Nonlinear PID Controller Parameter Optimization using Enhanced Genetic Algorithm for Nonlinear Control System

K. Vijayakumar*. T. Manigandan**

**Dr.Mahalingam College of Engineering and Technology, Pollachi, Tamilnadu, India, 642003*
(Tel:+91-9942243063; e-mail: vijay.aswath2008@ gmail.com,vijay.ice2008@gmail.com).
***P.A College of Engineering and Technology, Pollachi, Tamilnadu, India, 642002*
(e-mail:manigandan_t@yahoo.com)

Abstract: In this paper, an Enhanced Genetic Algorithm (EGA) based proportional–integral-derivative (PID) controller is presented for control of nonlinear dynamic process. In EGA, the crossover and elite offspring are optimized using Ant colony Optimization (ACO) which improves the convergence characteristics and optimization capabilities of traditional Genetic Algorithm (GA).The proposed algorithm is implemented for closed loop control of Continuous Stirred Tank Reactor (CSTR) process. The performance of the proposed scheme is validated through the simulation results and by comparing with the conventional counterparts. The integral performance criteria viz., Integral Square Error (ISE), Integral Absolute Error (IAE), Integral Time weighted Absolute Error (ITAE) of the EGA implemented CSTR system revealed a reduction of ISE equal to 1.5704e-4 at 50-150 sampling interval when compared to conventional GA. The results show that, EGA based nonlinear PID is more suitable for servo and regulatory operations.

Keywords: ACO, CSTR, Genetic algorithms, Integral performances, PID controller

1. INTRODUCTION

In process industries, PID controllers are widely preferred for servo and regulatory tracking than the advanced control techniques such as, Model Predictive Control, Fuzzy and Neural modelling, Adaptive control etc., because of its simple architectures and robustness behaviour (Ibrahim et al., 2014; Ruiyao Gao et al., 2002). Most of the chemical processes such as CSTR, distillation column, bio reactor, etc., are nonlinear systems and they have got dynamic behaviour dominated by the system parameters.

The nonlinear process modelling and identification over its widespread operating region plays a dynamic role in controller performance and its design due to variation in operating condition from time to time. The multiple model technique evades these issues in nonlinear system modelling, which is formulated by splitting the entire operating region into different regions and then the local PID controller is tuned for each region. (Wen Tan et al., 2006; Praksh et al., 2009) have reported several PID tuning techniques such as Ziegler–Nichols (Z–N) method, Cohen–Coon (C–C) method, Internal Model Control (IMC) method, Gain-Phase margin (G-P) method with ISE, IAE, and ITAE as the objective function to be minimized. The local PID controller is not effective when the system is highly nonlinear and complex in nature, because of the varying operating conditions. However, the Nonlinear PID controller (N-PID), which reflects the nonlinear relations of the input and output variables, can eradicate these issues. (Su et al., 2005; Ruiyao Gao et al., 2002) has reported a nonlinear PID controller for the CSTR process using local model networks. (Prakash and Srinivasan, 2009) have also discussed about the N-PID controller design for the nonlinear model which has been obtained from local linear model fusion improves the closed loop performance. (Prakash and Srinivasan, 2009) have presented Takagi-Sugeno (T-S) fuzzy multiple models for the nonlinear process. The interpolation of the local model using T-S fuzzy weight is termed as multiple model of the process. The T-S model if-then rule represents the input-output relations of the process and it is used to formulate N-PID controller. (Christopher Hametner et al., 2013) have presented PID controller design for the nonlinear system using discrete-time local model networks.

The N-PID parameters K_p, K_i and K_d are tuned through the conventional tuning techniques (Wen Tan et al., 2006), each local model is tuned separately and combined using T-S fuzzy fusion techniques. The conventional PID tuning for the nonlinear system provides improper settings due to process parameter variations, which gives oscillatory response and poor robustness behaviour. To achieve satisfactory servo and regulatory performance, it is necessary to have optimally tuned parameters of PID.(Wei-Der Chang et al., 2010) have discussed about N-PID control system design using the improved Particle Swarm Optimization (PSO). (Rajinikanth and Latha, 2012) have presented a controller parameter optimization for nonlinear systems using Enhanced Bacterial Foraging Algorithm (E-BFA). (Wei-Der Chang, 2013) has presented a nonlinear CSTR control system design using an Artificial Bee Colony (ABC) algorithm.

Genetic Algorithms (GA) are the heuristic random search optimization technique which works based on the mechanism of natural selection. The GA attracted great attention among researchers for optimal PID design due to its higher potentials and providing optimal solution in high dimensional problem space. (Valarmathi et al., 2009; Wei-Der Chang, 2007) have discussed about the real-coded GA for system identification and controller tuning. In order to achieve better convergence and optimized values form GA, the crossover sites and elite offspring need to be properly selected.

In this paper, ACO based GA is proposed for selecting possible crossover sites and optimization of reproduction offsprings to enhance the searching ability of the conventional GA. The foraging behaviour of ants to get food is the inspiration for the development of Ant Colony Optimization (ACO) (Colorni, 1991; Tavares et al., 2013). The proposed EGA examines more combinations of crossover sites using positive feedback, distributed search, and constructive greedy heuristic method to create better crossover and elite offsprings. The optimization of crossover and elite offsprings are based on the experience of the simulated ant in the tour. The experimental results show that the proposed scheme enhances the performance of the GA and provides better convergence characteristics with improved optimization.

The rest of the paper is organized as follows: Section.2 and 3 elaborates the state of art GA and proposed EGA. Section.4 describes the nonlinear PID controller design using EGA and the simulation studies of proposed schemes were also given for comparison. The brief conclusion of the work done is given in section.5.

2. OVERVIEW OF GENETIC ALGORITHM

The GA performs selection, Crossover and mutation operations to create crossover offsprings(K_x) and mutation offsprings(M_{os}). These values are used to find the next generation population (P_{new}). From the literatures (Daniel Carmona Morales et al., 2012; Gholamreza Farahani et al. 2012; Hasanien and Muyeen, 2012; Indranil Pan et al., 2011; Tang et al., 2001; Teo Lian Seng et al., 1999; Mohd Sazli Saad et al., 2002), it is found that GA is widely applied in controller parameter optimisation problems. In this study, the real coded GA due to its less computation time (Valarmathi et al., 2009). The pseudo code of GA is given in the following steps:

Step.1: Generate random initial population ($P^{Initial}$)

Table 1. GA Parameters.

Name of the Parameter	Initial values
crossover probability (C_r)	0.8
Maximum generation (M_g)	50
Population size (P_s)	100
Elite count (e)	2
Chromosome length (cl)	15
Number of Crossover off springs(n_x)	78
Number of Mutation off springs(n_m)	20

Step.2: The cross over (n_x), mutation (n_m), and total number of parents (n_p) required to create next generation population are calculated as follows:

$$n_x = round\_to\_nearest\_real((C_r \times P_s) - e) \quad (1)$$

$$n_m = P_s - e - n_x \quad (2)$$

$$n_p = 2n_x + n_m \quad (3)$$

Where C_r is the fraction that represents crossover rate.

Step.3: The fitness function is estimated for the initial population.

Step.4: Fitness scaling: The chromosomes are sorted based on fitness scores and then fitness scaling *Exp(i)* of i^{th} chromosome is calculated by rank based scaling using "(4)."

$$Exp(i) = \frac{Ep(i)}{\sum_{i=i}^{n_p} Ep(i)} \times n_p \quad (4)$$

$$Ep(i) = \left(\frac{1}{i}\right)^{0.5} \quad (5)$$

Step.5: Selection: The roulette wheel selection is used to select numbers of parents (P_{np}).

Step.6: Crossover: Two point crossover is performed on offsprings by using parents $P_{np}(1\ to\ 2n_x)$.

Step.7: Mutation: Apply mutation to evaluate the mutated off-spring.

The steps are repeated till the maximum number of generation is reached.

The two point crossover method uses randomly selected cross over sites. Therefore, no assurance can be made about the quality of offspring's. The convergence rate of the optimization can be improved through best crossover sites selection.

The Population Size (P_s) is assigned as 100 from the convergence analysis of various population sizes. The convergence curve and statistical parameter analysis are shown in Fig. 1 and Fig. 2.

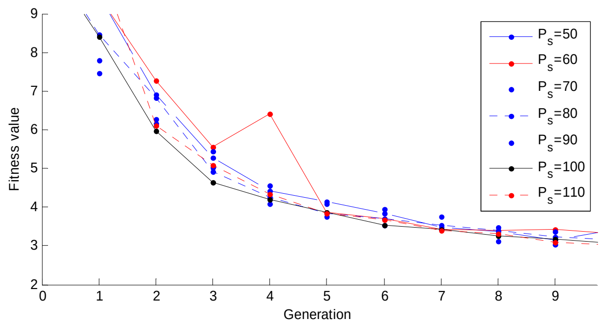
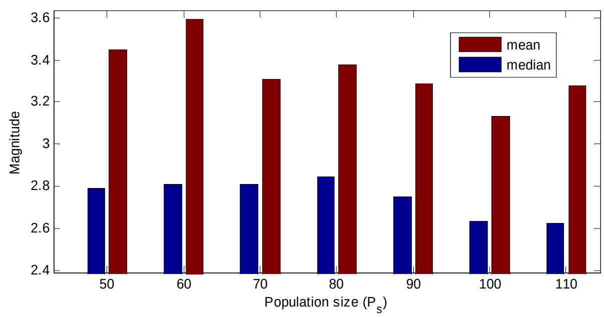
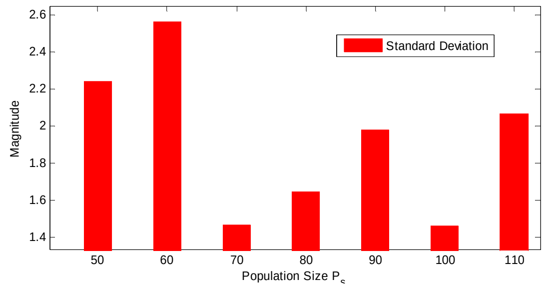


Fig. 1. Convergence of GA for different population size.



(a) Mean and median comparison of convergence curves.



(b) Standard deviation comparison.

Fig. 2. (a) & (b) Statistical comparison of Convergence curves.

3. ENHANCED GENETIC ALGORITHM

In recent years, hybridization approaches of evolutionary algorithms were reported by researchers (Haibin Duan et al., 2013; Pourya Hoseini and Mahrokh, 2013; Irina Ciornei and Elias Kyriakides, 2012) is preferred for the improved optimization performances.

In order to improve GA performance, Ant Colony Optimization (ACO) based Genetic Algorithm is proposed to create better crossover and reproduction offsprings through enhanced searching ability (Sina Tabakhi et al., 2014; Chandra Mohan and Baskaran, 2012; Rajasekar and Mohana Sundaram, 2012).

The crossover and elite offspring of GA is created by the simulated ant of ACO. The crossover sites of GA are considered as nodes and the artificial pheromone from the ant is deposited on the nodes during tour. The amount of pheromone deposited in the each node is inversely proportional to the total distance travelled by the ant to reach the food. The high pheromone deposited node is considered as minimization of the objective function and the same is used for offspring generation. These off springs are grouped together to form next generation population.

The proposed algorithm is used to find optimal PID settings for the nonlinear system with minimum ISE as objective function. The steps involved in the implementation of EGA based Nonlinear PID (N-PID) controller is explained below:

Step.1: Generate random initial population ($P^{Initial}$)

Table 2. EGA Parameters.

Name of the Parameter	**Initial values**
crossover probability (C_r)	0.8
Mutation probability(M_r)	0.2
Maximum generation (M_g)	50
Population size (P_s)	10
Elite count (e)	2
Chromosome length (cl)	15
Number of Crossover off springs(n_x)	6
Number of Mutation off springs(n_m)	2
Number of Ants (N_a)	20
Maximum tour (M_t)	20
Evaporation parameter (λ)	0.95
Relative Important Parameters	(α)=0.01, (β)=0.3
Initial inertial weight factor	$\mu = 0.02$
Initialize pheromone initial value and increment of pheromone	$\tau_{ij}(0) = \tau 0$ & $\Delta\tau_{ij}(0) = 0$

Step 2: Fitness function estimation.

Step.3: Fitness scaling: The chromosomes are sorted based on fitness scores, then the fitness scaling *Exp(i)* of i^{th} chromosome is calculated by rank based scaling using "(4)."

Step.4: Selection: The roulette wheel selection is used to select numbers of parents (P_{np}).

Step.5: From the selected parents, the first $2n_x$ numbers of parents are formed as colony (A_c).

Step.6: The simulated ant is made to visit each node based on the probabilistic action choice rule (Kan Jun-man, Zhang Yi (2012)).The probability for ant 'a', placed at node 'n', to visit node 'c' is expressed by Equation.(6).

$$\left.\begin{array}{ll} p^a_{n,c} = \dfrac{[\tau_{n,c}]^\alpha [\eta_{n,c}]^\beta}{\sum_{i=1}^{N^a_n} [\tau_{n,i}]^\alpha [\eta_{n,i}]^\beta} & \text{if } c \in N^a_n \\ p^a_{n,c} = 0 & \text{Otherwise} \end{array}\right\} \tag{6}$$

Where

$$[\tau_{n,c}] - \frac{1}{d_{n,c}} \tag{7}$$

$[\tau_{n,c}]$ - Pheromone intensity (calculated through distance ($d_{n,c}$) between crossover sites)

$[\eta_{n,c}]$ - Heuristic information about the nodes n and c

N^a_n - denotes the number of nodes.

α - Relative importance given to the pheromone intensity and β is the relative importance given to the visibility value.

Step.7: The update of pheromone is obtained by the equation "(8),"

$$\tau(i)_{nc} = \tau(i-1)_{nc} + \frac{\mu\theta}{d^k_{n,c}} \tag{8}$$

Where $d^k_{n,c}$ is the cost of the ant k and θ is the global pheromone updating constant.

In EGA, the weight factor μ is increased by increasing tour *'i'* using below expression;

$\mu(i) = \mu(i-1) + (i/MaxTour);$

The amount of pheromone deposit is increased when the tour 'i' increases, which results quick convergence with minimum distance.

Step.8:/* Global Update Rules*/
At the end of ant's tour, the pheromone deposit is updated by using "(9),"

$$\tau_{nc}(i) = [\tau(i)_{nc}]^\lambda + [\Delta p] \tag{9}$$

Where

$[\tau(i)_{nc}]$ - local update

λ - Evaporation parameter.

$$\Delta p = \tau(i)_{nc}^{b} + \tau(i)_{nc}^{w} \tag{10}$$

Where, $\tau(i)_{nc}^{b}$ is amount of pheromone deposited from best ant, $\tau(i)_{nc}^{w}$ is the amount of pheromone deposited from worst ant and 'd' is the cost of the ant.

$$\tau(i)_{nc}^{b} = \tau(i)_{nc}^{b} + \frac{\theta}{\min(d_{n,c}^{nk})} \qquad \text{nk=1,2,...k} \tag{11}$$

$$\tau(i)_{nc}^{w} = \tau(i)_{nc}^{w} - \frac{\beta\theta}{\max(d_{n,c}^{nk})} \qquad \text{nk=1,2,...k} \tag{12}$$

Step.9: If maximum tour is not reached then go to step 10. Otherwise go to step 7.

Step.10: Examine the nodes to produce the best crossover offspring and then corresponding distance travelled by the ant is considered for minimization of objective function.

Step.11: The new ant colony (A_n) is constructed through the offspring chromosomes and then repeat steps 7 to 9 to find new elite offspring.

Step.12: Mutation is carried out on the parents $P_{np}(2n_x$ to $n_p)$ to create mutation off springs.

Step.13: Group the elite off springs, crossover off springs and mutation off springs to form new population and assign ($P^{Initial}$) = new population;

Step.14: If N-PID parameters with minimum ISE is obtained then stop, otherwise go to step 2.

The mutation offsprings are evaluated from each generation and the fitness of crossover and elite offsprings have been obtained from the heuristic information provided by the simulated ant.

4. EGA BASED NONLINEAR PID CONTROLLER

The PID controller form is expressed as:

$$u(t) = K_p e(t) + K_i \int_0^t e(t)dt + K_d \frac{d}{dt} e(t) \tag{13}$$

Where e(t) is the error, 'u' is the input and K_p, K_i and K_d are the Proportional gain, Integral gain and Derivative gain respectively.

The IMC tuning formulae for local PID settings are given in equation.(14).

$$K_{p,i} = \frac{2\xi i}{\omega_{n,i} k_i \lambda} \qquad T_{r,i} = \frac{2\xi i}{\omega_{n,i}} \qquad T_{d,i} = \frac{1}{2\xi_i \omega_{n,i}} \tag{14}$$

Where $K_{p,i}$= Proportional gain, $T_{r,i}$=Integral time, $T_{d,i}$=Derivative time, ξ=Damping factor, $\omega_{n,i}$= Un-damped natural frequency and k_i=Steady state gain.

The local PID controller is not effective when the system is highly nonlinear and complex in nature, because PID parameters tuned for one particular operating point is not suitable for other operating point. Therefore, parameters need to be tuned every time when the operating region varies from one local linear model to others. The formulation of multiple model from linear models evade these issues in nonlinear system modelling. Firstly, the entire operating region of the system is divided into different regions for easy computation of local linear models and then secondly combined through fusion techniques to find nonlinear mode. (Prakash and Srinivasan, 2009) have presented Takagi-Sugeno (T-S) fuzzy fusion multiple models for the nonlinear process, the input-output relations of the process are expressed through the if-then rules of fuzzy.

In this paper, T-S based N-PID is used for the nonlinear dynamic chemical process, it can be generally modelled as;

$$\begin{aligned} \dot{x} &= f(x,u,v) \\ y &= g(y,w) \end{aligned} \tag{15}$$

Where 'f' and 'g' are the nonlinear functions, 'y' is the output and 'u'' is the input of the system, 'v' and 'w' are the disturbance vector and noise vector respectively. The local model structure for particular operating region of the system is expressed as follows:

$$\begin{aligned} \dot{x} &= f_i(x,u,v,\theta_i) \\ y &= g_i(y,w,\theta_i) \end{aligned} \tag{16}$$

Where 'θ' is the parameterized vector used to describe the system dynamics. The global structure from the interpolation of local model structure can be expressed as:

$$\begin{aligned} \dot{x} &= \sum_{i=1}^{N} f_i(x,u,v,\theta_i)\omega_i(\phi) \\ y &= \sum_{i=1}^{N} g_i(y,w,\theta_i)\omega_i(\phi) \end{aligned} \tag{17}$$

Where 'ω_i' is the interpolation function which can be expressed as:

$$\omega_i(\phi) = \frac{\rho_i(\phi)}{\sum_{j=1}^{N} \rho_j(\phi)} \tag{18}$$

Where 'ρ_i' is the model validity function and it is assumed to be unity for good model structure. The global system behaviour is described by a fuzzy fusion of all linear model outputs.

The grade of the membership function should be $\omega_i : \Phi \to [0,1]$ and it is a normalization of the model validity function ρ_i, and has the property $\sum_{i=1}^{N} \omega_i(\phi) = 1$ for all $\phi \in \Phi$.

The N-PID form is expressed as follows:

$$u_i(t) = k_{p,i}(e(t) - e(t-1)) + \frac{k_{p,i}}{T_{r,i}} Te(t) + \frac{(k_{p,i} * T_{d,i})}{T} \times (e(t) - 2*e(t-1) + e(t-2) + u_i(t-1)) \tag{19}$$

The optimal PID settings for better servo and regulatory performances can be achieved by adding new features into the tuning procedure. The population based search techniques such as GA and Simulated Annealing (SA) paid great attention for getting higher efficiency and providing optimal solution in high dimensional problem space. The GA has much preference in searching the optimal PID settings due to its high potential on optimization capability. The implementation of the EGA based PID for nonlinear process is given in Fig. 3.

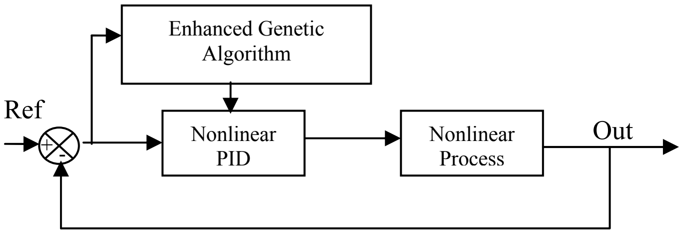


Fig. 3. Optimal PID for the nonlinear system.

The objective function is the Integral Square Error (ISE) performance criterion with respect to stability which is generally expressed in the form of:

$$ISE = \int e^2 dt = \int [y_d(t) - y(t)]^2 dt \tag{20}$$

The proposed algorithm is used to minimize ISE and find the optimal PID settings for the nonlinear system.

4.1 Nonlinear PID based on EGA for CSTR process

The nonlinear CSTR process shown in Fig. 4 is characterized by the nonlinear differential equation (21) and equation (22) and its nominal operating parameters are given in Table 3.

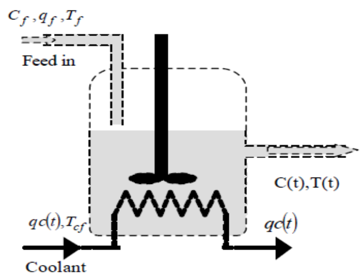


Fig. 4. CSTR Process.

$$\frac{dT}{dt} = \frac{q_f}{V}(T_f - T(t)) + K_1 C(t)\exp(-\frac{E}{RT(t)})$$
$$+ K_2 q_c(t)\left[1 - \exp\left(-\frac{K_3}{q_c(t)}\right)\right](T_{cf} - T(t)) \tag{21}$$

$$\frac{dC}{dt} = \frac{q_f}{V}(C_f - C(t)) - K_0 C(t)\exp\left(-\frac{E}{RT(t)}\right) \tag{22}$$

The control objective is to keep the concentration C(t) of the output product into a desired level by adjusting the inlet coolant flow rate qc(t).In CSTR process modelling, five operating regions were selected through local model networks and are shown in Table 4.

Table 3. CSTR Parameters.

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

Table 4. CSTR Stable Operating Regions.

Operating region	Concentration (C_0)	Temperature (T_0)	Coolant flow rate(q_{c0})
1	0.0795	443.4566	97
2	0.0885	441.1475	100
3	0.0989	438.7763	103
4	0.1110	436.3091	106
5	0.1254	433.6921	109

Where C_0, T_0, q_{c0} are the linearization points of the CSTR process. The fuzzy dynamic model of the CSTR process based local linear model is presented in detail by (Prakash et al., 2009). The local PID controller settings for the selected operating points were tuned through conventional IMC method based tuning techniques. The PID settings of the operating region.1 are determined as Kp=119.4321, Tr,i=0.3367 and Td,i=0.1926, other regions are also tuned similarly. These parameters are considered as initial values to find PID parameters from GA and EGA and they are listed in Table 5 and Table 6

Table 5. GA based PID settings.

Operating point	**K_{ci}**	**T_{ri}**	**T_{di}**
C_A = 0.0795, T=443.4566, q_c= 97	634.8	0.1774	0.2992
C_A = 0.0885, T=441.1475, q_c= 100	799.2	0.2983	0.2215
C_A = 0.0989, T=438.7763, q_c= 103	687.9	0.2780	0.2683
C_A = 0.1110, T=436.3091, q_c= 106	385.5	0.2876	0.2733
C_A = 0.1254, T=433.6921, q_c= 109	706.6	0.1852	0.2513

Table 6. EGA based PID settings.

Operating point	**K_{ci}**	**T_{ri}**	**T_{di}**
C_A = 0.0795, T=443.4566, q_c= 97	668.3	0.192	0.2621
C_A = 0.0885, T=441.1475, q_c= 100	799.9	0.299	0.1545
C_A = 0.0989, T=438.7763, q_c= 103	776.7	0.300	0.2672
C_A = 0.1110, T=436.3091, q_c= 106	350.7	0.299	0.2443
C_A = 0.1254, T=433.6921, q_c= 109	799.8	0.265	0.2388

The global controller i.e., nonlinear PID controller output is described by a fusion of all local linear PID controller outputs. For the improved closed loop response, the EGA based optimization of N-PID is done. The initial settings of variables involved in the EGA based N-PID are given in Table 2.

The proposed EGA for non-linear CSTR system is designed and implemented using MATLAB version 7.8. The selected operating regions for the EGA are given in Table.4. The stable region of the CSTR process is c(t)=[0,0.1357] and qc(t)=[0,110.8] (Ruiyao Gao et al., 2002).

The Table 7 shows the fitness comparison of the crossover offsprings produced by proposed method and other conventional methods. The proposed method uses only very minimum population size (P_s=10).

Table 7. Performance comparison of Crossover of GA.

Crossover Method	**Best Crossover offsprings Cost function values**		
	First generation cycle	**Second generation cycle**	**Third generation cycle**
Single point	2.62148e-3	2.62148e-3	2.6214e-3
Two Point	2.37604e-3	2.37604e-3	2.3760e-3
Arithmetic	2.46555e-3	2.39120e-3	2.3890e-3
Scattered	2.5127e-3	2.32906e-3	2.2283e-3
heuristic	2.4203e-3	2.39691e-3	2.3806e-3
intermediate	2.1796e-3	2.1796e-3	2.1516e-3
Proposed ACO based Crossover	2.21992e-3	2.10696e-3	2.0980e-3

The Cost function values of Best crossover offspring produced in the first three generations (different crossover schemes) is compared in Fig. 5.

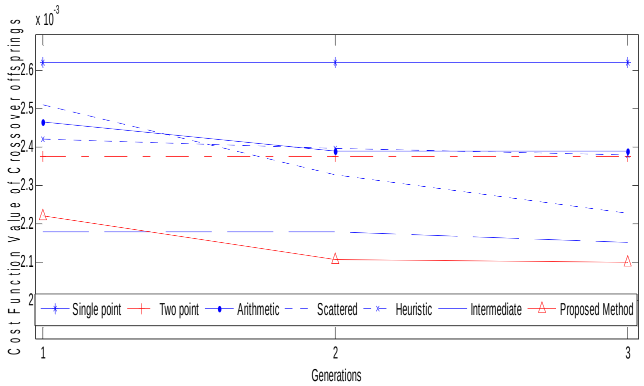
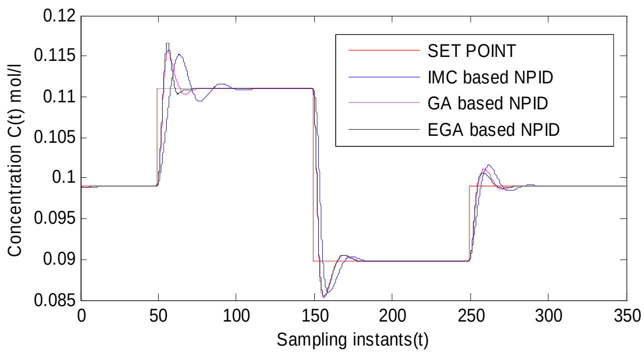
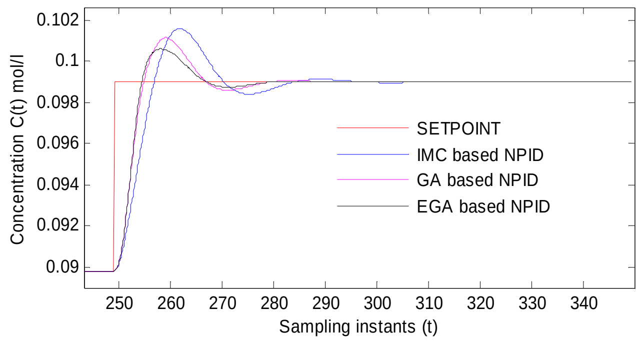


Fig. 5. Cost values of crossover offsprings.

To validate the effectiveness of the proposed EGA algorithm, closed loop servo and regulatory tracking performances and noise rejection responses were obtained for CSTR process. The proposed EGA provides the optimal PID controller gains as [835.4750 0.1924 0.2621] for [K_p,T_i,T_d] with the objective function ISE as 4.025e-8 at 0-50 sampling interval. The servo-regulatory tracking responses, convergence characteristics and noise rejection characteristics are shown in fig. 6 to fig.8 respectively. The control actions on the servo operation and for the noise rejection are shown in Fig. 9.



(a) Overall servo response.



(b) Servo response at one particular region.

Fig. 6. (a) & (b) Servo responses of the EGA based NPID.

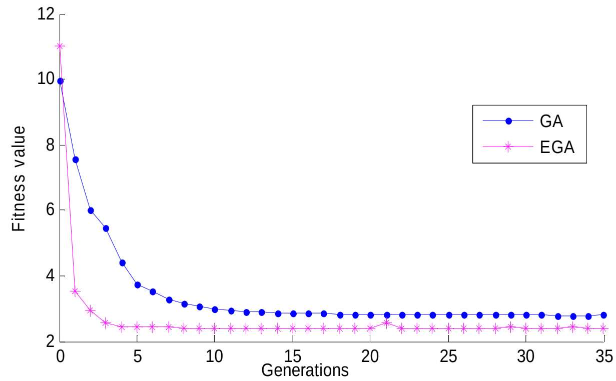


Fig.7. Convergence characteristics of EGA.

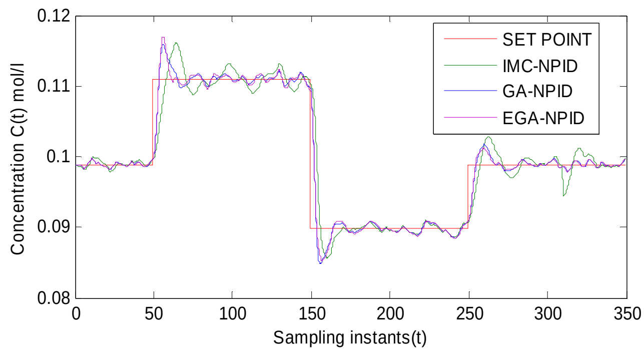
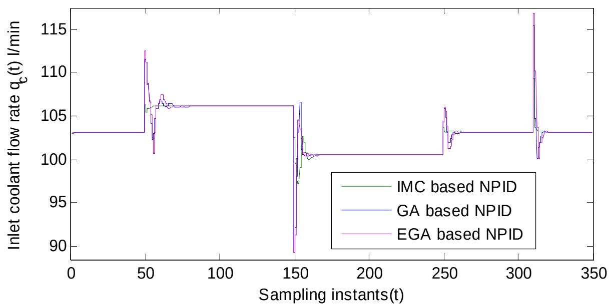
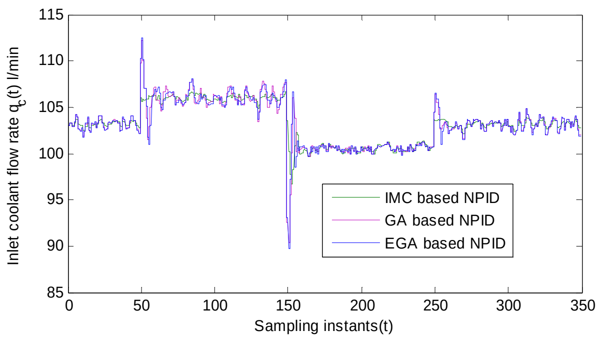


Fig. 8. Noise rejection characteristics of EGA.



(a) Servo operation (Coolant flow)



(b) Noise rejection (Coolant flow).

Fig. 9. Control action curves for servo and noise rejection.

The derived optimal EGA based N-PID parameters and the corresponding objective function ISE values at different sampling intervals are given in Table 8 and Table 9. In order to evaluate the proposed scheme performance it is compared with conventional GA based PID. The closed loop responses and ISE values demonstrate that the proposed EGA has quick convergence with good computational efficiency.

Table 8. Optimal PID settings.

Type of Controller	Operating Point	PID settings		
		$K_{p,i}$	$T_{r,i}$	$T_{d,i}$
GA based PID	1	634.8768	0.1774	0.2992
	2	799.2724	0.2983	0.2215
	3	687.9284	0.2780	0.2683
	4	385.5384	0.2876	0.2733
	5	706.6820	0.1852	0.2513
EGA based PID	1	835.4750	0.1924	0.2621
	2	999.9445	0.2994	0.1545
	3	970.9830	0.3000	0.2672
	4	438.4630	0.2992	0.2443
	5	999.7715	0.2651	0.2388

Table 9. Comparison of ISE, IAE and ITAE values.

Sampling Instants	ISE		
	IMC based NPID	GA based NPID	EGA based NPID
0 – 50	5.2632e-7	1.6492e-7	4.0250e-8
50 – 150	8.2020e-4	6.0777e-4	4.5073e-4
150 – 200	2.3964e-3	1.4767e-3	1.1044e-3
200 – 300	4.0563e-4	3.7061e-4	2.5222e-4
300 – 350	5.3893e-10	4.7535e-10	1.1250e-12
Sampling Instants	**IAE**		
	IMC based NPID	**GA based NPID**	**EGA based NPID**
0 – 50	53.7758e-3	1.5619e-3	7.1541e-4
50 – 150	1.0732e-1	9.2002e-2	6.3187e-2
150 – 200	1.3327e-3	1.6693e-5	1.8848e-5
200 – 300	6.9266e-2	6.5703e-2	4.6830e-2
300 – 350	9.8116e-5	9.1376e-5	3.1879e-5
Sampling Instants	**ITAE**		
	IMC based NPID	**GA based NPID**	**EGA based NPID**
0 – 50	4.3158e-2	1.4492e-3	7.6016e-3
50 – 150	6.3041	4.3749e-1	3.5030
150 – 200	1.5063e-1	1.4231e-4	2.0361e-3
200 – 300	1.7782e+1	1.3959	1.1982e+1
300 – 350	3.0347e-2	2.3137e-3	9.7365e-3

5. CONCLUSIONS

In this paper, an optimized nonlinear PID control system for the nonlinear process using EGA is presented. The proposed EGA uses GA through ACO to enhance local and global search capabilities of the Genetic Algorithm towards the crossover and reproduction using simulated ant of ACO. Experimental explanation of the proposed EGA gives optimised N-PID settings with minimization of the objective function (ISE). To show the effectiveness of the proposed method in the nonlinear PID control system design, the servo and regulatory tracking response of the nonlinear CSTR process is illustrated. With the objective function ISE under different operating regions, the results show quicker convergence of the proposed method.

REFERENCES

Chandra Mohan, B. and Baskaran, R. (2012). A survey: Ant Colony Optimization based recent research and implementation on several engineering domain. *Expert Systems with Applications,* 39, 4618–4627.

Christoph Hametner, Christian H. Mayr, Martin Kozek and Stefan Jakubek, (2013). PID controller design for nonlinear systems represented by discrete-time local model networks. *International Journal of Control,* 86, 1453-1466.

Daniel Carmona Morales, Jorge E. Jimenez-Hornero, Francisco Vazquez, Fernando Morilla, (2012). Educational Tool for Optimal Controller Tuning Using Evolutionary Strategies. *IEEE transactions on education,* 55, 48-57.

Gholamreza Farahani. (2012). Computing Optimum Coefficients of PID Controller with Genetic Algorithm.*38th annual conference on IEEE Industrial Electronics Society,* 2192-2197.

Hasanien, H.M., and Muyeen, S. M. (2012). Design Optimization of Controller Parameters Used in Variable Speed Wind Energy Conversion System by Genetic Algorithm. *IEEE transactions on sustainable energy,* 3, 200-208.

Haibin Duan, Qinan Luo, Guanjun Ma, and Yuhui Shi, (2013). Hybrid Particle Swarm Optimization and Genetic

Algorithm for Multi-UAV Formation Reconfiguration. *IEEE Computational intelligence magazine,* 8, 16-27.

Hong MAN, and Cheng SHAO. (2012). Nonlinear Predictive Adaptive Controller for CSTR Process. *Journal of computational information systems,* 8, 9473-9479.

Ibrahim H.E.A., Hassan F.N., and Anas O. Shomer. (2014). 'Optimal PID control of a brushless DC motor using PSO and BF techniques' *Ain Shams Engineering Journal,* 5, 391–398.

Indranil Pan, Saptarshi Das, and Amitava Guptaa. (2011). Tuning of an optimal fuzzy PID controller with stochastic algorithms for networked control systems with random time delay. *ISA Transactions,*50, 28–36.

Irina Ciornei and Elias Kyriakides. (2012). Hybrid Ant Colony-Genetic Algorithm (GAAPI) for Global Continuous Optimization. *IEEE transactions on systems, man, and cybernetics—part b: cybernetics*, 42, 234-245.

Jimoh O. Pedro, Muhammed Dangor, Olurotimi A. Dahunsi, and Montaz Ali, M. (2013). Differential Evolution-Based PID Control of Nonlinear Full-Car Electrohydraulic Suspensions. *Hindawi Publishing Corporation Mathematical Problems in Engineering,* 2013, 1-13.

Kan Jun-man and Zhang Yi. (2012). Application of an Improved Ant Colony Optimization on Generalized Traveling Salesman Problem. *2012 International Conference on Future Electrical Power and Energy Systems Energy Procedia,* 17, 319 – 325.

Karam M. Elbayomy, Jiao Zongxia, Zhang Huaqing. (2008). PID Controller Optimization by GA and Its Performances on the Electro-hydraulic Servo Control System. *Chinese Journal of Aeronautics,* 21, 378-384.

Mohd sazli saad, Hishamuddin Jamaluddin, and Intan zaurah Mat Darus. (2012). Implementation of PID controller tuning using differential evolution and genetic algorithm. *International journal of innovative computing, information and control,* 8,7761-7779.

Muhammet unal, Ayca Ak, Vedat Topuz, and Hasan Erdal. (2013). *optimization of PID controllers using ant colony and genetic algorithms. studies in computational intelligence,* Chapter 3-5, Springer, Newyork.

Oguzhan Hasancebi and Fuat Erbatur. (2000). Evaluation of crossover techniques in genetic algorithm based optimum structural design. *Computers and Structures*, 78, 435-448.

Prakash, J. and Srinivasan, K. (2009). Design of nonlinear PID controller and nonlinear model predictive controller for a continuous stirred tank reactor. *ISA Transaction,* 48, 273-282.

Pourya Hoseini, and Mahrokh G. Shayesteh. (2013). Efficient contrast enhancement of images using hybrid ant colony optimisation, genetic algorithm, and simulated annealing. *Digital Signal Processing,* 23, 879–893.

Rajinikanth, V. and Latha, K. (2012). Controller Parameter Optimization for Nonlinear Systems Using Enhanced Bacteria Foraging Algorithm. *Hindawi Publishing Corporation Applied Computational Intelligence and Soft Computing,* 2012, 1-12.

Rajasekar, N. and Mohana Sundaram, K. (2012). Feedback controller design for variable voltage variable speed induction motor drive via Ant Colony Optimization. *Applied Soft Computing,* 12, 2132–2136.

Ruiyao Gao, O'dywer Aidan, and Coyle Eugene. (2002). A Nonlinear PID control for CSTR using local model networks. *Proceedings of 4th world congress on intelligent control and automation,* 3278- 3282.

Sina Tabakhi, Parham Moradi and Fardin Akhlaghian. (2014). An unsupervised feature selection algorithm based on ant colony optimization. *Engineering Applications of Artificial Intelligence,* 32, 112–123.

Su, Y.X., Dong Sun, and Duan, B.Y. (2005). Design of an enhanced nonlinear PID controller. *Mechatronics,* 15, 1005–1024.

Tang K. S., Kim Fung Man, Guanrong Chen, and Sam Kwong. (2001). An optimal fuzzy PID controller. *IEEE transactions on industrial electronics,* 48, 757-765.

Teo Lian Seng, Marzuki Bin Khalid and Rubiyah Yusof. (1999). Tuning of a Neuro-Fuzzy controller by Genetic Algorithm. *IEEE transactions on systems, man, and cybernetics—part b: cybernetics,* 29, 226-236.

Tavares Neto, R.F. and Godinho Filho, M. (2013). Literature review regarding Ant Colony Optimization applied to scheduling problems: Guidelines for implementation and directions for future research. *Engineering applications of artificial intelligence,* 26, 150–161.

Valarmathi, k., Devaraj, D., and Radhakrishnan, T.K. (2009). Real-coded genetic algorithm for system identification and controller tuning. *Applied Mathematical Modelling*, 33, 3392–3401.

Wen Tan, Jizhen Liu, Tongwen Chen, and Horacio J. Marquez. (2006). Comparison of some well-known PID tuning formulas. *Computers and Chemical Engineering,* 30, 1416–1423.

Wei-Der Chang. (2007). Nonlinear system identification and control using a real-coded genetic algorithm. *Applied Mathematical Modelling*, 31, 541–550.

Wei-Der Chang, and Shun-Peng Shih. (2010). PID controller design of nonlinear systems using an improved particle swarm optimization approach. *Commun Nonlinear Sci Numer Simulat*,15, 3632–3639.

Wei-Der Chang. (2013). Nonlinear CSTR control system design using an artificial bee colony algorithm. *Simulation Modelling Practice and Theory,* 31, 1–9.

Ying Li, Gang Wang, Huiling Chen, Lian Shi, and Lei Qin. (2013). An Ant Colony Optimization Based Dimension Reduction Method for High-Dimensional Datasets. *Journal of Bionic Engineering,* 10, 231–241.