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Research Article

Nonconvex Economic Dispatch Using Particle Swarm Optimization with Time Varying Operators

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This paper presents a particle swarm optimization (PSO) to solve hard combinatorial constrained optimization problems such as nonconvex and discontinuous economic dispatch (ED) problem of large thermal power plants. Several measures have been suggested in the control equation of the classical PSO by modifying its operators for better exploration and exploitation. The inertia operator of the PSO is modulated by introducing a new truncated sinusoidal function. The cognitive and social behaviors are dynamically controlled by suggesting new exponential constriction functions. The overall methodology effectively regulates the velocity of particles during their flight and results in substantial improvement in the classical PSO. The effectiveness of the proposed method has been tested for economic load dispatch of three standard test systems considering various operational constraints like valve-point loading effect, prohibited operating zones (POZs), network power loss, and so forth. The application results show that the proposed PSO method is very promising.

1. Introduction

The economic dispatch (ED) aims at determining the optimal scheduling of thermal generating units so as to minimize the fuel cost while satisfying several operational and power system network constraints. The generator fuel cost functions are invariably nonlinear and also exhibit discontinuities due to prohibited operating zones (POZs). In addition, the valve-point loading effect causes nonconvex characteristic with multiple minima in the generator fuel cost functions and thus imposes challenges of obtaining the global optima for high dimensional ED problems. Thus, ED is a highly nonlinear, complex combinatorial, nonconvex, and multiconstraint optimization problem with continuous decision variables.

The classical mathematical methods like gradient, Lagrange relaxation methods, and so forth, except dynamic programming, are not suitable for such complex optimization problems. The modern metaheuristic search techniques such as particle swarm optimization (PSO), genetic algorithms (GAs), biogeography-based optimization (BBO), differential evolution (DE), ant colony optimization (ACO), artificial bee colony (ABC), and hybrid swarm intelligent based harmony search algorithm (HHS) [1, 2] have shown potential to solve such complex ED problems due to their ability to obtain global or near global solution but are computationally demanding especially for modern power systems which are large and complex.

The PSO has several advantages over other metaheuristic techniques in terms of simplicity, convergence speed, and robustness [3]. It provides convergence to the global or near global optima, irrespective of the shape or discontinuities of the cost function [4]. The potential of PSO to handle nonsmooth and nonconvex ELD problem was demonstrated by [5, 6]. However, the performance of the PSO greatly depends on its parameters and it often suffers from the problems such as being trapped in local optima due to premature convergence [6], lack of efficient mechanism to treat the constraints [7], and loss of diversity and performance in optimization process [8]. PSO is a population based metaheuristic optimization technique in which the movement of the particles is governed

by the two stochastic acceleration coefficients, that is, cognitive and social components and the inertia component [5]. In order to enhance the exploration and exploitation capabilities of PSO, the components affecting velocity of particles should be properly managed and controlled.

Several methods have been reported in the recent past to enhance the computational efficiency of the classical PSO. A constriction factor was suggested in the velocity updating equation to assure convergence of PSO [9–11]. However, the exact determination of this factor is computationally demanding. Selvakumar and Thanushkodi [12] modified cognitive behavior of the swarm by communicating with the worst particle. This method provides some additional diversity to the particle by the worst experience component, but showing poor local searching ability unless it is hybridized with certain other heuristic approaches. Roy and Ghoshal [13] proposed crazy PSO (CPSO), where the particle velocity is randomized within predefined limits. The idea was to randomize the velocity of some of the particles, referred to as "crazy particles," by applying a predefined probability of craziness to maintain the diversity for global search and better convergence. However, the value of predefined probability of craziness can only be achieved after several experimentations. Some attempts [14–18] have been made to vary the cognitive and social behavior of the swarm during the search process by dynamically controlling the acceleration coefficients within maximum and minimum bounds. Again the determination of limiting values of these acceleration coefficients is a difficult task, as it required many simulations. Coelho and Lee [19] randomized cognitive and social behavior of the swarm using chaotic sequences and Gaussian distribution, respectively. Selvakumar and Thanushkodi [20] proposed civilized swarm optimization (CSO), by combining society-civilization algorithm (SCA) with PSO to improve communication. The proposed algorithm provides clustered search that results in better exploration and exploitation of the search space but needs several experimentations to determine the optimum values of the control parameters of CSO. Efforts have also been made to suggest a new formulation of the control equation [6, 7]. Safari and Shayeghi [6] proposed iteration PSO (IPSO), where one additional velocity component pertaining to the best fitness of the current iteration is added in the control equation of the classical PSO to avoid local trap, but parameter setting is essential. Vlachogiannis and Lee [7] suggested new control equation in improved coordinated aggregation PSO (ICAPSO) for better communication among particles to enhance local search. They allowed particles to interact with its own best experience along with all other particles have better experience on aggregate basis, instead of the global best experience. However, the authors accepted that the performance of the proposed method is quite sensitive to various parameters setting and their tuning is essential. Chaotic PSO (CPSO) of [21] proposed adapted inertia weight which varies dynamically with fitness value for exploration and chaotic local search was used to determine the particle position for better exploitation. The improved PSO (IPSO) of [22] suggested chaotic inertia weight which decreases and oscillates simultaneously under the decreasing line in a chaotic manner. In this way, additional diversity is introduced, but it requires tuning of chaotic control parameters.

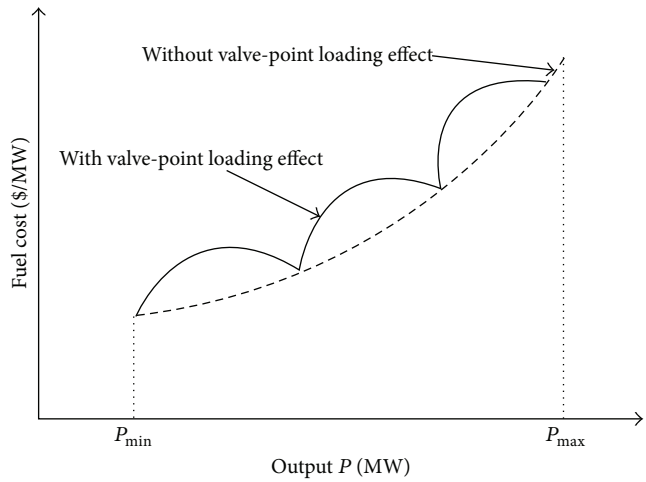

Figure 1: Fuel cost function with and without valve-point loading effect.

This paper attempts to overcome drawbacks of some existing PSO methods and presents a modified version of PSO for economic load dispatch of power systems. Several measures have been incorporated in the control equation by modifying operators of the classical PSO by introducing new constriction functions. The proposed method effectively controls and regulates the components affecting velocity of particles so as to ensure better exploration (searching new areas) and exploitation (fine tuning of the current solution). A correction algorithm is also suggested to repair infeasible solutions whenever appeared in the computational process. The proposed method is self-adjusting and does not require experimentations to obtain the optimal values of control parameters and thus overcome the drawbacks of existing PSO methods. The effectiveness of the proposed method has been investigated on three standard test systems considering various operational constraints like valve-point loading effect, prohibited operating zones (POZs), network power loss, and so forth. The application results show that the proposed PSO method is very promising.

2. Problem Formulation

The generator cost function is usually considered as quadratic, when valve-point loading effects are neglected. The large turbine generators usually have a number of fuel admission valves which are operated in sequence to meet out increased generation. The opening of a valve increases the throttling losses rapidly and thus the incremental heat rate rises suddenly. This valve-point loading effect introduces ripples in the heat-rate curves which introduces nonconvexity in the generator fuel cost function as shown in Figure 1. The effect of valve-point loading effects can be modeled as sinusoidal function in the cost function. Therefore, the

objective function for the nonconvex ED problem may be stated as

$$\text{Minimize } F(P_{Gi}) = \sum_{i=1}^{N_G} \left(a_i + b_i P_{Gi} + c_i P_{Gi}^2\right) + \left|e_i \sin\left(f_i \left(P_{Gi\min} - P_{Gi}\right)\right)\right|, \quad (1)$$

where a_i, b_i, and c_i are the cost coefficients of the ith generator, e_i and f_i are the valve-point effect coefficients, P_{Gi} is the real power output of the ith generator, and N_G is the number of generating units in the system.

Subject to the following constraints:

(1) *Power Balance Constraint*. The total power generation of all generators must be equal to the sum of total power demand plus the network power loss. The network power loss can be evaluated using B-coefficient loss formula [21, 23]. Therefore, the generator power balance equation may be stated as follows:

$$\sum_{i=1}^{N_G} P_i = PD + \sum_{i=1}^{N_G}\sum_{j=1}^{N_G} P_{Gi} B_{ij} P_{Gj} + \sum_{i=1}^{N_G} P_{Gi} B_{i0} + B_{00}, \quad (2)$$

where B_{ij} is the transmission loss coefficient $i = 1, 2, \ldots, N_G$ and $j = 1, 2, \ldots, N_G$, B_{i0} is the ith element of the loss coefficient vector. B_{00} is the loss coefficient constant.

(2) *Generator Constraint*. For stable operation, power output of each generator is restricted within its minimum and maximum limits. The generator power limits are expressed as follows:

$$P_{Gi}^{\min} \le P_{Gi} \le P_{Gi}^{\max}. \quad (3)$$

(3) *Prohibited Operating Zones*. Prohibited operating zones lead to discontinuities in the input output relation of generators. Prohibited zones divide the operating region between minimum and maximum generation limits into disjoint convex subregions [14, 20]. The generation limits for the ith unit with j number of prohibited zones can be expressed as follows:

$$\begin{gathered} P_{Gi}^{\min} \le P_{Gi} \le P_{Gi,1}^{L}, \\ P_{Gi,j-1}^{U} \le P_{Gi} \le P_{Gi,j}^{L}, \\ P_{Gi,N_{PZi}}^{U} \le P_{Gi} \le P_{Gi}^{\max}; \\ i \in \{1, 2, \ldots, N_{GPZ}\}, \quad j \in \{2, 3, \ldots, N_{PZi}\}, \end{gathered} \quad (4)$$

where superscripts L and U stand for the lower and upper limit of prohibited operating zones of generators. N_{GPZ} and N_{PZi} denote the total number of generators with prohibited zones and the total number of prohibited zones for the ith generator, respectively.

3. Proposed PSO

The classical PSO is initialized with a population of random solutions and searches for optima by updating particle positions. The velocity of the particle is influenced by the three components: initial, cognitive, and the social component. Each particle updates its previous velocity and position vectors according to the following model [3, 24, 25]:

$$\begin{gathered} v_i^{k+1} = W v_i^k + c_1 \times \text{rand}_1() \times \frac{pbest_i - s_i^k}{\Delta t} \\ + c_2 \times \text{rand}_2() \times \frac{gbest_i - s_i^k}{\Delta t}, \\ s_j^{k+1} = s_j^k + v_j^{k+1} \times \Delta t, \end{gathered} \quad (5)$$

where v_i^k is the velocity of ith particle at kth iteration, $\text{rand}_1()$ and $\text{rand}_2()$ are random numbers between 0 and 1, s_i^k is the position of ith particle at kth iteration, c_1, c_2 are the acceleration coefficients, $pbest_i$ is the best position of ith particle achieved based on its own experience, $gbest_i$ is the best particle position based on overall swarm experience, Δt is the time step, usually set to 1 second, and W is the inertia weight which is allowed to decrease linearly as follows:

$$W = W_{\min} + \frac{(W_{\max} - W_{\min}) \times (\text{itr}_{\max} - \text{itr})}{\text{itr}_{\max}}, \quad (6)$$

where $W_{\min}$ and $W_{\max}$ are the minimum and maximum value of inertia weight, respectively, $\text{itr}_{\max}$ is the maximum number of iterations and itr is the current number of iteration.

For better performance of PSO, the particles must fly with higher velocities during the early flights to enhance global search and should be relatively slow during later flights of the journey to improve local search. Therefore, with appropriate regulation of particle's velocity during the journey, the performance of PSO could be improved. Initially, the impact of cognitive component must be high and that of the social component be less to ensure global exploration of the search space by all particles without trapping into a local minima. During later search, the impact of social component must increase and that of the cognitive component must decrease to divert all particles towards global best to improve the convergence. This is essential for a good balance between exploration and exploitation as suggested by [15].

In classical PSO, only the initial velocity component using inertia weight is regulated dynamically. However, the cognitive and social behavior of the swarm, though randomized to ensure diversity, is statically controlled by assigning constant values to acceleration coefficients. These cognitive and social components of velocity are added in the regulated initial velocity component to decide the movement of particles. This probably results in uncontrolled particle velocities during the whole computation process and thus causes insufficient exploration and exploitation of the search space. This results in poor convergence due to local trapping. Therefore, a modified control equation (7) is suggested for dynamically regulating particle's velocity during their whole course of

the flight. The modifications suggested in the control equation are explained as follows:

$$v_i^{k+1} = W \times v_i^k + \zeta_1 \times C_{1b} \times \text{rand}_1() \times \frac{pbest_i - s_i^k}{\Delta t} + (1-\zeta_1) \times C_{1p} \times \text{rand}_2() \times \frac{s_i^k - ppoor_i}{\Delta t} + \zeta_2 \times C_2 \times \text{rand}_3() \times \frac{gbest_i - s_i^k}{\Delta t}. \quad (7)$$

In (7), the inertia weight is modified to regulate the tradeoff between the global exploration and the local exploitation of the swarm. The poor experience $ppoor_i$ has been added to improve the cognitive component. Further, dynamic acceleration coefficients have been introduced using constriction functions ζ_1 and ζ_2 to regulate the cognitive and social behaviors of the swarm. These modifications are discussed in the following sections.

3.1. Inertia Weight Update. In [25], Shi and Eberhart suggested linear modulation of the inertia weight. This trend is followed to solve ELD problems using PSO by many researchers till date and some of them can be mentioned as [4, 6, 8, 12, 13, 15, 19, 20, 25, 26], and so forth. In the proposed method, the inertia weight has been allowed to vary in accordance with a truncated sinusoidal function rather than to decrease linearly. The modulations suggested to update the inertia weight is governed by the following relation:

$$W = W_{\min} + (W_{\max} - W_{\min}) \cos^2\left(\frac{\theta}{2}\right); \quad 0 \le \theta \le \pi, \quad (8)$$

where $\theta = X \times \text{itr} + Y$ and the coefficients X and Y are given by (9). itr is the iteration count which is in general varied from $\text{itr}_{\min}$ to $\text{itr}_{\max}$

$$X = \frac{\pi}{(\text{itr}_{\max} - \text{itr}_{\min})}, \quad Y = \frac{-\pi \times \text{itr}_{\min}}{(\text{itr}_{\max} - \text{itr}_{\min})}. \quad (9)$$

Figure 2 shows a comparison of the conventional linear modulation and sinusoidal modulation for the inertia weight to be employed in the proposed PSO. It can be depicted from the figure that using the sinusoidal variations in the inertia weight, the inertia component of the velocity of particles maintained always higher during the early half and lower during the later half of the search, when compared with its linear variations. Therefore, using sinusoidal modulations the coarse search is enhanced during the early half by exploring larger search space with higher values assigned to particle velocities. And, during the later half, the fine search is enhanced by assigning lower values to particle velocities. This facilitates particles to explore the regions in the close proximity of near global solution.

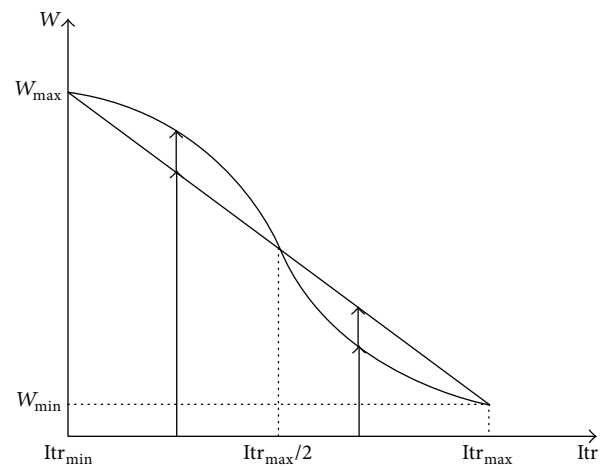

Figure 2: Comparison of linear and sinusoidal modulations of inertia weight.

3.2. Updating of Poor Experience. The cognitive behavior was split in [12] by considering the worst experience, in addition to the best experience, of the particle. Though this modification provides additional diversity, it still demands a local random search to enhance exploitation potential of the PSO. This occurs as the particle's velocity is not well regulated during later part of the search. Therefore, the concept of poor experience $ppoor_i$ is suggested, instead of the worst experience, to improve cognitive behavior of the swarm. Here the current fitness of each particle is compared with its fitness value in the preceding iteration, and if it is found less, it will be treated as the poor experience. This concept is different than that of [12], where the worst particle is determined by considering the whole past experience of the particle movement. The poor particle produces much less diversity than the worst particle and thus exploit the region near global optima, during later iterations, in much better way without the support of any local random search.

3.3. Dynamic Control of Acceleration Coefficients. In classical PSO, the cognitive and social behaviors are governed by assigning static values to acceleration coefficients. Many researchers, as discussed earlier, suggested that these acceleration coefficients must be dynamically controlled to regulate particle's velocity during the whole computation process. In the present work, the acceleration coefficients are dynamically controlled by suggesting new exponential constriction functions ζ_1 and ζ_2. These constriction functions dynamically regulate the cognitive and social behaviors of the swarm, thus limiting particles' velocities during their whole course of the flight and are given by

$$\zeta_1 = e^{-\mu_1 \eta}, \quad \zeta_2 = k e^{\mu_2 \eta}, \quad (10)$$

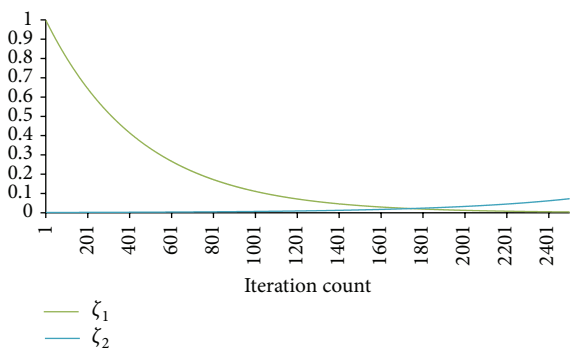

Figure 3: Proposed exponential constriction functions.

Table 1: Particle encoding for the proposed PSO.

P_{G1}	P_{G2}	$\cdots$	P_{Gi}	$\cdots$	P_{GN}

where

$$\eta = \frac{\text{itr}}{\text{itr}_{\max}}; \quad \text{itr}_{\min} \le \text{itr} \le \text{itr}_{\max},$$
$$k = \frac{\zeta_1 C_{1b}}{\zeta_2 C_2}. \tag{11}$$

The coefficient of exponent μ_1 has been considered −5.5, as the term $e^{-\mu_1 \eta}$ is not perceptible at the end of search. With μ_2 as 4, the coefficient k is determined for exact match of ζ_1 and ζ_2 at two-third of the search. The variation in ζ_1 and ζ_2 with iterations is shown in Figure 3 for the above mentioned value of the exponent coefficients. It can be depicted from the figure that the dominance of cognitive behavior falls sharply and that of the social behavior rises gradually as the search progresses. Thus, during the early part of the computational search, the cognitive behavior is well dominated over the social behavior of the swarm to enhance the global search for most probable area having the global optima. However, during the later part, it is the social behavior of the swarm that dominates over its cognitive counterpart. This may enhance local exploitation by the swarm to search global or near global optima.

These alterations in the control equation of the classical PSO regulate particle velocity within predefined bounds without any additional formulation as reported in many improved versions of PSO [4, 6–8, 10, 13–16, 18, 21, 26], yet preserving diversity due to the stochastic nature of cognitive and social behaviors of the swarm.

3.4. Particle Encoding and Initialization. The solution of an ED problem is the set of most optimal generations for the desired objective(s) bounded by certain operational constraints. In the proposed PSO, the particles are encoded in real numbers as the set of current generations in MW, as shown in Table 1.

Where P_{Gi} denotes generation of the ith generator in MW, the initial population is randomly created with predefined number of particles to maintain diversity. Each of these particles satisfies problem constraints defined by (2)–(4). Infeasible particle, if appeared, is not rejected but corrected using a correction algorithm as described later in the section. This improves the computational efficiency of the PSO. The fitness of each particle is evaluated using (1) and then *pbest*, *ppoor*, and *gbest* are initialized. The initial velocity of particles is assumed to be zero.

3.5. Correction Algorithm. The velocity and position update may create infeasible solutions. Infeasible individuals are not rejected but are corrected to feasible individuals by using a correction algorithm. For the purpose, the generations of all generators are adjusted by their respective bounded generation limits and then the error is calculated from the power balance equation. The error in the power is equally distributed among all generators and the procedure is repeated till the error is reduced to a predefined mismatch value ϵ. In this work the mismatch is considered as 0.001. This reduces the computational burden of PSO.

3.6. Elitism and Termination Criterion. In stochastic based algorithms like PSO, the solution with the best fitness in the current iteration may be lost in the next iteration. Therefore, the particle with the best fitness is kept preserved for the next iteration. The algorithm is terminated when either all particles reach to the best position or the predefined maximum iteration number is reached. The flow chart of the proposed method is shown in Figure 4.

4. Simulation Results

The proposed algorithm is tested on 13-generator system [23] and 40-generator system [23]. The control parameters used for all these systems to solve the ED problem using classical and proposed PSO are considered as mentioned in Table 2. The proposed algorithm has been developed using MATLAB and simulations have been carried on a personal computer of Intel i5, 3.2 GHz, and 4 GB RAM.

4.1. Case Study 1: 13-Generator System. The proposed method is applied on 13 thermal generating units which consist of valve-point effect and network power losses. The thermal generating units' data and B-coefficient power loss data are referred from [23]. The ED problem is solved for a power demand of 2520 MW. The simulation results obtained for the best and average fuel cost, total power output, and power losses after 100 independent trails using proposed PSO are presented in Table 3. The table shows that the proposed PSO is capable of obtaining better best, average, and best fuel costs with smaller power loss than other available existing stochastic methods in reasonable CPU time. Thus, the proposed method provides good quality solution to solve complex nonconvex ED problems. The best generating schedule obtained using the proposed PSO is presented in Appendix.

4.2. Case Study 2: 40-Generator System with Valve-Point Effect. The effectiveness of the proposed method is now investigated

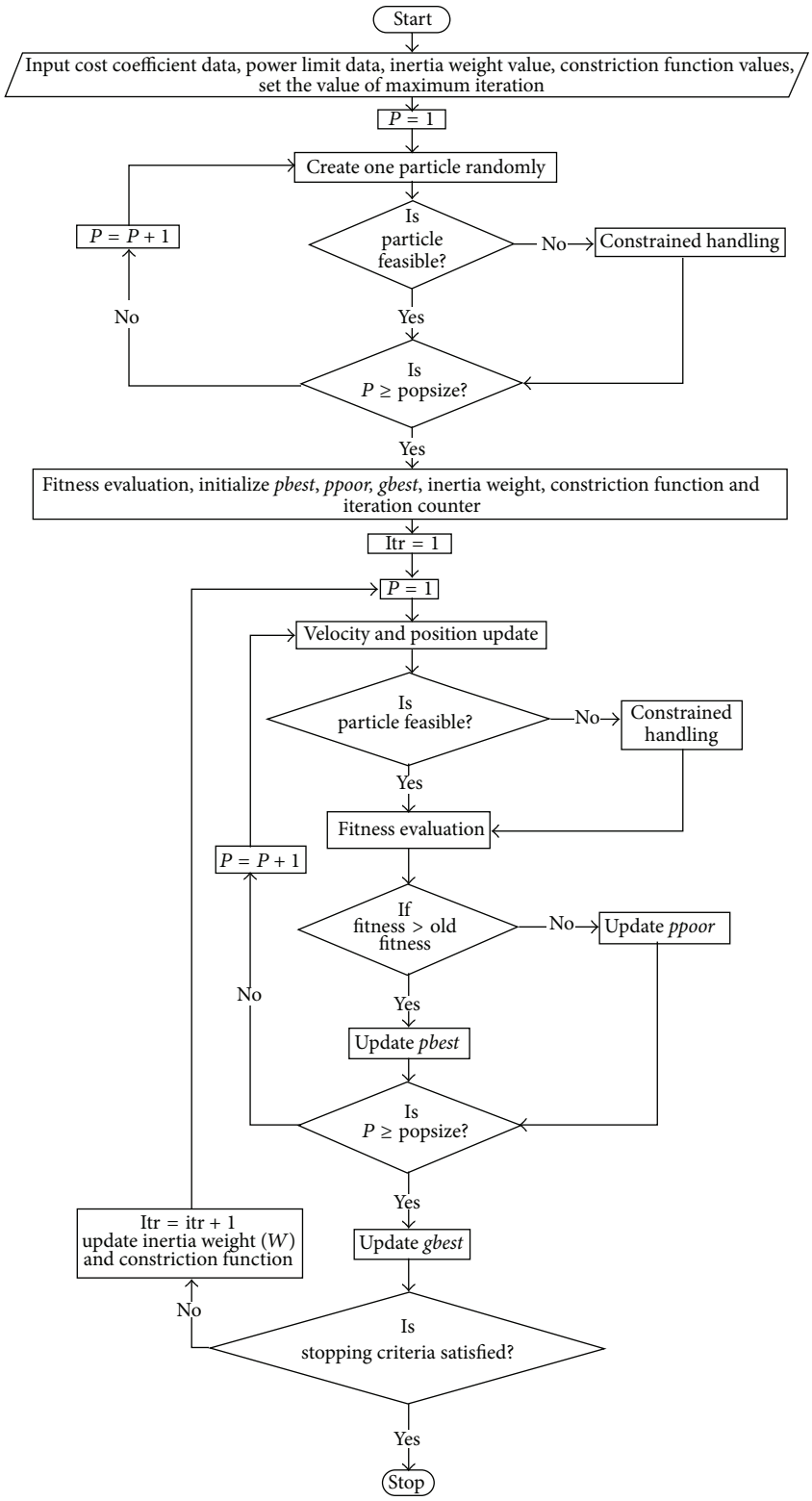

Figure 4: Flow chart of the proposed PSO.

Table 2: Various parameters for classical PSO and proposed PSO.

Method	$W_{\min}/W_{\max}$	C_{1b}	C_{1p}	C_2	μ_1	μ_2	$\text{itr}_{\max}$	Population size
Classical PSO	0.1/0.9	2	—	2	—	—	2500	100
Proposed PSO	0.1/0.9	1.5	0.5	2	−5.5	4	2500	100

Table 3: Comparison results for case study 1.

Method	Best fuel cost ($/hr)	Average fuel cost ($/hr)	Worst fuel cost ($/hr)	Total power (MW)	Power loss (MW)	CPU time (s)
GA [27]	24632.42	24874.93	25188.59	2559.87	39.87	2.25
DE [27]	24819.32	25217.64	25656.40	2562.34	42.34	2.58
HDE [27]	24591.76	24739.53	25074.90	2559.16	39.16	3.57
STHDE [27]	24560.08	24706.63	24872.44	2564.33	44.33	2.98
ICA-PSO [7]	24540.06	24561.46	24589.45	2559.05	39.05	21.5
SDE [1]	24514.88	24516.31	—	2560.43	40.43	—
Proposed PSO	24514.46	24514.58	24515.26	2558.07	38.07	2.96

Table 4: Comparison results for case study 2.

Method	Best fuel cost ($/hr)	Average fuel cost ($/hr)	Worst fuel cost ($/hr)	CPU time (s)
SQP [28]	122904.4243	124883.7692	126585.2290	10.80
EP-SQP [29]	122323.9700	122379.6300	—	997.73
PSO-SQP [29]	122094.6700	122245.2500	—	733.97
PSO-LRS [12]	122035.7946	123382.0000	125740.6300	31.61
NPSO [12]	121704.7391	122221.3697	122995.0976	8.23
NPSO-LRS [12]	121664.4308	122981.5913	122209.3185	20.74
DEC-SQP [30]	121741.9800	123367.6500	125397.9600	925.63
DEC(2)-SQP(1) [28]	121741.9793	122295.1278	122839.2941	14.26
ACO [31]	121532.4100	121606.4500	121679.6400	52.45
FCASO [32]	121516.4700	122082.5900	—	145.2
SOH-PSO [14]	121501.1400	121853.5700	122446.3000	—
TSARGA [33]	121463.0700	122928.3100	124296.5400	696.0
CPSO-SQP [34]	121458.5400	122028.1600	—	
GA-PS-SQP [29]	121458.0000	122039.0000	—	46.98
ABC [35]	121441.0300	121995.8200	—	30.02
CCPSO [22]	121412.5362	121445.3269	121525.4934	19.3
ICA-PSO [7]	121422.1000	—	—	139.9
DE/BBO [36]	121420.8948	—	—	12
HHS [37]	121415.5920	121615.8544	—	16.39
IPSO [2]	121412.8660	121509.5223	121546.8420	42.89
NAPSO [8]	121412.5700	—	—	12.7
CSA [38]	121412.5355	121520.4106	121810.2538	3.03
Proposed PSO	121412.5355	121432.3215	121564.3454	9.99

Table 5: Comparison results for case study 3.

Method	Best fuel cost ($/hr)	Average fuel cost ($/hr)	Worst fuel Cost ($/hr)	CPU time (s)
PSO [8]	124875.8523	125162.7011	—	—
FAPSO [8]	122261.3706	122471.0751	122597.5196	19.6
NAPSO [8]	121491.0662	121491.2756	121491.5261	12.7
CSA [38]	121487.7727	121611.3170	122162.9295	14.7
Proposed PSO	121487.7718	121511.3114	121753.7157	8.4

on the most popular test generating system taken from [23]. This system consists of 40 thermal units with nonconvexity in cost function due to valve-point loading effects. The expected power demand for this test system is 10500 MW. The results obtained after 100 independent trials of the proposed PSO are presented and compared with a variety of other available existing deterministic and population based or their hybrid techniques in Table 4. The table validates the effectiveness of the proposed PSO as it generates either comparable or better best fuel cost than other several established techniques including hybrid techniques. The table also shows that the proposed PSO is less computationally demanding than many other references including some latest ones. Although, NPSO [12] and CSA [38] demand less CPU time than the proposed PSO, but the proposed method is capable of generating better quality solution. Thus the proposed PSO is promising to solve nonconvex ED problems. The optimal dispatch of thermal generators obtained by the proposed PSO can be referred to in Appendix.

4.3. Case Study 3: 40-Generator System with Valve-Point and POZs. Finally, the effectiveness of the proposed method is investigated on the 40 generators test generating system with discontinuities in the cost function due to prohibited operating zones. The units 10–14 have POZs as given in [8] (POZ 2). The expected power demand for this test system is 10500 MW. The results obtained after 100 trials of the proposed PSO are presented and compared with other available existing population based techniques in Table 5. The table shows that the proposed PSO is capable of generating comparable or better result in less computational time than other established available methods. The better value of average fuel cost is obtained by proposed method than other methods. This shows robustness of the proposed PSO. Thus the high dimensional nonconvex discrete ED problems can be effectively and efficiently solved using the proposed PSO. The optimal dispatch of thermal generators obtained by the proposed PSO can be referred to in Appendix.

5. Discussion

In order to appreciate and understand the performance of the proposed method a comparison of cognitive and social behavior of particle in PSO and the proposed PSO is shown in Figures 5 and 6, respectively. Figure 5 shows that, in the classical PSO, the cognitive and social behaviors of particle velocity vary randomly throughout the computational process within limits of 0 to 2. The proposed constriction functions used to guide the cognitive and social behaviors of the swarm are allowed to vary exponentially as shown in Figure 6. The lower and upper limits of these behaviors are governed by (10). However, the sum of the best and poor cognitive behavior of the swarm remains constant during the computation process. This plays an important role in providing sufficient diversity by the poor experience during the whole flight of the swarm. It can be seen from Figure 6 that, using proposed PSO, the modulations of cognitive (best), cognitive (poor), and social behaviors though randomly distributed are dynamically controlled within exponential bounds of 1.5, 0.5, and 0.15, respectively. This constitutes a marked difference with other versions of existing PSO. Thus the particles experience entirely different cognitive and social behaviors during their flights and need no additional mechanism to bind their velocities.

Any stochastic based search technique must be designed to accomplish global exploration and tends to facilitate local exploitation. In order to investigate the effectiveness of each of these modifications, a set of convergence characteristics for the best and average fuel cost obtained during a sample trial for 40 generators system is shown in Figures 7 and 8, respectively. In Figure 7, the characteristic "a" is for the conventional PSO, "b" refers to "a" with sinusoidal modulation in inertia weight, "c" refers to "b" with improved cognitive behavior due to poor experience, and "d" refers to the proposed PSO. It can be observed from the figure that the performance of the PSO is somewhat improved when inertia weight is sinusoidally modulated and is further improved with a good margin when poor experience of particles is also considered. However, these two modifications do not seem to be sufficient to exploit the promising region effectively and efficiently. This leads to premature convergence due to local trappings which can be depicted from "d". In d, the proposed constriction functions regulate particles' velocities so that they can fly more comprehensively in the search space. In fact, due to higher initial cognitive component than the social component, the proposed PSO becomes more competent to explore wider search space during the initial phase and thus identify the promising region in about 1000 iterations. However, particles move with strong communication and thus intensively exploit the region near the global optima during later part of the search owing to high values of social component. Finally, all particles converge towards the global minima as can be observed from Figure 8. Thus, the proposed PSO provides better exploration and exploitation of the search space and produces better quality solutions. These results also highlight that the modifications suggested in the control equation of the classical PSO are very effective as it makes the proposed PSO perform much better.

The proposed method offers better exploration and exploitation of the search space because the velocity of particles is regulated throughout their flight. The movement of a sample particle in the classical PSO and the proposed PSO is illustrated in Figures 9 and 10, respectively. These figures show the traces of initial, cognitive, and social components of particle's velocity and also the overall velocity imparted to it during a sample trial.

The classical PSO searches for about 400 iterations, as shown in Figure 9. After this, all the three components of particle's velocity became insignificant and thus the particle gets trapped into local minima. Figure 10(b) shows the cognitive component for the best experience which is then superimposed by its poor experience as in Figure 10(c) to obtain the overall cognitive component as in Figure 10(d). It can be concluded from Figure 10(d) that the poor experience is contributing to tune the cognitive behavior of the swarm. The social component, as shown in Figure 10(e), is providing

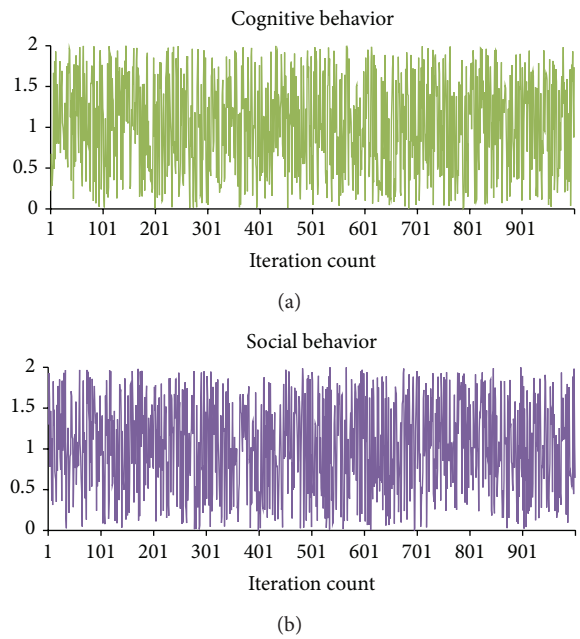

Figure 5: (a) Cognitive behavior and (b) social behavior in classical PSO.

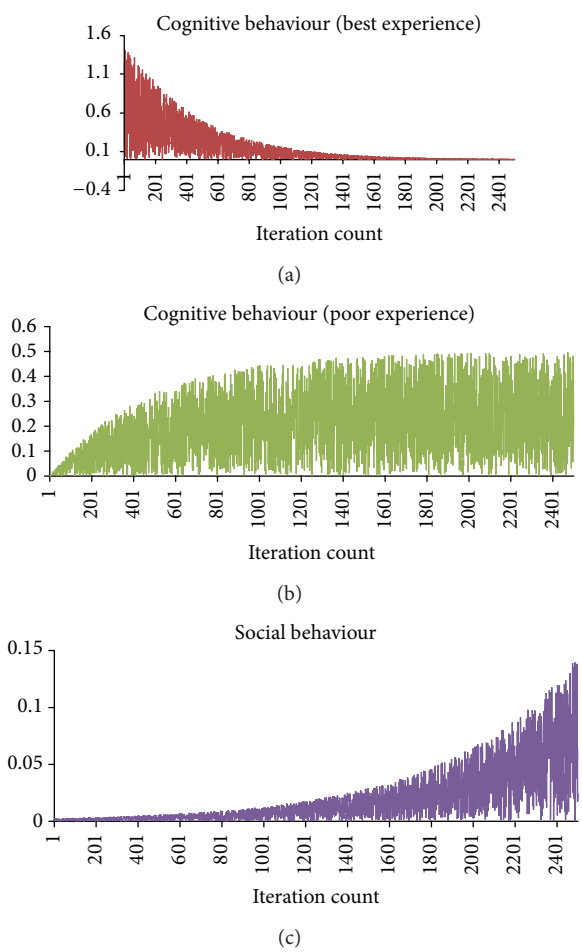

Figure 6: (a) Cognitive behavior (best experience), (b) cognitive behavior (poor experience), and (c) social behavior in proposed PSO.

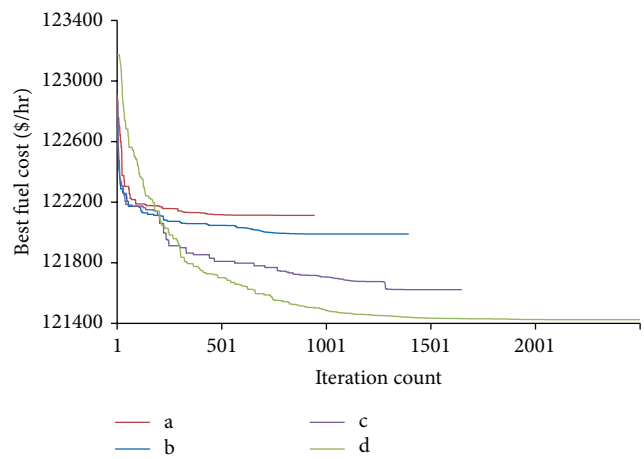

Figure 7: Effect on the convergence for best fuel cost by suggested modifications in the proposed PSO.

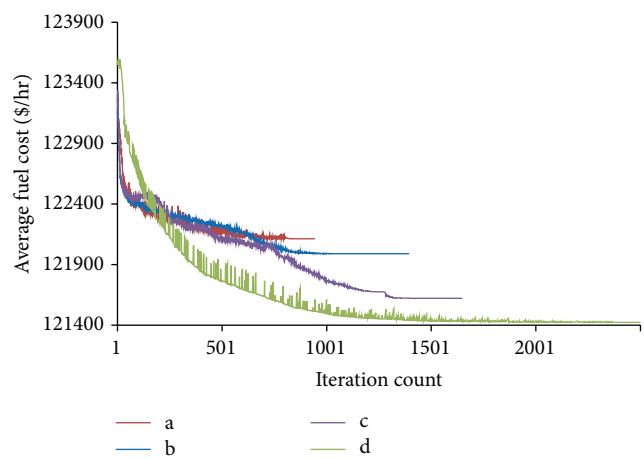

Figure 8: Effect on the convergence for average fuel cost by suggested modifications in the proposed PSO.

fine tuning as desired in high dimensional optimization problem. It should be noted that the social component has been kept quite weak in this work, as compared to other published literature till date and is one of the keys to obtain high quality solutions. In addition, the proposed modulation in inertia weight intends particles for better exploration and exploitation of the search space by imparting suitable velocity during the flight, as seen from Figure 10(a). The impact of improved initial, cognitive, and social components of particle's velocity is shown in Figure 10(f). The figure shows a marked improvement in particle movement during the whole computation while compared with Figure 9(d). In the proposed PSO, during early part of the search, the particles widely travelled in the search space yet their velocity is regulated by the poor experience as the social component is almost negligible. This facilitates the swarm to explore the region of global optima. However, in later part of the search, both poor and the social components are driving the swarm toward the global optima, as the cognitive best experience has been made quite weak during this part of the search.

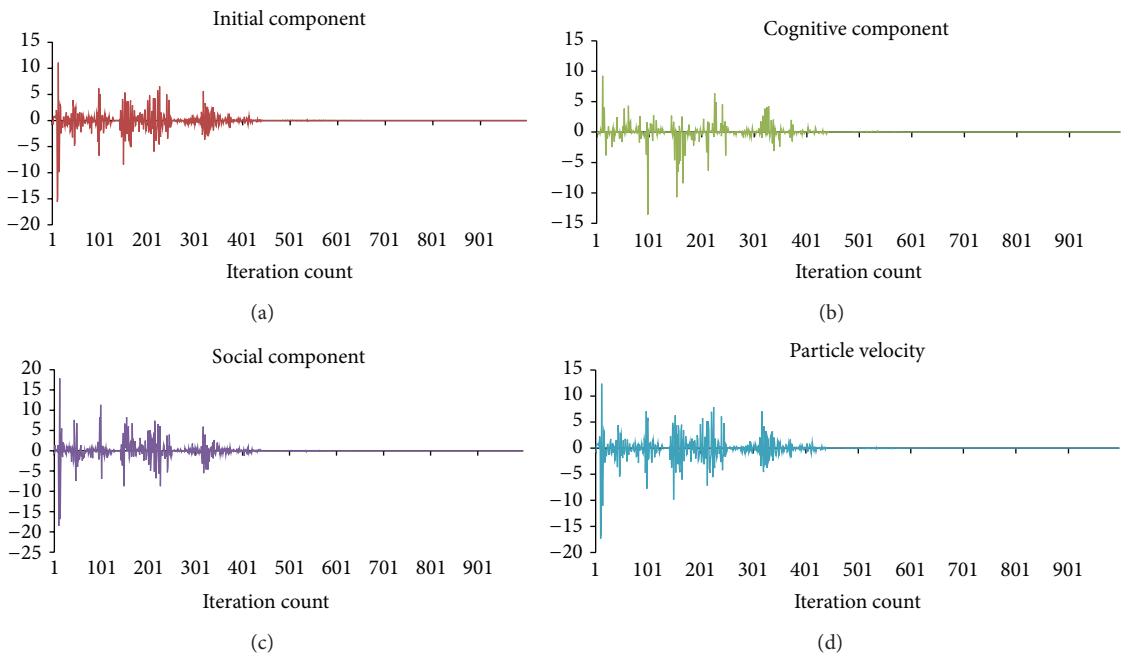

FIGURE 9: Particle velocity and its components in PSO.

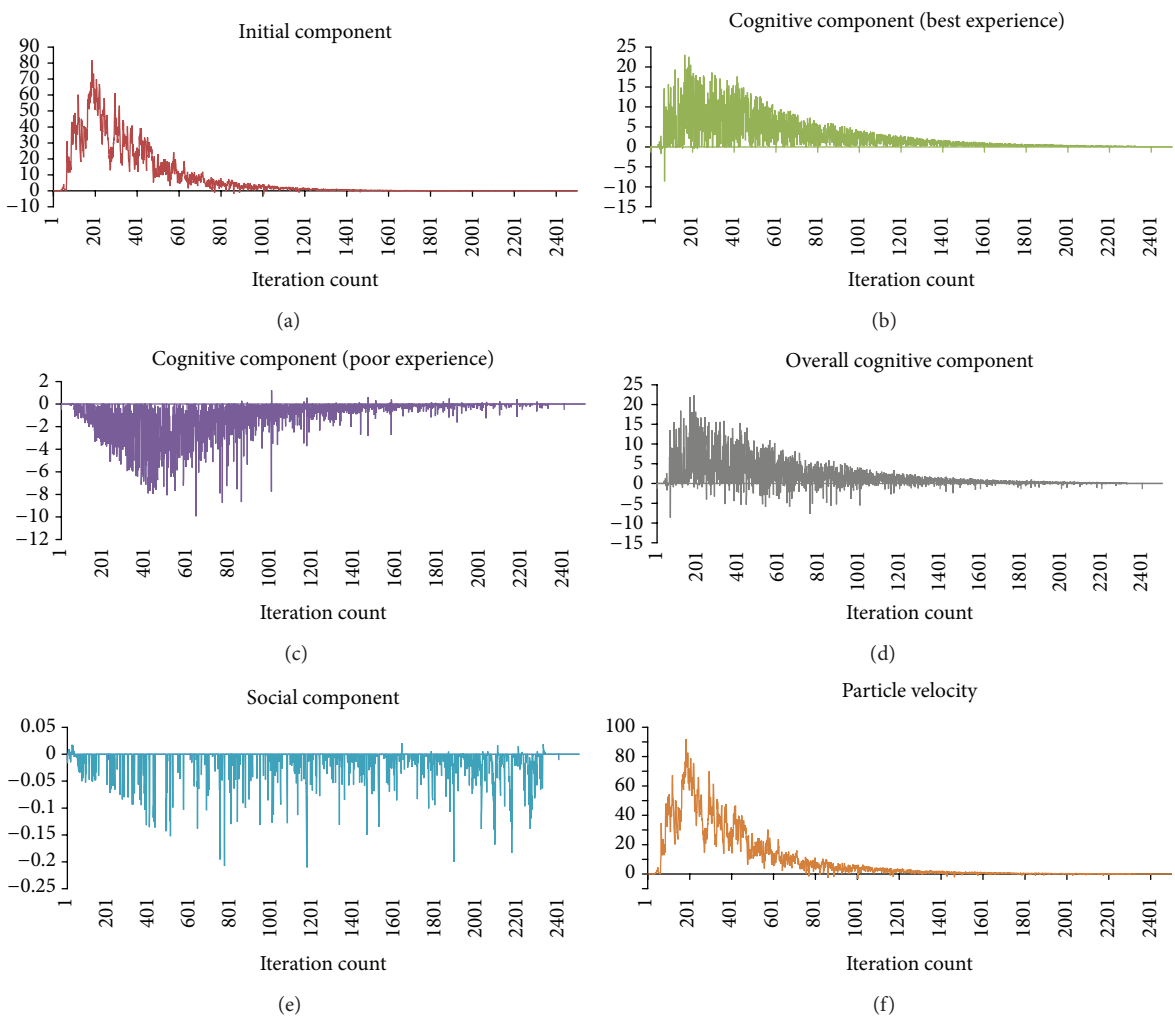

FIGURE 10: Particle velocity and its components in the proposed PSO.

This improves exploitation potential of the PSO for local search. Thus, the proposed PSO provides better exploration and exploitation of the search space and thus produces better quality solutions than the classical PSO or other existing stochastic based methods.

6. Conclusions

The economic dispatch is a highly complex combinatorial constrained optimization problem with continuous decision variables. The classical PSO has proven potential to solve such hard combinatorial constraints optimization problem, but it usually gets trapped into local minima while dealing with high dimensional ED problems. This paper presents a modified version of PSO to make it suitable for solving highly complex ED problems. The proposed method has been tested to solve ED problems of three different test systems of different dimensions with a variety of operational and network constraints. The application results are also compared with available existing PSO methods. The application results show that the proposed method is efficient and is usually not trapped in local minima. The comparison shows that proposed method is capable of giving better results than the existing PSO and other stochastic based methods. This may be due to the fact that proposed PSO essentially aims to regulate particle velocity during its whole course of flight in such a fashion so as to enhance exploration and exploitation potentials of the PSO. The operators in the proposed PSO are made to vary dynamically by introducing new truncated sinusoidal and exponential functions. The concept of poor particle is introduced to improve the cognitive behavior of the swarm and also maintain a good balance between cognitive and social behavior of the swarm during the whole course of the flight. These modifications guide the swarm to identify the area where the global optima may exist. Thereafter, particles have suitable velocities to wandering within in this area to explore global or near global solution. Further, it has been observed that in the proposed PSO, the particle is accelerated more comprehensively during whole of its flight than in the classical PSO. This causes better exploration of the search space during the early part and better exploitation during the later part of the search. It is noteworthy that the proposed PSO is free from any mechanism to avoid local trapping and does not require any empirical formula to bound particle's velocity. Moreover, the proposed algorithm is robust as it generates better quality solutions irrespective of the initial position of the particles. The proposed PSO can be extended to solve ED problems with the inclusion of more objectives and constraints like environmental issues, reserve capacity, network security, network congestion management, and so forth.

Appendix

See Table 6.

Table 6: Optimal generating schedule for case studies 1, 2, and 3.

Unit	Case study 1 Power (MW)	Case study 2 Power (MW)	Case study 3 Power (MW)
1	628.3185	110.799825	110.799789
2	298.8000	110.799825	110.799807
3	298.8000	97.3999130	97.3998080
4	159.7400	179.733100	179.733093
5	159.7400	87.7999050	87.7998250
6	159.7400	140.000000	140.000000
7	159.7400	259.599650	259.599600
8	159.7300	284.599650	284.599496
9	159.7400	284.599650	284.599700
10	76.20000	130.000000	130.000000
11	113.3200	94.0000000	168.798140
12	92.10000	94.0000000	168.041419
13	92.10000	214.759790	125.000000
14	—	394.279370	400.000000
15	—	394.279370	394.279018
16	—	394.279370	394.279205
17	—	489.279370	489.279397
18	—	489.279370	489.279380
19	—	511.279370	511.279377
20	—	511.279370	511.279299
21	—	523.279370	523.279354
22	—	523.279370	523.279373
23	—	523.279370	523.279372
24	—	523.279370	523.279365
25	—	523.279369	523.279377
26	—	523.279370	523.279400
27	—	10.0000000	10.0000000
28	—	10.0000000	10.0000000
29	—	10.0000000	10.0000000
30	—	87.799902	87.7998910
31	—	190.000000	190.000000
32	—	190.000000	190.000000
33	—	190.000000	190.000000
34	—	164.799825	164.799766
35	—	194.397782	164.799800
36	—	200.000000	164.799803
37	—	110.000000	110.000000
38	—	110.000000	110.000000
39	—	110.000000	109.998798
40	—	511.279370	511.279348

Conflict of Interests

The authors declare that there is no conflict of interests regarding the publication of this paper.

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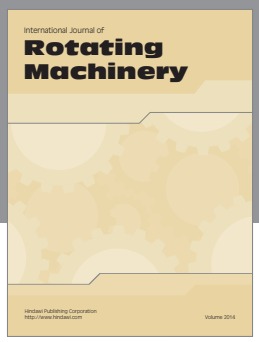

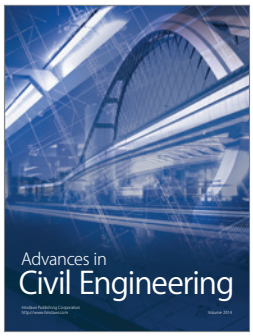

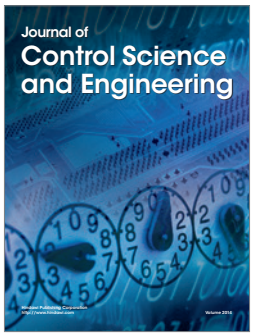

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