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DESIGN OF OPTIMUM PID CONTROLLER FOR NONLINEAR PROCESS USING EVOLUTIONARY ALGORITHMS

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ABSTRACT

In past decades, PID controller was mostly preferred because of its robust behavior in a spread over range of operating conditions. However the conventional PID tuning procedure is not suitable for getting the optimized controller parameters under the identified operating regions. Therefore, an optimum Particle Swarm Optimization (PSO) based Proportional-Integral-Derivative (PID) controller is proposed for controlling the nonlinear process with optimized PID parameters settings. The PSO computation technique has many advantages like high quality solution, less computation time and good convergence characteristics. The tuning of PID parameters through optimization algorithms provides high quality solution for nonlinear processes. The performance indices such as ISE, IAE and ITSE were studied to evaluate the proposed controller performances. The proposed PID controller is presented to a nonlinear Continuous Stirrer Tank Reactor (CSTR) process for controlling the concentration by manipulating its feed flow rate. From the results, it is observed that the PSO-PID provides better control accuracy than other methods such as Simulated Annealing (SA) and Genetic Algorithm (GA) based controllers.

Keywords: *PID, Genetic Algorithm, Simulated Annealing, Particle swarm optimization, CSTR*

1. INTRODUCTION

In recent years, several process control techniques such as PID, fuzzy based, neural based, neuro-fuzzy based, and Adaptive Neuro-Fuzzy Inference System based control have been used in process industries. Among all techniques, Proportional-Integra-Derivative (PID) control provides good control accuracy and robustness and with minimum number of control parameters to be adjusted. PID controller is the most often used control system in industry [10]. It is well known for its error correction ability in control systems and stabilizing process. However, the plants with high nonlinearity, high time-delay and high order can't be controlled effectively using a simple PID controller [20]. Many conventional PID tuning approaches such as Cohen-Coon method, Ziegler Nichols Ziegler, etc., [16] have been presented in literature paper. The conventional tuning techniques are not sufficient to handle the complex processes. Hence, the advanced PID tuning techniques based on Artificial Intelligence (AI) and Evolutionary Algorithms (EA) are preferred to achieve good control accuracy.

The meta-heuristic approaches [19] are used for the proper tuning of PID controllers in the complex process control. The optimum settings of the PID can be derived for the process in the search space based on evolutionary algorithms. The Genetic Algorithm (GA), Simulated Annealing (SA), Particle Swarm Optimization (PSO), neural networks, Ant Colony Optimization (ACO) are some of the heuristic techniques mostly preferred to find the optimum settings of PID.

GA and SA are adaptive heuristic search methods based on evolutionary algorithms of natural selection and genetics [6],[17].GA and SA have got much attraction among researchers in the tuning of PID control parameters, which requires little knowledge about the system and does not require specified search space. Therefore, GA and SA can solve nonlinear multi-objective optimization problems [3]. GA with parallel search techniques provides faster computation than SA [19]. Though GA and SA are being used in optimization problem, there are many drawbacks such as high average fitness, premature convergence and less search capacity [12].

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The PSO was developed by Kennedy and Eberhart from the simulation of a simplified social system. The PSO computation technique has the advantages like high quality solution, less computation time and good stable convergence characteristics than other methods [8]. Because of the better optimization and solving the optimal PID controller, the PSO based PID is proposed for complex nonlinear CSTR system [11].

The performance of the proposed technique is evaluated in-terms of simple performance criteria i.e. rise time, settling time and integral performance criteria i.e. ISE, IAE and ITSE [16]. The proposed algorithm is presented to nonlinear CSTR process to show its effectiveness. CSTR is highly nonlinear process; the control objective is to control the concentration by adjusting its inlet coolant flow rate. The results of performance criteria's are also presented to evaluate the performance of the proposed method than other methods such as GA and SA based PID.

2. LINEAR MODEL OF PROCESS

A highly nonlinear CSTR process is shown in Fig.1, irreversible and exothermic reaction is assumed to occur in the reactor.

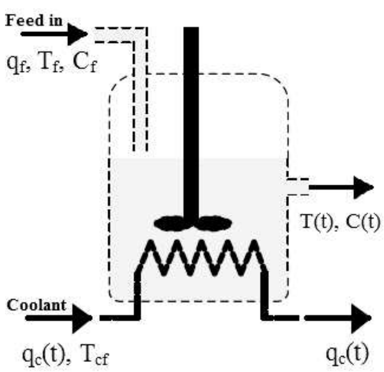

Figure.1 CSTR Process

The process nonlinear differential equations [11] are given in eqn. (1) and eqn. (2)

$$\frac{dT}{dt} = \frac{q_f}{V}(T_f - T(t)) + K_1 C(t)\exp(-\frac{E}{RT(t)})$$
$$+ K_2 q_c(t)\left[1 - \exp\left(-\frac{K_3}{q_c(t)}\right)\right](T_{cf} - T(t)) \quad (1)$$

$$\frac{dC}{dt} = \frac{q_f}{V}(C_f - C(t)) - K_0 C(t)\exp\left(-\frac{E}{RT(t)}\right) \quad (2)$$

The objective of the controller is to keep the concentration C(t) of the product into desired level by adjusting the inlet coolant flow rate $q_c(t)$. The nominal parameter settings of the process are given in Table.1

Table.1 CSTR Parameters

q_f = Inlet flow rate, 100 l/m	T_f= Inlet temperature, 350K
C_f= Inlet concentration,1mol/l	T_{cf}= Coolant temperature, 350K
V= Volume of tank, 100 L	E/R= Activation energy, 104K
K_1= 1.44xe^{13}	K_2= 0.01
K_3= 700	K_0= 7.2xe^{10}

In CSTR process modeling, the operating regions around the stability region are selected through the local model networks. The selected 3 local operating regions are given in Table.2.

Table.2 CSTR Stable operating regions

Operating region.1	C_{01} =0.0795,, T_{01}=443.4566, q_{co1}= 97
Operating region.2	C_{02} = 0.0885,T_{02}=441.1475, q_{co2}=100
Operating region.3	C_{03} = 0.0989,T_{03}=438.7763, q_{co3}= 103

Where C_0, T_0, q_{co} are the linearization points of the CSTR process.

2.1 PID Controller

The proper tuning of the PID controller aims for a desired behavior and improves the dynamic performance by reducing the steady state error. The local PID controller is designed for the identified three operating regions through the conventional empirical Ziegler Nichols tuning techniques. The control signal is derived from the following PID structure given in eqn. (3)

$$u(t) = K_P e(t) + K_I \int_0^t e(t)dt + K_d \frac{de(t)}{dt} \quad (3)$$

Local PID controller for CSTR process is designed by considering its steady state operating values. The state space model of the linearised model of the CSTR process is obtained from the solution of eqn.(4) .

The linear state space model of CSTR is expresses as follows.

$$\dot{x} = Ax + Bu$$
$$y = Cx + Du \quad (4)$$

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The conventional tuning of PID is not sufficient to handle the higher order processes, highly nonlinear systems and time varying systems. Hence many heuristic optimization techniques such as GA, SA and PSO are used to find out the optimum PID controller parameters. The performance of optimized PID controller is verified through the integral performance criteria ISE, IAE and ISTE. The well optimized PID controller has good control accuracy and result in performance criteria minimization.

3. OPTIMIZATION ALGORITHM

The Evolutionary Algorithms (EA) and Swarm Intelligence (SI) are the most commonly used optimization techniques. EA is a problem solving technique based on the biological evolution. SI systems are the population of simple objects interacting locally and with their environment such as PSO and ACO. Evolutionary computing techniques involve generally many meta-heuristic optimization approaches such as GA, SA, and Differential evolution. In this paper, GA, SA and PSO based optimal PID controller is implemented for the nonlinear processes.

3.1 GA Based Optimization of PID Controller

Genetic algorithms are population based search theory. From literatures Salvatore Caorsi et.al [14], Stephane Gerbex et.al[15], Ronald Setia et.al[13], A.Lahiri et.al [2], Jae Seok Choi et.al[7], it is found that GAs are applied in various optimization problems. The GAs work through the following parameters: Chromosomes population, Selection according to fitness, crossover to create new offspring and mutation of new offspring. The steps involved in GA-PID implementation is expressed as follows:

Step.1: The initial population of 3X20 for generation '0' is created within the range of 0 to 1 by standard normal distribution. Where 3 represents the genome length and 20 represents total population.

Step.2: All created individuals of this population are passed through the objective function to evaluate the score of chromosomes. The cost function of PID tuning is defined as a function that accepts a matrix of order 1X3 and assigns the values to k_p, k_i, k_d then calculates the fitness score.

Step.3: The elite count (E) is assigned as 2. The total number of cross over kids (nX_{over}), The number of mutation kids($nM_{mutation}$), and the total number of parents(nParents) to be created in each generation is calculated by relations.

nX_{over} = (CF × population size)-E

$nM_{mutation}$ = population size-E-nX_{over}

nParents = (2× nX_{over}) + $nM_{mutation}$

Where CF is crossover fraction

Step.4: The fitness scaling: The fitness scores (IAE||ITAE||ITSE||ISE) are sorted in the ascending order, the lowest cost chromosome is kept first. The scaling of the expectation of chromosome (i) is calculated by rank based scaling using equation (5).

$$Ex(i) = \frac{Ex(i)}{\sum_{i=i}^{nParents} Ex(i)} \times nParents \qquad (5)$$

Step.5: Selection

The expectation value of the chromosome is a measure of possibility to take the current chromosome to next generation. A roulette wheel selection that has slots for all expectation values is assumed with random initial position. The entire roulette wheel will be covered by the step size equal to the number of parents required for next generation.

Step.6: Crossover

The range 1 to (2 * nX_{over}) of selected Parents is used for crossover and remaining parents are chosen for mutation process. Two parents are selected as pair and new off spring is created through two point crossover [5].

Step.7: Mutation

The mutation is controlled by two factors i.e. scale and shrink co-efficient. The scale value determines the gene's range and the value of scale is reduced proportionally to the number of generation to avoid algorithm to take more random search. The pseudorandom values are obtained from the standard normal distribution to do the mutation on the parents. The kids produced by the crossover mutation and Elite kids are grouped together to create a population for next generation.

Step.8: Stopping criteria

These genetic operators are imposed on population till the maximum number of generation is reached.

3.2 SA Based Optimization of PID Controller

The simulated annealing introduced by Kirkpatrick is originated from the mechanism of annealing in solids, considering coercing a solid into a low energy state. SA techniques use an analogous set of controlled cooling operations for optimization problems, in effect transforming a poor solution into a highly optimized solution and it has the ability to escape from trapping in local minimum [18]. The elements of SA based PID tuning is expressed as follows:

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Step.1: Objective function: The SA objective function is similar to the energy equation in thermal systems. The objective function in PID optimization is minimizing the values of performance indices expressed in equations (12) to (14).
Step.2: Starting point: The search is started with high initial value to avoid the algorithm being trapped in local frozen state [18].
Step.3: Acceptance Criteria: If the new point is better than the previous one, accept the solution. Otherwise accepting criteria is done randomly based on a Boltzmann probability density [9]. The solution is accepted only the probability equation given in (6) is satisfied.

$$p' > \frac{1}{1+e^{\frac{\Delta E}{T}}} \qquad (6)$$

Step.4: Temperature adjustment: The temperature is determined by using the exponential function that describes the tradeoff between the iteration count and the re annealing stage [1]. The temperature is calculated by using the equation (7).

$$T = \alpha^{i} \qquad (7)$$

Where α is temperature cooling factor, i-iteration count.

The 100 solution points are accepted and then re-annealing is carried out. Annealing is done in random steps that are proportional to the temperature T.
Step.5: Stopping criteria: If the iteration count reaches the specified maximum value then the algorithm is terminated and the best value of controller parameter that minimizes the objective function is returned.

3.3 PSO Based Optimization of PID Controller

PSO is population based searching method of optimization. Every individual particle represents a solution of optimization problem [4]. These particles fly around the search space with a defined velocity until an unchanged position is encountered. In PSO two models are used such as social-only model and a cognition-only model. In social only model the particle ignores their own experience and adjusts their behavior with respect to the individual near to them. In the cognition-only model individuals are treated as an isolated being. The position change and velocity change is done only based on these two models [19]. The searching of PSO based optimal PID implementation is described in below steps
Step.1: The initial population of specified size is created based on bound constraints of the controller parameter. Initialize the PSO parameters such as cognitive attraction, social attraction, velocities, p_{bests} and g_{best} .
Step.2: Determine the cost function of the each individual in the initial population using the objective function.
Step.3: For every individual, compare the p_{best} value with its cost function value. If the value of p_{best} is greater than the current fitness, then assign the current fitness to p_{best}. The best fitness among the current fitness value is assigned to global best (g_{best}).
The inertia weight Iw, is calculated using

$$\text{Iw} = UI - \frac{LI \times (i-1)}{i_{\max} - 1} \qquad (8)$$

Where UI is upper inertia,
LI is lower inertia,
i-current generation and
i_{max} is the maximum generation.
The calculation of lower inertia is based on the equation

$$\text{LI} = \frac{c1 + c2}{2} - 1 \qquad (9)$$

Step.4: Accelerate the velocity 'v' of each individual 'G' according to equation (10)

$$v_{j,p:i:d}^{t+1} = Iw \times v_j^t + c_1 .* rand * (p_{best\ .j,p:i:d} - G^t_{best\ .j,p:i:d}) + c_2 .* rand * (g_{best,p:i:d} - G^t_{best,p:i:d}) \qquad (10)$$

Where,
V_j – Velocity of particle j
Iw– Inertia weight factor
C_1-Cognitive attraction factor
C_2 – Social attraction factor
rand – Random number between 0 and 1
P_{best} – pbest of particle j
Gbest – gbest of the group
p - Change in velocity to proportional gain
i - Velocity update made to the integral gain
d - Velocity acceleration to derivative gain.
Step.5: Apply bound constrains on the velocity update value $v_{j,p:i:d}^{t+1}$ to maintain in the range of $v_g^{\min}$ to $v_g^{\max}$.
Step.6: Update the position of each individual 'G' according to equation (11)

$$G_{j,p:i:d}^{t+1} = G_{j,p:i:d}^{t} + v_{j,p:i:d}^{t+1} \qquad (11)$$

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Step.7: If the number of iterations attains the set value then do step 8, otherwise go to step 2.
Step.8: Terminate the velocity update and the latest g_{best} is the optimal values of PID-controller gain.

4. SIMULATION RESULTS

The dynamic and convergence response of the proposed method evaluation is done through integral performance criteria's such as ISE, IAE and ITSE. This is used to express the accuracy and speed of the proposed algorithm. The formulas for the evaluation criterion are expressed as follows:

Integral Absolute Error

$$IAE = \int_0^\infty |e(t)|dt \tag{12}$$

Integral Squared Error

$$ISE = \int_0^\infty e^2(t)dt \tag{13}$$

Integral Time Squared Error

$$ITSE = \int_0^\infty te^2(t)dt \tag{14}$$

Where e(t)=Set point-Process Variable=r(t)-y(t),

The proposed PSO-PID is implemented to control the concentration of the identified non-linear CSTR process to show its effectiveness. The CSTR parameters and the selected stable operating regions are given in Table.1 and 2. The PSO algorithm parameters for PSO-PID controller and PSO-PID optimized controller parameters are given inTable.3 and 4 respectively.

Table.3 PSO-PID Parameters

Parameters	Values
Lower bound[Kp,Ki,Kd]	[0 0 0]
Upper bound[Kp,Ki,Kd]	[100 100 100]
No. of Iterations	100
Population size	20
Cognitive attraction factor C_1	0.5
Social attraction factor C_2	1.25
Initial Inertia, w	0.9

Table.4 PSO-PID optimized parameters

Parameter	Values
Operating Point	C_0=0.0795;T_0=443.45
Iteration	100
Kp	97.8242
Ki	86.8616
Kd	97.5546
IAE	1.3511
Fitness Function	1.2005

The noise rejection ability of the PSO-PID controller and convergence characteristics of GA, SA, PSO algorithm in optimization process are shown in Fig.2 and 3. From the response curve, it is observed that the PSO-PID provides good noise rejection ability through the optimal PID settings.

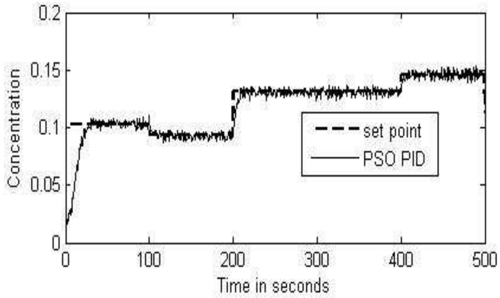

Figure.2 PSO-PID Noise rejection characteristics

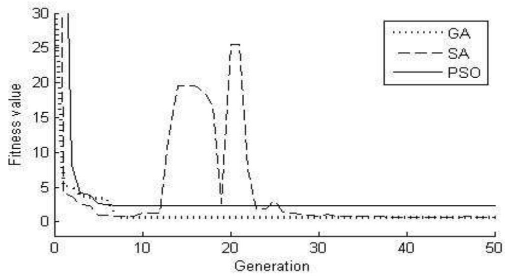

Figure.3 Convergence characteristics of GA, SA, & PSO

The convergence of any optimization algorithm must be within minimum time period or minimum number of iterations. From convergence characteristics curve it is clear that the PSO algorithm is converged in minimum number of generations. The dynamic response of the PSO-PID under servo and regulatory operation is obtained for the identified operating points of the CSTR process. The PSO-PID results are compared with GA and SA based PID for the same for the identified operating points. The effectiveness in-terms of integral performance criteria's (ISE, IAE and ISTE) are analyzed. The GA and SA algorithm parameters are shown in Table.5 and 6.

Table.5 GA Parameters

Parameters	Values
Lower bound[Kp,Ki,Kd]	[1 1 1]
Upper bound[Kp,Ki,Kd]	[100 100 100]

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No. of Generations	100
Population size	20
Crossover fraction	0.8
Elite count	2

Table.6 SA Parameters

Parameters	Values
Lower bound[Kp,Ki,Kd]	[1 1 1]
Upper bound[Kp,Ki,Kd]	[100 100 100]
No. of Iterations	1000
Initial Temperature	100
Maximum Function Evaluations	9000
Re-annealing iterations	100
Temperature cooling factor (α)	0.95

The servo and regulatory responses of the PSO-PID and comparison results are shown in fig.4 to 7.

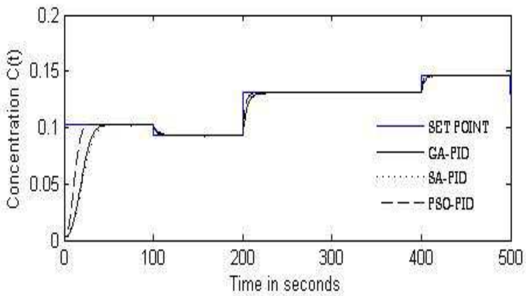

Figure.4 Servo response for I operating region

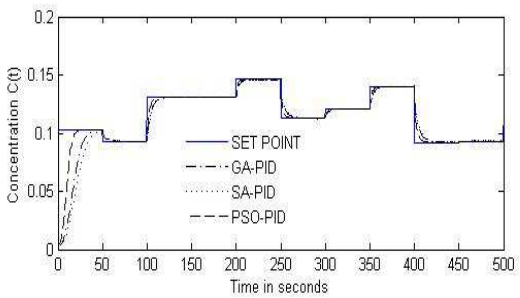

Figure.5 Servo response for II operating region

In order to validate the regulatory response of PSO-PID with SA-PID, GA-PID the closed loop CSTR system, the disturbance is introduced in loop and corresponding response is observed.

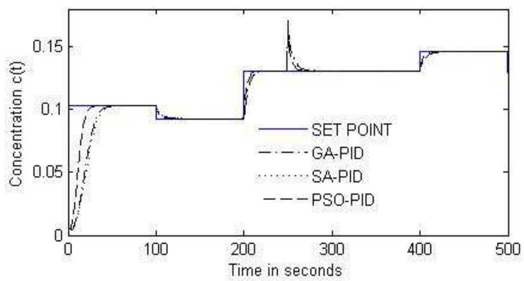

Figure.6 Regulatory response for III operating region

From the simulation and comparison responses, it is observed that the PSO-PID provides fast response with minimum rise time and minimum settling time i.e PSO-PID provides good control accuracy and faster convergence than other methods. The optimized PID settings, minimized values of the objective function and integral performance indices for I and II operating regions are given in Table. 7 and 8 (See Annexure). From the table, it is found that PSO-PID gives better optimized PID settings for the CSTR process under identified operating regions. For the first operating region C_{01} =0.0795,, T_{01}=443.4566 and q_{co1}= 97, PSO-PID provides Kp=78.855, Ki=74.824 and Kd=97.554 as optimized settings. The controller performance indices ISE=0.1034, IAE=1.3511 and ITSE=1.8258 were shown the proposed controller performance.

4. CONCLUSION

In this paper, PSO-PID evolutionary algorithm is proposed to find a proper PID control parameters for nonlinear process. From the simulation results it is observed that PSO-PID requires less convergence time as compared to GA and SA based PID because of its population density and hence less number of iterations is required. The servo and regulatory dynamic response shows that the PSO-PID provides better response than other methods. The closed loop response of the system has a better rise time, settling time, minimum overshoot and better integral performance indices such as ISE, IAE and ISTE. To show the effectiveness of the proposed PSO-PID, it is presented to the nonlinear CSTR process. From the results it is found that the PSO-PID provides better control accuracy, good convergence characteristics and better performance indices. In future, the hybridization of evolutionary techniques can be used to find optimal PID settings.

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Table.7 Optimized PID values for I operating region

PSO-PID	ISE= 0.1034	Obj.Fun	0.2115	GA-PID	ISE= 0.1096	Obj.Fun	0.0760	SA-PID	ISE= 0.1103	Obj.Fun	0.0750
		Kp	78.855			Kp	96.7980			Kp	97.8648
		Ki	74.824			Ki	69.5259			Ki	68.9849
		Kd	97.554			Kd	99.8110			Kd	99.9462
	IAE= 1.3511	Obj.Fun	1.2005		IAE= 2.2951	Obj.Fun	1.1683		IAE= 2.4461	Obj.Fun	1.1681
		Kp	97.8242			Kp	56.1781			Kp	61.3295
		Ki	86.8616			Ki	50.8846			Ki	47.3387
		Kd	105.22			Kd	99.8849			Kd	99.9960
	ITSE= 1.8258	Obj.Fun	1.6598		ITSE= 3.1867	Obj.Fun	0.5487		ITSE= 3.6680	Obj.Fun	0.5523
		Kp	101.051			Kp	85.6377			Kp	99.3991
		Ki	85.7153			Ki	56.1430			Ki	49.1669
		Kd	98.0915			Kd	99.9645			Kd	98.4161

Table.8 Optimized PID values for II operating region

PSO-PID	ISE= 0.1034	Obj.Fun	0.0206	GA-PID	ISE= 0.1078	Obj.Fun	0.0749	SA-PID	ISE= 0.1097	Obj.Fun	0.0766
		Kp	91.4220			Kp	96.9456			Kp	98.9367
		Ki	101.310			Ki	70.6003			Ki	45.7649
		Kd	99.4260			Kd	99.9192			Kd	99.6193
	IAE= 1.34621	Obj.Fun	1.1804		IAE= 1.6218	Obj.Fun	1.1699		IAE= 2.2833	Obj.Fun	1.1681
		Kp	69.3245			Kp	32.2030			Kp	1.9666
		Ki	87.1792			Ki	72.1549			Ki	51.077
		Kd	99.4915			Kd	99.4966			Kd	99.9325
	ITSE= 1.4975	Obj.Fun	1.1825		ITSE= 3.0561	Obj.Fun	0.5934		ITSE= 3.0561	Obj.Fun	0.5562
		Kp	99.9360			Kp	78.7918			Kp	80.0470
		Ki	104.5825			Ki	58.1995			Ki	48.9072
		Kd	92.5636			Kd	94.5974			Kd	49.8581