 0.26,-0.12 |
| PSO | [29.82, 0.95, 23.02] | | 9.30,0.18 | | 0.51,-0.21 | | 0.66,0.26 | | 0.35,0.20 | | 0.31,-0.17 |
| | | | 10.05,0.11 | | 0.43,-0.18 | | 0.34,0.14 | | 0.42,0.16 | | 0.28,-0.16 |
| GA | [25.22, 0.59, 12.30] | 8, 7, 35 | 11.21,0.10 | 7, 35, 30 | 1.24,-0.29 | 7, 30, 35 | 1.70,0.38 | 7, 35, 40 | 0.72,0.27 | 7, 40, 35 | 0.95,-0.26 |
| | | | 9.28,0.09 | | 0.44,-0.16 | | 0.65,0.17 | | 0.84,0.20 | | 0.64,-0.20 |
| DE | [29.96, 0.68, 13.93] | | 11.08,0.21 | | 1.29,-0.30 | | 1.68,0.38 | | 0.76,0.28 | | 0.94,-0.26 |
| | | | 8.35,0.10 | | 0.63,-0.19 | | 0.57,0.17 | | 0.60,0.19 | | 0.48,-0.15 |
| PSO | [27.39, 0.63, 13.07] | | 11.13,0.15 | | 1.26,-0.30 | | 1.70,0.38 | | 0.74,0.28 | | 0.94,-0.26 |
| | | | 8.43,0.06 | | 0.69,-0.21 | | 0.62,0.17 | | 0.67,0.20 | | 0.84,-0.23 |
| GA | [28.32, 0.93, 22.48] | 7, 6, 35 | 8.06,0.39 | 6, 35, 30 | 0.56,-0.22 | 6, 30, 35 | 0.50,0.21 | 6, 35, 40 | 0.33,0.20 | 6, 40, 35 | 0.25,-0.16 |
| | | | 13.51,0.04 | | 0.47,-0.13 | | 0.42,0.12 | | 0.31,0.10 | | 0.33,-0.11 |
| DE | [28.80, 0.92, 22.39] | | 8.03,0.39 | | 0.57,-0.22 | | 0.51,0.21 | | 0.34,0.20 | | 0.25,-0.16 |
| | | | 12.11,0.03 | | 0.29,-0.11 | | 0.33,0.11 | | 0.39,0.11 | | 0.34,-0.11 |
| PSO | [28.31, 0.94, 22.43] | | 8.04,0.40 | | 0.57,-0.22 | | 0.51,0.21 | | 0.34,0.20 | | 0.25,-0.16 |
| | | | 14.12,0.02 | | 0.29,-0.09 | | 0.38,0.11 | | 0.34,0.10 | | 0.29,-0.09 |

(i) Online GA optimization gives best experimental ISE as 8.79 for SR1, and 10.83 for SR5, and optimized parameters as $[K_1, K_2, K_3]$ = [22.68, 0.64, 27.93] for SR1, and [28.52, 0.76, 23.18] for SR5. We know that GA assumes the population member with least ISE in a particular generation as elitist member. For online experimentation, it is possible that a population member has different ISE values over successive generations, as shown in Fig. 13(a) and Fig. 15(a).

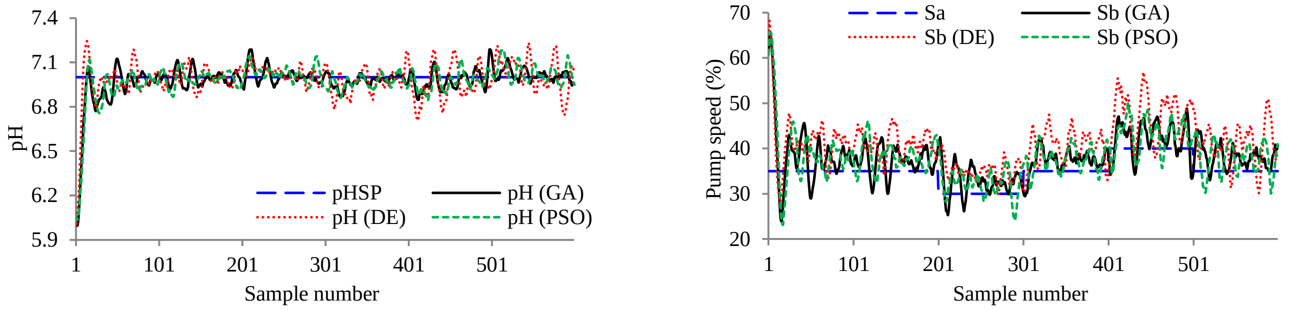
(ii) Online DE optimization gives best experimental ISE as 9.79 for SR1, and 11.39 for SR5, and optimized parameters as $[K_1, K_2, K_3]$ = [26.94, 0.850, 28.06] for SR1, and [28.64, 0.77, 29.79] for SR5.

(iii) Online PSO gives best experimental ISE as 9.34 for SR1, and 9.46 for SR5, and optimized parameters as $[K_1, K_2, K_3]$ = [25.50, 0.64, 27.97] for SR1, and [28.87, 0.78, 23.88] for SR5.



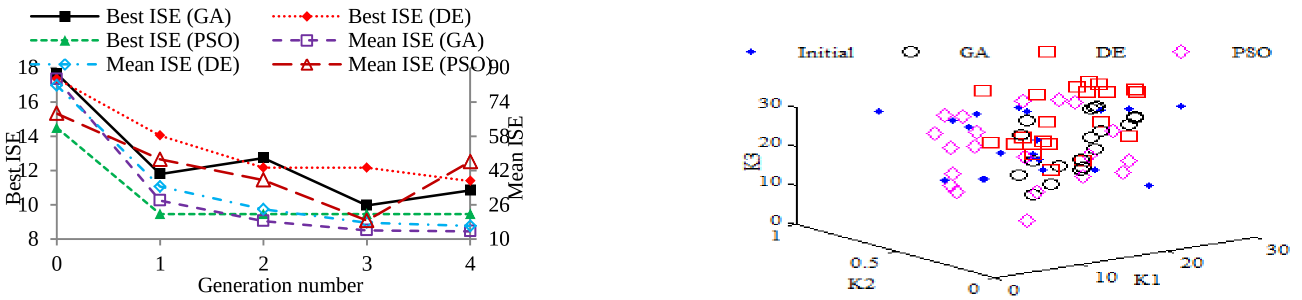
(a) (b)

Fig. 13 Online GA, DE, and PSO based FLC optimization for SR1 operations (a) best and mean values, (b) initial and final population members



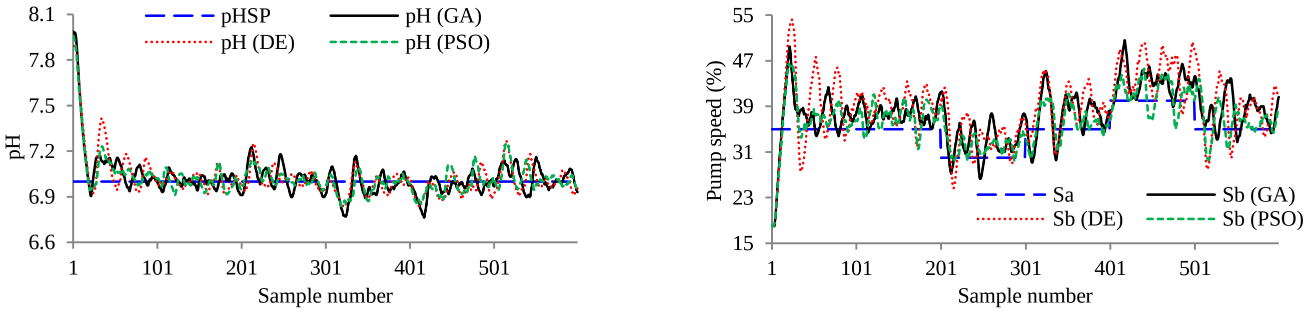
(a) (b)

Fig. 14 Online GA, DE, and PSO based FLC optimization for SR1 operations (a) pH responses, (b) pumps speed variations



(a) (b)

Fig. 15 Online GA, DE, and PSO based FLC optimization for SR5 operations (a) best and mean values, (b) initial and final population members



(a) (b)

Fig. 16 Online GA, DE, and PSO based FLC optimization for SR5 operations (a) pH responses, (b) pumps speed variations

Table 4 Experimental performance of online GA, DE, and PSO based FLC for SR1 and SR5 operations

| Optimization methods | Optimized parameters [K1,K2,K3] | 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 |
| GA | [22.68,0.64,27.93] | 6, | 7.49,-0.12 | 7, | 0.35,-0.19 | 7, | 0.22,0.13 | 7, | 0.53,0.15 | 7, | 0.19,-0.14 |
| DE | [26.94,0.85,28.06] | 7, | 5.77,-0.24 | 35, | 0.31,-0.14 | 30, | 0.77,0.22 | 35, | 1.65,0.29 | 40, | 1.30,-0.23 |
| PSO | [25.50,0.64,27.97] | 35 | 7.71,-0.12 | 30 | 0.33,-0.14 | 35 | 0.31,0.14 | 40 | 0.48,0.16 | 35 | 0.50,-0.19 |
| GA | [28.52,0.76,23.18] | 8, | 8.15,0.10 | 7, | 0.72,-0.23 | 7, | 0.84,0.23 | 7, | 0.57,0.24 | 7, | 0.56,-0.16 |
| DE | [28.64,0.77,29.79] | 7, | 8.80,0.08 | 35, | 0.57,-0.25 | 30, | 0.55,0.17 | 35, | 0.63,0.17 | 40, | 0.84,-0.26 |
| PSO | [28.87,0.78,23.88] | 35 | 7.42,0.09 | 30 | 0.29,-0.14 | 35 | 0.52,0.16 | 40 | 0.60,0.15 | 35 | 0.63,-0.25 |

# 5 Conclusion

In this paper, Armfield® Process Control Teaching System (PCT40) along with Process Vessel Accessory (PCT41) and pH Sensor Accessory (PCT42) has been used for testing performance of modeling and control strategies developed for strong acid-strong base i.e. Hydrochloric acid (HCl)-Sodium Hydroxide (NaOH) neutralization process. Feedforward ANN structure using tapped delay line is applied to model Armfield pH neutralization system using total 32750 data samples covering pH range from 4 to 10 for training, validation, and testing of the network. It is found that for three delayed input-output samples, ANN model using LM training function gives reasonably acceptable performance values. The feedback control of Armfield pH neutralization process for servo and regulatory operations has been done using optimized Mamdani Fuzzy Inference System (FIS) based Fuzzy Logic Control (FLC). The global optimization techniques namely Genetic algorithm (GA), Differential Evolution (DE), and Particle Swarm Optimization (PSO) are used to optimize pH controller parameters i.e. scaling factors $K_1$, $K_2$ and $K_3$ for normalized error, change in error and change in output respectively for FLC. Offline optimization uses dynamic ANN model, and online optimization uses Armfield neutralization process. Servo and regulatory operations incorporate dynamic pH variations from 6 to 9, and disturbance variable variations from 30% to 40% in acidic stream flowrates. The offline optimized fuzzy logic controller performance using GA, DE and PSO in terms of Integral Square of Error (ISE) is near to the experimentally obtained result. Based on final population convergence result for offline optimization with moderate number of generations it is concluded that DE is best followed successively by PSO and GA. To address nonlinearity of pH neutralization process, fuzzy logic controllers are designed for six different regions of dynamic pH range from 6 to 9 in piecewise manner. Based on experimental responses of fuzzy logic controller it is concluded that piecewise optimization using GA, DE and PSO results in improved performance. Finally, GA, DE and PSO based online optimization of piecewise fuzzy logic controller are carried for pH setpoint changes from 6 to 7, and 8 to 7, with acidic flow rate variations from 30% to 40% at pH setpoint of 7. The ISE performance values confirm that all three global optimization techniques give approximately similar results. Based on ease of implementation for online optimization with small number of generations it is concluded that DE has most simplistic algorithm followed successively by PSO and GA.

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