An Improved Particle Swarm Optimization with Multiple Strategies for PID Control System Design

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***Abstract*—In this paper, an improved particle swarm optimization (PSO) with multiple subpopulations is developed for PID control system designs. The original single population needs to be divided into several subpopulations, and each subpopulation then tackles a corresponding performance index of the system. Under this proposed structure, several PID controllers can be simultaneously designed to meet different performance indexes when the algorithm is executed only one time. It is a great improvement because the general PSO algorithm with a single population can only deal with one performance index. To demonstrate the feasibility of the proposed scheme, a complicated chemical nonlinear process called the continuously stirred tank reactor (CSTR) is illustrated. Three different kinds of control operations are simulated including the step response control, set-point tracking control, and unstable equilibrium point control. For each control case five different performance indexes are assigned to guide the PID controller design combined with the nonlinear CSTR system. Simulation results will sufficiently confirm the superiority of the proposed algorithm.**

***Index Terms*—Multi-strategy particle swarm optimization, subpopulations, PID control, continuously stirred tank reactor (CSTR); nonlinear systems.**

I. Introduction

Particle swarm optimization (PSO) was proposed by Kennedy and Eberhart in 1995 and has been proven to be an effective and simple algorithm for solving engineering optimization problems. This algorithm consists of two basic adjusting mechanisms to update the related design parameters for achieving the optimization, i.e., the velocity and position updating formulas. The initial idea is motivated from the social behavior of fish and bird swarms. Over recent two decades, it has been widely applied in a variety of engineering fields and has successively solved many optimization problems because of the excellent searching capacity, for examples, the signal processing [2][3], power system optimization design [4]-[6], controller design problem [7][8], job shop scheduling [9][10], and other engineering application researches [11]-[16].

In recent years, a multi-population or multi-swarm architecture for meta-heuristic algorithms were successively developed and discussed [17]-[23]. In the proposed techniques, the original single population used in the algorithm is replaced by multiple ones in order to prompt the algorithm searching capacity or to tackle some particular problems. In [17], the authors developed a multi-population electromagnetic algorithm to track the dynamic changes. Each sub-population takes charge in exploring or exploiting the search space. In [21], a variation of fly optimization algorithm (FOA) was presented and named multi-swarm FOA to significantly improve the performance. By examining some benchmark functions, simulation results show that the proposed method has an effective improvement in its performance over original FOA. Furthermore, in our previous work a modified PSO algorithm has been proposed for solving multimodal function optimization problems [22]. The original population is also divided into several subpopulations and the best particle in each subpopulation is enrolled and then utilized in the modified velocity updating formulas. The proposed scheme has successfully solved the multimodal function optimization.

Another topic of this paper is about the proportional-integral-derivative (PID) control system design. It is well known that PID controller has been used for a long time in most of practical industries because of its simplification in architecture and mature theory analysis. This kind of controller structure is still popular and accepted even though a large of new control techniques have successively proposed. As shown in its name, the PID controller has three control behaviors including the proportion, integration, differentiation on the system error corresponding to three control gains: proportional gain K_p, integral gain K_i, and derivative gain K_d, respectively. The PID controller design problem lies in how to properly and reasonably design these gains in order for meeting certain control specification and requirement. Recently, the related studies on the PID control system have been massively reported and discussed by means of different design strategies [24]-[30]. In [26], a new PID controller design method was proposed based on the direct synthesis (DS) approach of controller design in frequency domain. The PID controller parameters are derived through frequency response matching with the DS controller. An interval type-2 fuzzy PID controller was developed and applied in controlling an inverted pendulum on a cart system with an uncertain model. Simulation and practical results show that the proposed method has a better control performance over the type-1 fuzzy PID controller [27].

In this paper, a multi-strategy PSO algorithm with multiple subpopulations is employed to design several PID controllers in accordance with several control performance indexes. In

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the proposed manner, the number of subpopulations is equal to the number of the PID controllers which will be designed. Each subpopulation is to tackle a defined performance index in order to obtain a corresponding PID controller. The following five well-known integral performance indexes are considered including the integral of absolute error (IAE), the integral of squared error (ISE), the integral of time multiplied by absolute error (ITAE), the integral of time multiplied by squared error (ITSE), and the integral of square of time multiplied by error (ISTE), respectively. Thus, after executing the proposed algorithm one time there can simultaneously derive several PID controller outcomes, not only a PID controller, for satisfying corresponding performance indexes. It is rather different from the general PSO algorithm with a single population which was applied into the PID control system design. On the other hand, the controlled plant considered in this study is the continuously stirred tank reactor (CSTR) that is a highly nonlinear process system and always occurs in the actual chemical industry. The rest of this paper is summarized in the following. In Section II, an improved PSO algorithm with multiple control strategies is firstly introduced. Section III simply describes the structure of PID controller and the controlled plant of the CSTR. Design steps for PID controller design in the CSTR system are given based on the proposed PSO algorithm in Section IV. In Section V, three different kinds of control cases are simulated and many simulation results are also demonstrated including the designed PID controllers and their convergence trajectories. Finally, a simple conclusion and future work is addressed in Section VI.

II. An Improved PSO Algorithm with Multiple Control Strategies

In the general PSO, the algorithm begins with generating a single population which consists of many particles. These initial particles are randomly chosen from certain interval defined previously. Each of them represents a possible candidate solution for the optimized problem. Some important information during the evolution needs to be recorded; that is, the individual best for each particle and the global best for the whole population. The individual best denoted by *pbest* is the best one for each particle until the present iteration, and the global best denoted by *gbest* refers to the best one for all particles in the population. Traditionally, these two particle information significantly guides the updating direction of all particles in the next iteration over the searching space. To evaluate the particle's performance, it is necessary to define a proper cost function for the designed problem. In general, a so-called better particle means its cost function evaluated is smaller in solving the minimization problem.

In order to formulate the PSO algorithm, let the vector $\Theta = [\theta_1, \theta_2, \cdots, \theta_n]$ be the representation of a particle where θ_j is the designed parameter of the optimization problem for $j = 1, 2, \cdots, n$, and n is the number of designed parameters. Many such particles further form a population that will be evolved by certain mechanisms. In the general PSO, there are two main updating formulas to guide the particle's moving, i.e., the velocity updating formula and position updating formula given by Eqs. (1) and (2)

$$v_{ij}(k+1) = w \cdot v_{ij}(k) + c_1 \cdot r_1 \cdot (pbest_{ij}(k) - \theta_{ij}(k)) + c_2 \cdot r_2 \cdot (gbest_j(k) - \theta_{ij}(k)), \quad (1)$$

$$\theta_{ij}(k+1) = \theta_{ij}(k) + v_{ij}(k+1), \quad (2)$$

where θ_{ij}, $pbest_{ij}$, and $gbest_j$ represent the jth position components of the ith particle, the ith individual best particle, and the global best particle, respectively, v_{ij} is the jth velocity component of the ith particle, all for $i = 1, 2, \cdots, N$ and $j = 1, 2, \cdots, n$, and N is the number of particles (population size), w is the inertia weight for balancing the global and local search, c_1 and c_2 are two positive constants assigned by the designer, r_1 and r_2 are two random numbers uniformly chosen from the interval [0, 1]. In the traditional fashion, the PSO utilizes these two formulas to achieve the optimization.

Another improved version of the PSO algorithm was recently developed for solving the multimodal function minimization problem in our previous work [22]. This kind of multimodal function often consists of several optima which may be the global and local solutions. By using the general PSO, however, it cannot find out all of optima synchronously because the algorithm contains only one global best particle and it can catch one optimum at best. As a result, the general PSO with a single population is not applicable to solving such a multimodal function optimization problem. In the modified version, a single initial population used in the algorithm is partitioned into several subpopulations, and the best particle inside each subpopulation needs to be recorded instead of the global best particle. Subsequently, all particles included in the same subpopulation are moved and adjusted according to this best particle information. The number of best particles is equal to the number of subpopulations. It means that the proposed algorithm contains several best particles to catch different optimums separately and synchronously. Under this manner, the global best particle $gbest_j$ in Eq. (1) is replaced by the best particle of each subpopulation, and the relationship among subpopulations is fully independent on one another.

This paper will present a new controller design method with multiple control strategies based on the developed algorithm as mentioned above. Fig. 1 displays the diagram of the proposed method where N denotes the population size; that is, the number of particles in the original single population and M is the number of subpopulations assigned. Under this architecture, each subpopulation contains N/M particles and has an individual best particle denoted by the red. Each best particle only guides the particles that are in the same subpopulation. Moreover, each subpopulation is to deal with one corresponding control strategy, and therefore the proposed scheme can solve for M control strategies to derive M design outcomes simultaneously when the algorithm is executed one time. This proposed scheme is superior to the general one because of having M design outcomes, not only one outcome. It is noticed again in the proposed method that $gbest_j$ used in the velocity updating formulas of Eq. (1) is the best particle of each subpopulation, not the global best particle, and all of particles within the same subpopulation are guided according to this particle.

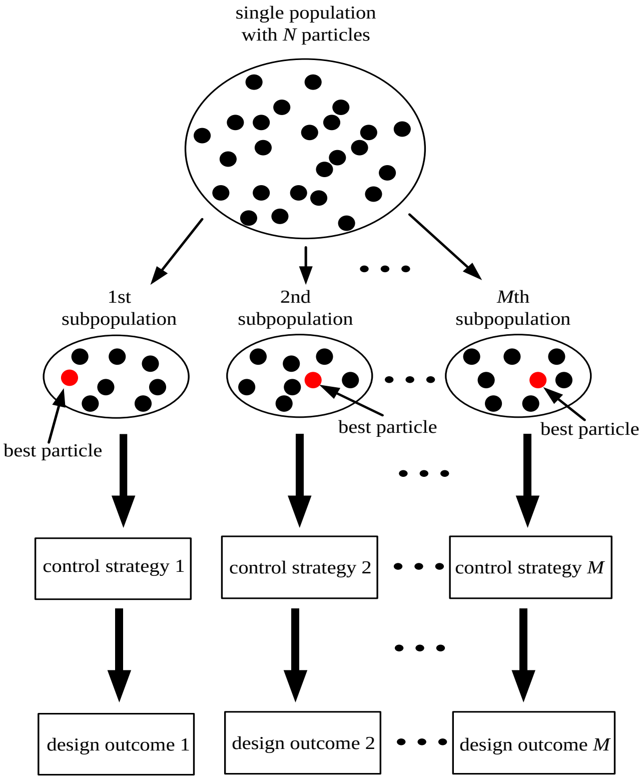

Fig. 1. The diagram of the proposed method with multiple control strategies.

III. PID Controller and the Controlled Plant of CSTR

In the PID controller, there are three designed control parameters or gains including the proportional gain K_p, integral gain K_i, and derivative gain K_d. The key of designing PID controller lies in how to give the right values for them to meet certain control specifications. The original PID control law can be expressed by

$$u(t)=K_p\left[e(t)+\frac{1}{T_i}\int_0^t e(\tau)d\tau+T_d\frac{d}{dt}e(t)\right], \tag{3}$$

where u is the control input to the controlled plant, e is the error signal between the desired output and actual plant output, K_p is the proportional gain, T_i is the integral time constant, and T_d is the derivative time constant. In addition, Eq. (3) can be further rewritten as

$$u(t)=K_p\cdot e(t)+K_i\int_0^t e(\tau)d\tau+K_d\frac{d}{dt}e(t), \tag{4}$$

where $K_i=K_p/T_i$ represents the integral gain and $K_d=K_pT_d$ is the derivative gain. For convenience, let the gain vector be $\Theta=[\theta_1,\theta_2,\theta_3]=[K_p,K_i,K_d]$ for the use of the proposed PSO algorithm. In the viewpoint of the PSO, this gain vector represents the particle that is also a candidate solution of the system design.

The controlled plant considered in this study is the continuously stirred tank reactor (CSTR). It is a highly nonlinear process system and often occurs in the practical chemical industry. Such a CSTR system exhibits several nonlinear features such as having multiple equilibriums and system dynamics significantly depending on the parameters. Consequently, it is rather difficult and needs more efforts over the general system when the CSTR is controlled. The dynamical equation of the CSTR system can be described by [24]

$$\dot{x}_1=-x_1+D_a(1-x_1)\exp\left(\frac{x_2}{1+x_2/\varphi}\right), \tag{5a}$$

$$\dot{x}_2=-(1+\delta)x_2+B\cdot D_a(1-x_2)\exp\left(\frac{x_2}{1+x_2/\varphi}\right)+\delta\cdot u, \tag{5b}$$

$$y=x_1, \tag{5c}$$

where x_1 and x_2 are the dimensionless reactant concentration and reactor temperature, respectively, the control input u is the dimensionless cooling jacket temperature and is supplied by the PID controller, y represents the system output. System parameters contained in the CSTR are D_a, φ, B, and δ which corresponds to the Damökhler number, activated energy, heat of reaction, and heat transfer coefficient, respectively, and their nominal values are given by $D_a=0.072$, $\varphi=20$, $B=8$ and $\delta=0.3$. Under these given parameters, the open-loop CSTR system, i.e., let $u=0$, consists of three equilibrium points: $(x_1,x_2)=(0.144,0.886)_s$, $(x_1,x_2)=(0.445,2.74)_{un}$, and $(x_1,x_2)=(0.765,4.705)_s$ where the subscript s and un stand for the stable and unstable points, respectively. Fig. 2 clearly displays the phase portraits of states x_1 and x_2 from various initial values converging to two stable equilibrium points and diverging from the unstable one [24]. It is a challenging control problem when the system state is regulated from the stable point to the unstable point.

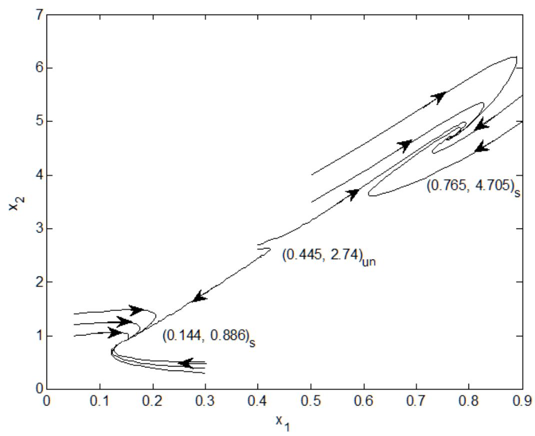

Fig. 2. Phase portraits of states x_1 and x_2 from various initial values when $u=0$.

IV. PID Controller Design Steps Using the Proposed Method for the CSTR

In this section, the design steps of PID controller are clearly demonstrated based on the improved PSO algorithm for the CSTR system. Fig. 3 shows the overall diagram of PID control system where y_d is the desired output given by the designer, y is the output of the CSTR, e is the error signal between y_d and y, u is the control input generated by the PID controller to the controlled plant, K_p, K_i, and K_d are three control gains that will be designed by the proposed scheme. Moreover, five well-known integral performance indexes that correspond to five control strategies used in the improved PSO algorithm are considered in this study, including the integral of absolute error (IAE), integral of squared error (ISE), integral of time multiplied by absolute error (ITAE), integral of time multiplied by squared error (ITSE), and integral of square of time multiplied by error (ISTE) defined as follows [31]:

$$\mathrm{IAE} = \int_0^\infty |e(t)| dt, \tag{6}$$

$$\mathrm{ISE} = \int_0^\infty e^2(t) dt, \tag{7}$$

$$\mathrm{ITAE} = \int_0^\infty t \cdot |e(t)| dt, \tag{8}$$

$$\mathrm{ITSE} = \int_0^\infty t \cdot e^2(t) dt, \tag{9}$$

$$\mathrm{ISTE} = \int_0^\infty (t \cdot e(t))^2 dt. \tag{10}$$

The control purpose is to adjust PID control gains so that these indexes can reach a minimum value. According to these five different performance indexes, there can solve for five different PID controller outcomes by the proposed method when the algorithm is executed only one time. Thus, in the case the number of subpopulations employed is also five as the same with the number of indexes defined.

Based on the improved PSO algorithm with multiple control strategies, the design steps of PID controller for the CSTR system are listed below:

Step I. Create an initial population consisting of N particles that are randomly generated from the interval $[0, 1]$.

Step II. Partition the original population into $M = 5$ subpopulations by the order of particles, and there are $N/5$ particles contained in each subpopulation.

Step III. Check whether the number of iterations G is accomplished. If yes, the algorithm stops; otherwise, Step IV is executed.

Step IV. Evaluate the corresponding performance indexes as described above for each subpopulation and record the individual best particle *pbest* for each particle and the best particle *gbest* for each subpopulation, respectively.

Step V. Perform the modified velocity updating formula of Eq. (1) for each particle, where the global best is replaced by the best particle of each subpopulation.

Step VI. Execute the position updating formula of Eq. (2) for each particle.

Step VII. Go back to Step III.

V. Simulation Results

In the following simulations, the related parameters used in the improved PSO algorithm are listed in Tab. 1, and the sampling time of the system here is set to $T = 0.1$ for implementing the differential equations of Eq. (5). The above mentioned five different performance indexes as shown in Eqs. (6)-(10) are all considered. Each subpopulation is utilized to tackle one corresponding index. After executing the algorithm once we can obtain five different sets of PID controllers for each simulation case. In order to demonstrate the feasibility of the proposed method, three different control cases for the controlled plant of the CSTR are simulated including (a) the step response control, (b) the set-point tracking control, and (c) the unstable equilibrium point control.

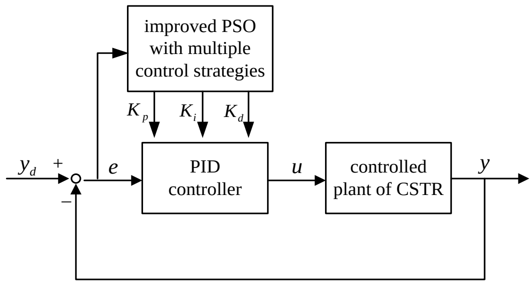

Fig. 3. PID controller design using the improved PSO with multiple control strategies for the controlled plant of CSTR.

TABLE I. Related Parameters Setting Used in the Improved PSO Algorithm

Population size	Number of subpopulations	Number of iterations	Inertia weight	Two positive constants
$N = 150$	$M = 5$	$G = 1000$	$w = 0.8$	$c_1 = c_2 = 1.0$

- Step response control

In the first example, a simple step response control is examined by the proposed scheme. Here, two initial states of the nonlinear CSTR system are assumed to be $x_1(0) = 0.3$ and $x_2(0) = 0.3$, and the system parameter $B = 1$ is given for this simulation case. The control purpose is that the system output is regulated to $y_d = 0.5$ from the initial value $y(0) = x_1(0) = 0.3$. After executing the proposed algorithm, five different sets of PID controllers are derived according to five different performance indexes. Simulation results are listed in Tab. 2 and displayed in Figs. 4-9, respectively. Tab. 2 lists all the derived PID controller gains and their final evaluated performance index values. It can be seen that the design outcomes are different because of different performance indexes. In addition, Fig. 4 then shows the step responses according to the derived PID controllers, and their convergence trajectories of PID gains with respect to the number of iterations are shown in Figs. 5-9, respectively. They can approximate the steady states after about 100 iterations.

TABLE II: PID Control Gains Derived by Different Performance Indexes for the Step Response Control

	K_p	K_i	K_d	Final value
IAE	142.60	143.70	30.60	0.08698174
ISE	124.34	259.40	43.52	0.01220084
ITAE	124.07	122.04	22.83	0.02184555
ITSE	142.49	189.96	32.75	0.00162059
ISTE	138.31	154.87	27.07	0.00046836

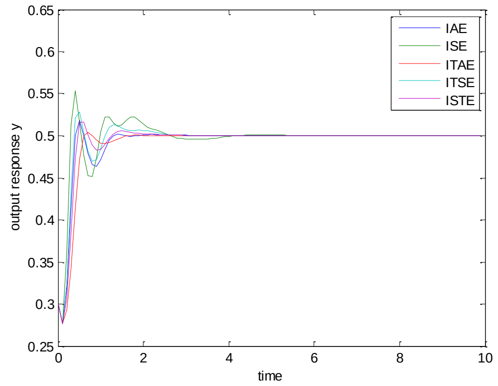

Fig. 4. Step responses by five different performance indexes.

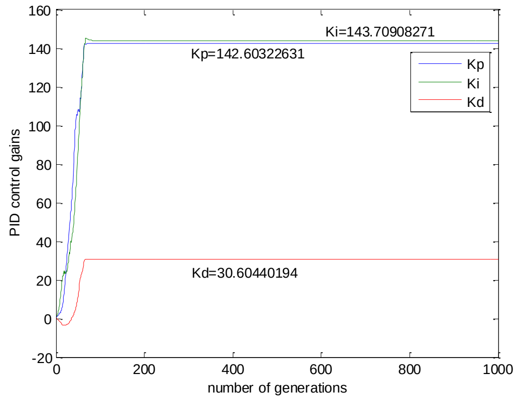

Fig. 5. Trajectories of PID control gains by IAE index.

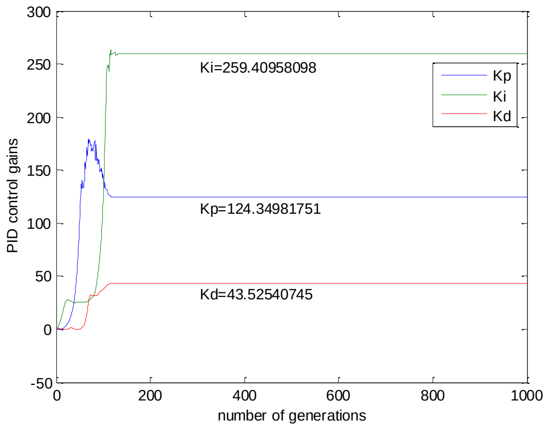

Fig. 6. Trajectories of PID control gains by ISE index.

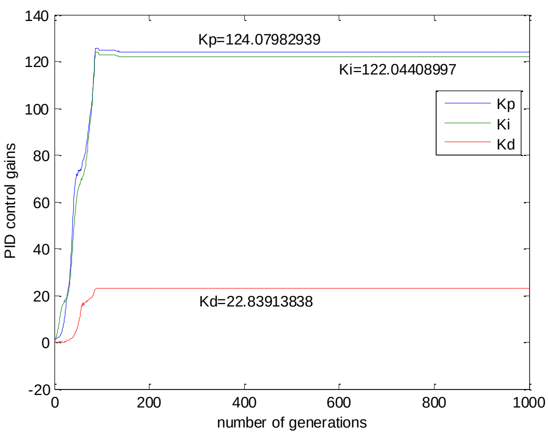

Fig. 7. Trajectories of PID control gains by ITAE index.

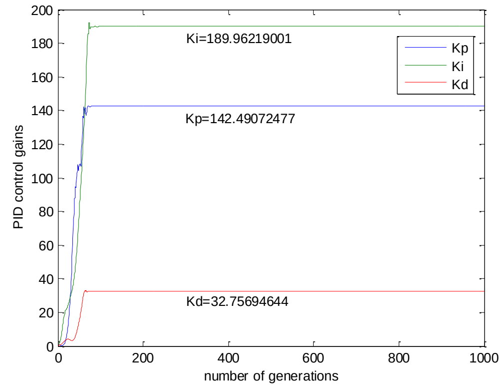

Fig. 8. Trajectories of PID control gains by ITSE index.

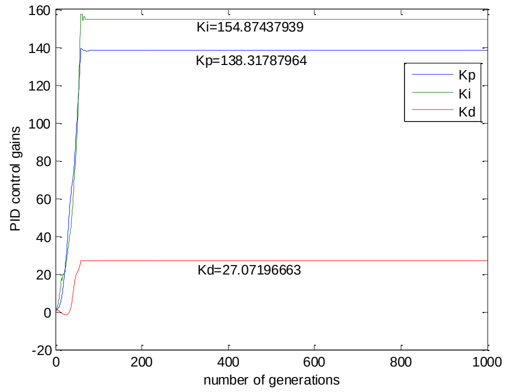

Fig. 9. Trajectories of PID control gains by ISTE index.

• Set-point tracking control

In this case, it is assumed that the desired output y_d has different set points with respect to time t which is defined by

$$y_d = \begin{cases} 0.7, & 0 \le t < 10 \\ 0.4, & 10 \le t < 20 \\ 0.5, & 20 \le t < 30 \\ 0.45, & 30 \le t < 40. \end{cases}$$

Also, the initial states and system parameter are given by $x_1(0) = 0.3$, $x_2(0) = 0.3$, and $B = 1$ as same with the above case. Numerical results and trajectory convergences for the derived PID control gains are listed in Tab. 3 and shown in Figs. 10-15, respectively, when the proposed algorithm is performed once. Tab. 3 provides the final PID control gain results derived by different performance indexes for the set-point tracking control. The output responses for tracking control are then plotted in Fig. 10. This figure reveals a satisfactory outcome from all the index methods by the proposed method. Figs. 11-15 then display the convergences of PID control gains with respect to the number of iterations. In the case, after nearly 50 iterations all trajectories already enter the steady states.

TABLE III: PID CONTROL GAINS DERIVED BY DIFFERENT PERFORMANCE INDEXES FOR THE SET-POINT TRACKING CONTROL

	K_p	K_i	K_d	Final value
IAE	101.58	95.93	22.86	0.41943302
ISE	93.84	95.76	26.26	0.08054584
ITAE	80.55	60.87	25.44	3.04598550
ITSE	87.71	63.84	28.56	0.38097177
ISTE	86.87	59.26	31.96	4.53151823

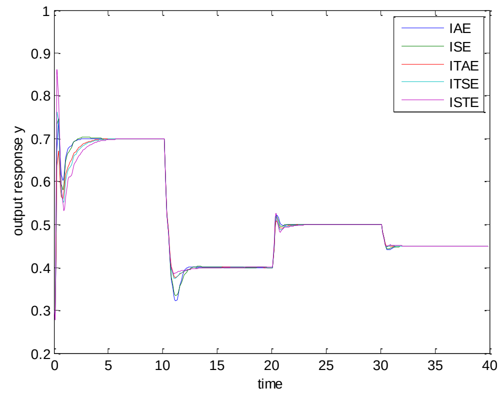

Fig. 10. Set-point tracking controls by five different performance indexes.

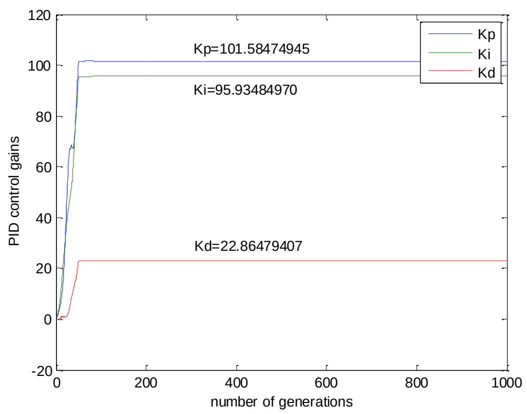

Fig. 11. Trajectories of PID control gains by IAE index.

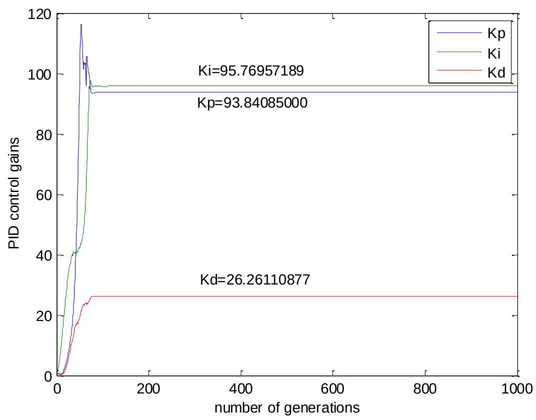

Fig. 12. Trajectories of PID control gains by ISE index.

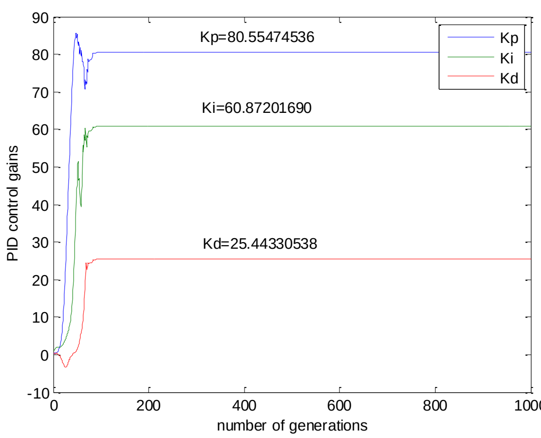

Fig. 13. Trajectories of PID control gains by ITAE index.

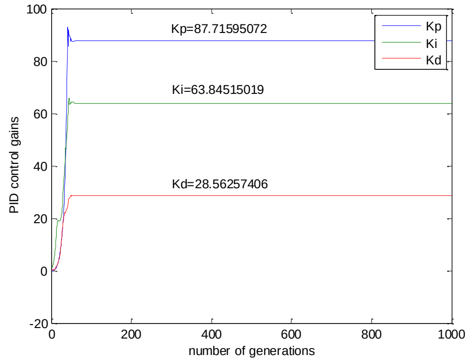

Fig. 14. Trajectories of PID control gains by ITSE index.

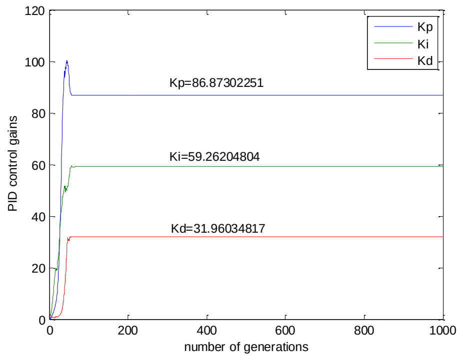

Fig. 15. Trajectories of PID control gains by ISTE index.

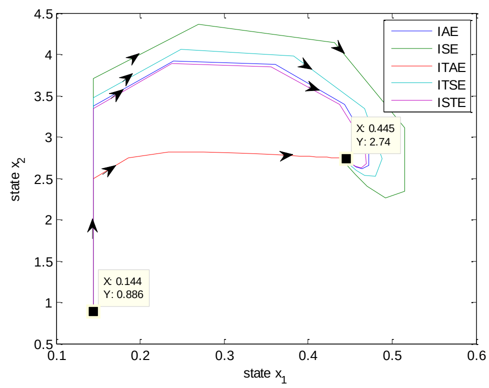

Fig. 16. Control trajectories in the phase portrait from one stable point $(0.144, 0.886)_s$ to another unstable point $(0.445, 2.74)_{un}$ using five different index methods.

• Unstable equilibrium point control

In Section III, we have explained that the open-loop CSTR system consists of two stable equilibrium points $(0.144, 0.886)_s$ and $(0.765, 4.705)_s$, and one unstable equilibrium point $(0.445, 2.74)_{un}$ when the nominal values are given for the system parameters. It is a fairly challenging control problem if the system states can be regulated to the unstable equilibrium from one of stable points by means of the designed controller. Thus, the control goal here is to force the system states from the stable equilibrium point $(0.144, 0.886)_s$ to the unstable one $(0.445, 2.74)_{un}$ using the proposed design scheme. In order to achieve that, the desired output of the system is simply set to $y_d = 0.445$. Simulation results are shown in Fig. 16 and listed in Tab. 4, respectively. Fig. 16 clearly displays control trajectories in the phase portrait of x_1 and x_2 by five different design methods. They all reach the unstable equilibrium point. Finally, the obtained

PID controllers are listed in Table IV for references.

TABLE IV. PID CONTROL GAINS DERIVED BY DIFFERENT PERFORMANCE INDEXES FOR THE UNSTABLE EQUILIBRIUM POINT CONTROL

	K_p	K_i	K_d	Final value
IAE	11.38	0.10	26.37	0.09908286
ISE	1.84	0.15	31.00	0.02247901
ITAE	13.51	0.04	16.51	0.08135106
ITSE	9.00	0.11	27.81	0.00203453
ISTE	11.68	0.10	26.08	0.00039815

VI. CONCLUSIONS AND FUTURE WORK

This paper has successfully presented a new design method for the PID controller to control a highly complex and nonlinear CSTR chemical process. In the proposed PSO structure, the single initial population is firstly partitioned into several individual subpopulations, and these subpopulations are fully independent on one another and never interchange any information. Each subpopulation is utilized to tackle one control strategy in order to derive a corresponding design outcome. Based on the improved PSO with multiple control strategies, several PID controller outcomes can be simultaneously derived in accordance with several performance indexes for the controlled plant of the CSTR when the algorithm is performed only one time. To confirm the applicability of the developed scheme, three different kinds of control cases are examined including the step response control, set-point tracking control, and unstable equilibrium point control. It can be concluded from all simulation results that the proposed method has a satisfactory control performance. For the future work, the proposed method may be further extended to solve the PID controller design problem for MIMO control systems.

REFERENCES

[1] J. Kennedy and R. Eberhart, "Particle swarm optimization," in *Proc. IEEE International Conference on Neural Networks*, Australia, 1995, pp.1942-1948.

[2] A. Subasi, "Classification of EMG signals using PSO optimized SVM for diagnosis of neuromuscular disorders," *Computers in Biology* and *Medicine*, vol. 43, pp. 576-586, 2013.

[3] M. K. Ahirwal, A. Kumar, and G. K. Singh, "Adaptive filtering of EEG/ERP through noise cancellers using an improved PSO algorithm," *Swarm and Evolutionary Computation*, vol. 14, pp. 76-91, 2014.

[4] Z. Pian, S. Li, and N. Zhang, "The application of adaptive PSO in power reactive optimization," *Procedia Engineering*, vol. 23, pp. 747-753, 2011.

[5] J. Y. Kim, K. J. Mun, H. S. Kim, and J. H. Park, "Optimal power system operation using parallel processing system and PSO algorithm," *Electrical Power and Energy Systems*, vol. 33, pp. 1457-1461, 2011.

[6] S. Panda, B. Mohanty, and P. K. Hota, "Hybrid BFOA-PSO algorithm for automatic generation control of linear and nonlinear interconnected power systems," *Applied Soft Computing*, vol. 13, pp. 4718-4730, 2013.

[7] J. S. Chiou and M. T. Liu, "Numerical simulation for fuzzy-PID controllers and helping EP reproduction with PSO hybrid algorithm," *Simulation Modelling Practice and Theory*, vol. 17, pp. 1555-1565, 2009.

[8] S. Panda, N. P. Padhy, "Optimal location and controller design of STATCOM for power system stability improvement using PSO," *Journal of Franklin Institute*, vol. 345, pp. 166-181, 2008.

[9] Q. Niu, B. Jiao, and X. Gu, "Particle swarm optimization combined with genetic operators for job shop scheduling problem with fuzzy processing time," *Applied Mathematics and Computation*, vol. 205, pp. 148-158, 2008.

[10] G. Zhang, X. Shao, P. Li, and L. Gao, "An effective hybrid particle swarm optimization algorithm for multi-objective flexible job-shop scheduling problem," *Computers & Industrial Engineering*, vol. 56, pp. 1309-1318, 2009.

[11] Z. Yu, J. Wei, and H. Liu, "Force-directed hybrid PSO-SNTO algorithm for acoustic source localization in sensor networks," *Signal Processing*, vol. 89, pp. 1671-1677, 2009.

[12] L. Zhao and Y. Yang, "PSO-based single multiplicative neuron model for time series predication," *Expert Systems with Applications*, vol. 36, pp. 2805-2812, 2009.

[13] A. Mahor and S. Rangnekar, "Short term generation scheduling of cascaded hydro electric system using novel self adaptive inertia weight PSO," *Electrical Power and Energy Systems*, vol. 34, pp. 1-9, 2012.

[14] Y. Z. Hsieh, M. C. Su, and P. C. Wang, "A PSO-based rule extractor for medical diagnosis," *Journal of Bimedical Informatics*, vol. 49, pp. 53-60, 2014.

[15] M. A. Mohandes, "Modeling global solar radiation using particle swarm optimization (PSO)," *Solar Energy*, vol. 86, pp. 3137-3145, 2012.

[16] B. Vasumathi and S. Moorthi, "Implementation of hybrid ANN-PSO algorithm on FPGA for harmonic estimation," *Engineering Applications of Artificial Intelligence*, vol. 25, pp. 476-483, 2012.

[17] A. M. Turky and S. Abdullah, "A multi-population electromagnetic algorithm for dynamic optimization problems," *Applied Soft Computing*, vol. 22, pp. 474-482, 2014.

[18] H. Pourvaziri and B. Naderi, "A hybrid multi-population genetic algorithm for the dynamic facility layout problem," *Applied Soft Computing*, vol. 24, pp. 457-469, 2014.

[19] L. Wang, B. Yang, and Y. Chen, "Improved particle swarm optimization using multi-layer searching strategy," *Information Sciences*, vol. 274, pp. 70-94, 2014.

[20] H. K. Sarakhs and M. S. Saremi, "Design of multilayer high-dispersion mirrors using multi-swarm optimization method," *Optik*, vol. 125, pp. 5618-5621, 2014.

[21] X. Yuan, X. Dai, J. Zhao, and Q. He, "On a novel multi-swarm fruit fly optimization algorithm and its application," *Applied Mathematics and* Computation, vol. 233, pp. 260-271, 2014.

[22] W. D. Chang, "A modified particle swarm optimization with multiple subpopulations for multimodal function optimization problems," *Applied Soft Computing*, vol. 33, pp. 170-182, 2015.

[23] G. Fornarelli and A. Giaquinto, "An unsupervised multi-swarm clustering technique for image segmentation," *Swarm and Evolutionary Computation*, vol. 11, pp. 31-45, 2013.

[24] W. D. Chang, "Nonlinear CSTR control system design using an artificial bee colony algorithm," *Simulation Modelling Practice and Theory*, vol. 31, 1-9, 2013.

[25] K. Premkumar and B. V. Manikandan, "Fuzzy PID supervised online ANFIS based speed controller for brush dc motor," *Neurocomputing*, vol. 157, pp. 76-90, 2015.

[26] M. N. Anwar and S. Pan, "A new PID load frequency controller design method in frequency domain through direct synthesis approach," *Electrical Power and Energy Systems*, vol. 67, pp. 560-569, 2015.

[27] M. E. Bardini and A. M. E. Nagar, "Interval type-2 fuzzy PID controller for uncertain nonlinear inverted pendulum system," *ISA Transactions*, vol. 53, pp. 732-743, 2014.

[28] B. Fang, "Design of PID controllers for interval plants with time delay," *Journal of Process Control*, vol. 24, pp. 1570-1578, 2014.

[29] J. Kang, W. Meng, A. Abraham, and H. Liu, "An adaptive PID neural network for complex nonlinear system control," *Neurocomputing*, vol. 135, pp. 79-85, 2014.

[30] H. Zhu, L. Li, Y. Zhao, Y. Guo, and Y. Yang, "CAS algorithm-based optimum design of PID controller in AVR system," *Chaos, Solitons, and Fractals*, vol. 42, pp. 792-800, 2009.

[31] M. S. Tavazoei, "Notes on integral performance indices in fractional-order control systems," *Journal of Process Control*, vol. 20, pp. 285-291, 2010.

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