A Comparative Study on Particle Swarm Optimization for Optimal Steady-State Performance of Power Systems

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***Abstract*—In this paper, three new particle swarm optimization (PSO) algorithms are compared with the state of the art PSO algorithms for the optimal steady-state performance of power systems, namely, the reactive power and voltage control. Two of the three introduced, the enhanced GPAC PSO and LPAC PSO, are based on the global and local-neighborhood variant PSOs, respectively. They are hybridized with the constriction factor approach together with a new operator, reflecting the physical force of passive congregation observed in swarms. The third one is based on a new concept of coordinated aggregation (CA) and simulates how the achievements of particles can be distributed in the swarm affecting its manipulation. Specifically, each particle in the swarm is attracted only by particles with better achievements than its own, with the exception of the particle with the best achievement, which moves randomly as a "crazy" agent. The obtained results by the enhanced general passive congregation (GPAC), local passive congregation (LPAC), and CA on the IEEE 30-bus and IEEE 118-bus systems are compared with an interior point (IP)-based OPF algorithm, a conventional PSO algorithm, and an evolutionary algorithm (EA), demonstrating the excellent performance of the proposed PSO algorithms.**

***Index Terms*—Coordinated aggregation (CA), particle swarm optimization (PSO), passive congregation, reactive power control, voltage control.**

I. Introduction

During the history of science of computational intelligence, many evolutionary algorithms (EAs) were proposed having more or less success in solving various nonlinear engineering optimization problems. Among them, the best are considered to be the popular particle swarm optimization (PSO) introduced by Kennedy and Eberhart [1], the ant-colony systems (ACS) introduced by Dorigo [2], and the cultural algorithms introduced by Reynolds [3]. In the last years, the effort is continued by the same and other researchers [4], [5] generating more effective EAs. The reason for the growing development of EA is that mathematical optimization methods, such as nonlinear programming, quadratic programming, Newton-based techniques, sequential unconstrained minimization, and interior point algorithms, have failed in handling nonconvexities and nonsmoothness in engineering optimization problems. The main advantage of EA is that they do not require the objective functions and the constraints to be differentiable and continuous [6]. However, their main problem remains the same, achieving the global best solution in the possible shortest time.

In this paper, we focus on PSO algorithms for power engineering discipline. In recent years, various PSO algorithms have been successfully applied in many power-engineering problems [7]–[18]. Among them, the hybrid PSO satisfactorily handled problems such as distribution state estimation [8] and loss power minimization [9] performing better convergence characteristics than conventional methods. However, these PSO algorithms are based on the original concept introduced by Kennedy and Eberhart [1].

In this paper, we proceed to the effort of developing more effective PSO algorithms by reflecting recent advances in swarm intelligence [19] and, in addition, by introducing new concepts. Under these conditions, two new hybrid PSO algorithms are proposed, which are more effective and capable of solving nonlinear optimization problems faster and with better accuracy in detecting the global best solution. The main concept of this development is based on the passive congregation [19] and a kind of coordinated aggregation observed in the swarms. Specifically, He *et al.* [20] introduced an operator of passive congregation in the global variant PSO, the general passive congregation (GPAC PSO). We expand the application of this operator in the local-neighborhood variant PSO [21] by enhancing it with the constriction factor approach [8], [22], which results in the local passive congregation (LPAC) PSO. Moreover, the GPAC PSO [20] is also enhanced with the constriction factor approach in this paper.

Another completely different type of PSO algorithm is introduced, which is based on the coordinated aggregation (CA) observed in swarms. The main idea behind the CA is based on the fact that the achievement of each particle is distributed in the entire swarm. At each iterative cycle of CA, each particle updates its velocity, taking into account the differences between its position and the positions of better achieving particles. These differences play the role of regulators and are called *coordinators* as they are multiplied by weighting factors. The ratios of differences between the achievement of a specific particle and the achievements of better particles to the sum of these differences are the weighting factors of coordinators. The best particle in the swarm is excluded from this process, as it regulates its velocity

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randomly. Specifically, the best particle changes its velocity according to a random coordinator, which takes into account the difference between the position of the best particle and the position of a randomly chosen particle in the swarm. This seems like the "craziness" concept adopted in [1] and helps CA to overcome premature convergence in local minima.

In this paper, the enhanced GPAC, LPAC, and CA are applied in two nonlinear optimization problems of power systems, namely, the reactive power and voltage control problems. The results obtained in the IEEE 30-bus and IEEE 118-bus systems are compared with those given by the primal-dual interior-point based optimal power flow (OPF) algorithm [23], a conventional PSO algorithm [8], [9], and a multiobjective evolutionary algorithm (EA) [24], demonstrating improved performance of the proposed algorithms.

This paper is organized as follows: the problems of reactive power and voltage control are formulated in Section II. Section III summarizes a conventional PSO algorithm, which is used effectively in power engineering problems. Section IV introduces the LPAC and the enhanced GPAC algorithms, and the CA algorithm is introduced in Section V. Section VI presents numerical results. Discussions and final conclusions with future works are outlined in Sections VII and VIII, respectively.

II. Reactive Power and Voltage Control

The proposed PSO algorithms are tested and compared with a conventional PSO algorithm on optimal steady-state performance of power systems in terms of minimization of: 1) power losses in transmission lines and 2) voltage deviations on load busses while satisfying several equality and inequality constraints [24]. Since the main focus of this paper is the performance evaluation of the new PSO algorithms, two nonlinear optimization problems are separately studied. Thus, a clear picture of the effectiveness of the proposed PSO algorithms will be given.

The first objective is to minimize the real power losses in transmission lines that can be expressed as

$$J_1 = P_{\text{Loss}}(\mathbf{x},\mathbf{u}) = \sum_{l=1}^{Nl} P_l \tag{1}$$

where $\mathbf{x}$ is the vector of depended variables, $\mathbf{u}$ is the vector of control variables, P_l is the real power losses at line-l, and Nl is the number of transmission lines.

The second objective is to optimize the voltage profile of the power system. The objective is to minimize the voltage deviations at load buses that can be expressed by

$$J_2 = VD(\mathbf{x},\mathbf{u}) = \sum_{i=1}^{Nd} |V_i - V_i^{sp}| \tag{2}$$

where V_i^{sp} is the pre-specified reference value at load bus-i, which is usually set at the value of 1.0 p.u., and Nd is the number of load buses.

As the search space in both problems, the following two vectors are considered:

$$x^T = [V_{L_1}, V_{L_2} \dots V_{L_{Nd}}, Q_{G_1}, Q_{G_2} \dots Q_{G_{Ng}} \; S_{L_1}, S_{L_2} \dots S_{L_{NL}}] \tag{3}$$

$$u^T = [V_{G_1}, V_{G_2} \dots V_{G_{Ng}}, Q_{C_1}, Q_{C_2} \dots Q_{C_{Nc}} \; T_1, T_2 \dots T_{NT}] \tag{4}$$

where x is the vector of dependent variables consisting of load bus voltages V_L, generator reactive power outputs Q_G, and transmission line loadings S_L, and $\mathbf{u}$ is the vector of control variables consisting of generator voltages V_G, transformer tap settings T, and shunt VAR compensations Q_c.

The equality constraints of both optimization problems are typical load flow equations as follows:

$$P_{G_i} - P_{D_i} - f_{P_i}(\mathbf{x},\mathbf{u}) = 0 \tag{5}$$

$$Q_{G_i} - Q_{D_i} - f_{Q_i}(\mathbf{x},\mathbf{u}) = 0 \tag{6}$$

where f_{P_i} and f_{Q_i} are the real and reactive power flow equations at bus-i, respectively; P_{G_i} and Q_{G_i} are the generator real and reactive power at bus-i, respectively; and P_{D_i} and Q_{D_i} are the load real and reactive power at bus-i, respectively.

The inequality constraints in both problems represent the system operating constraints.

Generation constraints: Generator voltages V_G and reactive power outputs Q_G are restricted by their limits as follows:

$$V_{G_i}^{\min} \le V_{G_i} \le V_{G_i}^{\max} \quad i = 1,2 \dots NG \tag{7}$$

$$Q_{G_i}^{\min} \le Q_{G_i} \le Q_{G_i}^{\max} \quad i = 1,2,\dots NG \tag{8}$$

where NG is the number of generators.

Switchable VAR constraints: Switchable VAR compensations Q_c are restricted by their limits as follows:

$$Q_{C_i}^{\min} \le Q_{C_i} \le Q_{C_i}^{\max} \quad i = 1,2,\dots NC \tag{9}$$

where NC is the number of switchable VAR sources.

Transformer constraints: Transformer tap settings T are bounded as follows:

$$T_i^{\min} \le T_i \le T_i^{\max} \quad i = 1,2 \dots NT \tag{10}$$

where NT is the number of transformers.

Security constraints: This term refers to the constraints of load voltages at load buses V_L and transmission line loadings S_L as follows:

$$V_{L_i}^{\min} \le V_{L_i} \le V_{L_i}^{\max} \quad i = 1,2 \dots Nd \tag{11}$$

$$S_{L_i} \le S_{L_i}^{\max} \quad i = 1,2 \dots Nl \tag{12}$$

where Nd is the number of load buses, and Nl the number of transmission lines.

III. Conventional Particle Swarm Optimization

PSO is a swarm intelligence algorithm, inspired by the social dynamics and an emergent behavior that arises in socially organized colonies. PSO algorithm exploits a population of individuals to probe promising regions of search space. In this context, the population is called swarm and the individuals are called particles or agents.

In PSO algorithms, each particle moves with an adaptable velocity within the regions of decision space and retains a memory of the best position it ever encountered. The best position ever attained by each particle of the swarm is communicated to all other particles. As a conventional PSO, we consider the state-of-the-art hybrid PSO algorithm [8], [9]. Specifically, the conventional PSO assumes an n-dimensional search space $S \subset R^n$, where n is the number of decision variables in the optimization problem, and a swarm consisting of N-particles.

In PSO, variables are defined as follows.

The position of the ith particle at time-t is an n-dimensional vector denoted by

$$S_i(t) = (s_{i,1}, s_{i,2}, \ldots, s_{i,n}) \in S. \tag{13}$$

The velocity of this particle at time-t is also an n-dimensional vector

$$V_i(t) = (v_{i,1}, v_{i,2}, \ldots, v_{i,n}) \in S. \tag{14}$$

The best previous position of the ith particle is a point in S, denoted by

$$P_i = (p_{i,1}, p_{i,2}, \ldots, p_{i,n}) \in S. \tag{15}$$

The global best position ever attained among all particles is a point in S denoted by

$$P_{gb} = (p_{gb,1}, p_{gb,2}, \ldots, p_{gb,n}) \in S. \tag{16}$$

Then, the PSO assumes that the swarm is manipulated by the equations

$$V_i(t+1) = k \cdot [w(t) \cdot V_i(t) + c_1 \cdot rand_1 \cdot (P_i - S_i(t)) + c_2 \cdot rand_2 \cdot (P_{gb} - S_i(t))] \tag{17}$$

$$S_i(t+1) = S_i(t) + V_i(t+1) \tag{18}$$

where $i = 1, 2, \ldots N$; C_1 and C_2 are the cognitive and the social parameters, respectively; and $rand_1$ and $rand_2$ are random numbers uniformly distributed within $[0, 1]$.

The inertia weighting factor for the velocity of particle-i is defined by the *inertial weight approach*

$$w(t) = w_{\max} - \frac{w_{\max} - w_{\min}}{t_{\max}} \cdot t \tag{19}$$

where $t_{\max}$ is the maximum number of iterations, and t is the current number of iterations; $w_{\max}$ and $w_{\min}$ are the upper and lower limits of the inertia weighting factor, respectively.

Moreover, in order to guarantee the convergence of the PSO algorithm, the constriction factor k is defined as [8], [9], [22], [25]–[27]

$$k = \frac{2}{\left|2 - \varphi - \sqrt{\varphi^2 - 4\varphi}\right|}, \quad \varphi = c_1 + c_2, \;\; \varphi \geq 4. \tag{20}$$

In this constriction factor approach (CFA), the basic system equations of the PSO (17), (18) can be considered as difference equations. Therefore, the system dynamics, namely, the search procedure, can be analyzed by the eigenvalue analysis and can be controlled so that the system behavior has the following features.

1) The system converges.
2) The system can search different regions efficiently.

In the CFA, the φ must be greater than 4.0 to guarantee stability. However, as φ increases, the factor k decreases and diversification is reduced, yielding slower response. Therefore, we choose 4.1 as the smallest φ that guarantees stability but yields the fastest response. It has been observed here, and also in other papers [25], that $4.1 \leq \varphi \leq 4.2$ leads to good solutions. The CFA results in convergence of the agents over time. Unlike other PSO methods, the CFA ensures the convergence of the search procedure based on mathematical theory. Therefore, the CFA can generate higher quality solutions than the basic PSO approach.

However, the constriction factor only considers dynamic behavior of one agent and ignores the effect of the interaction among agents. Namely, the equations were developed with a fixed set of best positions (*pbest* and *gbest*), although *pbest* and *gbest* change during the search procedure in the basic PSO equation [28].

IV. Passive Congregation-Based PSO

According to the local-neighborhood variant of the PSO algorithm (L-PSO) [21], each particle moves toward its best previous position and toward the best particle in its restricted neighborhood. As the local-neighborhood leader of a particle, its nearest particle (in terms of distance in the decision space) with the better evaluation is considered. Since the constriction factor approach generates higher quality solutions in the basic PSO, we enhance the L-PSO [21] with the constriction factor [22]. However, it has been shown recently that more biological forces than those adopted in the state-of-the-art PSO are essential for preserving the swarm's integrity. Specifically, Parrish and Hammer [19] have proposed mathematical models to show how these forces organize the swarms. These can be classified in two categories: the *aggregation* and the *congregation* forces.

Aggregation refers to the swarming of particles by nonsocial, external physical forces. There are two types of aggregation: passive aggregation and active aggregation. Passive aggregation is a swarming by physical forces, such as the water currents in the open sea group the plankton [19], [20]. In this paper, we do not consider passive aggregation, since particles (solution candidates in the optimization problems) are not aggregated passively via physical forces. Active aggregation is a swarming by attractive resources such as the place with the most food. The second term in the conventional PSO algorithm (17) (the global best position) represents the active aggregation [19], [20].

Congregation, on the other hand, is a swarming by social forces, which is the source of attraction of a particle to others and is classified in two types: social and passive. Social congregation usually happens when the swarm's fidelity is high, such as genetic relation. Social congregation necessitates active information transfer, e.g., ants that have high genetic relation use antennal contacts to transfer information about location of resources [19], [20], [29]–[32]. We do not consider social congregation in this paper because it frequently displays a division of labor. Finally, passive congregation is an attraction of a particle to other swarm members, where there is no display of social behavior since particles need to monitor both environment and their immediate surroundings such as the position and the speed of neighbors [19], [20]. Such information transfer can be employed in the passive congregation. In this paper, we propose a hybrid L-PSO with passive congregation operator (PAC) called LPAC PSO. Moreover, the global variant-based passive congregation PSO (GPAC) [20] is enhanced with the constriction factor approach [8], [22].

The swarms of the enhanced GPAC and LPAC are manipulated by the velocity update

$$V_i(t+1) = k \cdot [w(t) \cdot V_i(t) + c_1 \cdot rand_1 \cdot (P_i - S_i(t)) + c_2 \cdot rand_2 \cdot (P_k - S_i(t)) + c_3 \cdot rand_3 \cdot (P_r - S_i(t))] \quad (21)$$

where $i = 1, 2, \ldots, N$; c_1, c_2, and c_3 are the cognitive, social, and passive congregation parameters, respectively; $rand_1$, $rand_2$, and $rand_3$ are random numbers uniformly distributed within $[0, 1]$; P_i is the best previous position of the ith particle; P_k is either the global best position ever attained among all particles in the case of enhanced GPAC or the local best position of particle-i, namely, the position of its nearest particle-k with better evaluation in the case of LPAC; and P_r is the position of passive congregator (position of a randomly chosen particle-r). The positions are updated using (18).

The positions of the ith particle in the n-dimensional decision space are limited by the minimum and maximum positions expressed by vectors

$$\left[S_i^{\min}, S_i^{\max}\right]. \quad (22)$$

In this paper, the minimum and maximum position vectors of (22) express the inequality constraints.

The velocities of the ith particle in the n-dimensional decision space are limited by

$$\left[-V_i^{\max}, V_i^{\max}\right] \quad (23)$$

where the maximum velocity in the lth dimension of the search space is proposed as

$$v_{i,l}^{\max} = \frac{s_{i,l}^{\max} - s_{i,l}^{\min}}{Nr}, \quad (l = 1, 2, \ldots, n) \quad (24)$$

where $s_{i,l}^{\min}$ and $s_{i,l}^{\max}$ are the limits in the l-dimension of the search space. The maximum velocities are constricted in small intervals in the search space for better balance between exploration and exploitation. Nr is a chosen number of search intervals for the particles. It is an important parameter in the enhanced GPAC and LPAC PSO algorithms. A small Nr facilitates global exploration (searching new areas), while a large one tends to facilitate local exploration (fine tuning of the current search area). A suitable value for the Nr usually provides balance between global and local exploration abilities and consequently results in a reduction of the number of iterations required to locate the optimum solution.

The basic steps of the enhanced GPAC and LPAC are listed below.

Step 1) Generate a swarm of N-particles with uniform probability distribution, initial positions $S_i(0)$, and velocities $V_i(0)$, $(i = 1, 2, \ldots N)$, and initialize the random parameters. Evaluate each particle-i using objective function f (e.g., f to be minimized).

Step 2) For each particle-i, calculate the distance d_{ij} between its position and the position of all other particles: $d_{ij} = \|S_i - S_j\|$ $(i \neq j = 1, 2, \ldots, N)$, where S_i and S_j are the position vectors of particle-i and particle-j, respectively.

Step 3) For each particle-i, determine the nearest particle, particle-k, with better evaluation than its own, i.e., $d_{ik} = \min_j(d_{ij})$, $f_k \leq f_i$, and set it as the leader of particle-i.
In the case of enhanced GPAC, particle-k is considered as the global best.

Step 4) For each particle-i, randomly select a particle-r and set it as passive congregator of particle-i.

Step 5) Update the velocities and positions of particles using (21) and (18), respectively.

Step 6) Check if the limits of positions (22) and velocities (23), (24) are enforced. If the limits are violated, then they are replaced by the respective limits.

Step 7) Evaluate each particle using the objective function f. The objective function f is calculated by running a load flow. In the case where for a particle no load flow solution exists, an error is returned and the particle retains its previous achievement.

Step 8) If the stopping criteria are not satisfied, go to Step 2.

The enhanced GPAC and LPAC PSO algorithms will be terminated if one of the following criteria is satisfied: 1) no improvement of the global best in the last 30 generations is observed, or 2) the maximum number of allowed iterations is achieved (in this paper, 100).

Finally, we can indicate that the last term of (21), added in the conventional PSO velocity update (17), displays the information transferred via passive congregation of particle-i with a randomly selected particle-r. This passive congregation operator

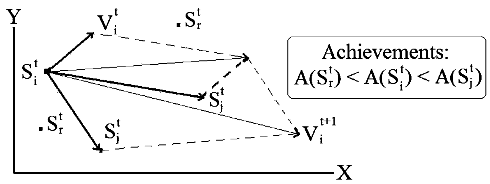

Fig. 1. Swarm's manipulation concept of CA PSO.

can be regarded as a stochastic variable that introduces perturbations to the search process. For each particle-i, the perturbation is proportional to the distance between itself and a randomly selected particle-r rather than an external random number, namely, the turbulence factor introduced in [20] and [33]. The constriction factor approach helps the convergence of algorithm more than the turbulence factor because: 1) in the early stages of the process, where distance between particles is large, the turbulence factor should be large, avoiding premature convergence; and 2) in the last stages of process, as the distance between particles becomes smaller, the turbulence factor should be smaller too, enabling the swarm to converge in the global optimum [20]. Therefore, LPAC is more capable of probing the decision space, avoiding sub-optimums and improving information propagation in the swarm than other conventional PSO algorithms.

V. Coordinated Aggregation-Based PSO

The coordinated aggregation is a completely new operator introduced in the swarm, where each particle moves considering only the positions of particles with better achievements than its own, with the exception of the best particle, which moves randomly. The coordinated aggregation can be considered as a type of active aggregation where particles are attracted only by places with the most food.

Fig. 1 depicts how the position of a particle-i in a two-dimensional decision space changes. In this figure, particle-i has worse achievement than particles-j but better than particles-r. Specifically, at each iterative cycle-t of CA, each particle-j with better achievement than particle-i regulates the velocity of the second. The velocity of particle-i is adapted by means of coordinators multiplied by weighting factors. The differences between the positions of particles-j and the position of particle-i, $S_j(t) - S_i(t)$ are defined as *coordinators* of particle-i velocity. The ratios of differences between the achievement of particle-i, $A(S_i)$ and the better achievements by particles-j, $A(S_j)$ to the sum of all these differences are called achievement's weighting factors $w_{(ij)}(t)$

$$w_{ij} = \frac{A(S_j) - A(S_i)}{\sum_l A(S_l) - A(S_i)} \quad j, l \in T_i \tag{25}$$

where T_i represents the set of particles-j with better achievement than particle-i.

The steps of CA PSO algorithm are listed below.

Step 1) *Initialization:* Generate N-particles. For each particle-i, choose initial position $S_i(0)$ randomly. Calculate its initial achievement $A(S_i(0))$ using the objective function f and find the maximum $(A_g(0) = \max_i A(S_i(0)))$ called the global best achievement. Then, particles update their positions in accordance with the following steps.

Step 2) *Swarm's manipulation:* The particles, except the best of them, regulate their velocities in accordance with the equation

$$V_i(t+1) = w(t) \cdot V_i(t) + \sum_j rand_j \cdot w_{ij}(t) \cdot (S_j(t) - S_i(t)) \quad j \in T_i \tag{26}$$

where $i = 1, 2, \ldots, N$; the random parameter $rand_j$ is used to maintain the diversity of the population and is uniformly distributed within the range $[0, 1]$; $w_{ij}(t)$ are achievement's weighting factors; and the inertia weighting factor $w(t)$ is defined by (19). The role of the inertia weighting factor is considered critical for the CA convergence behavior. It is employed to control the influence of the previous history of the velocities on the current one. Accordingly, the inertia weighting function regulates the tradeoff between the global and local exploration abilities of the swarms [5].

Step 3) *Best particle's manipulation (craziness):* The best particle in the swarm updates its velocity using a *random coordinator* calculated between its position and the position of a randomly chosen particle in the swarm. The manipulation of best particle seems like the crazy agents introduced in [1] or the turbulence factor introduced in [20] and [33] and helps the swarm escape from the local minima.

Step 4) Check if the limits of velocities (23) and (24) are enforced. If the limits are violated, then they are replaced by the respective limits.

Step 5) *Position update:* The positions of particles are updated using (18). Check if the limits of positions (22) are enforced. In this paper, the minimum and maximum position vectors of (22) express the inequality constraints.

Step 6) *Evaluation:* Calculate the achievement $A(S_i(t))$ of each particle-i using the objective function f. The achievement is calculated by running a load flow. In the case where for a particle no load flow solution exists, an error is returned and the particle retains its previous achievement.

Step 7) If the stopping criteria are not satisfied, go to Step 2. The CA algorithm will be terminated if no more improvement of the global best achievement in the last 30 generations is observed or the maximum number of allowed iterations is achieved (in this paper, 100).

Step 8) *Global optimal solution:* Choose the optimal solution as the global best achievement

$$S_g = \arg\max A_g(S_g.). \tag{27}$$

VI. Performance Evaluation

The main focus of this paper is the comparison of the three alternative PSO algorithms with the conventional PSO algorithm [8], [9], the primal-dual interior-point-based OPF algorithm [23], called IP-OPF, and a multiobjective evolutionary algorithm (EA) [24] in the optimization of steady-state performance in power systems. Specifically, they need to handle two optimization problems, namely, minimization of 1) real power losses in transmission lines and 2) voltage deviation on load buses. The criterion for the comparison is the achievement of global optimum solution in the shortest computing time. In addition to the primary goal, observation will be made on the stochastic behavior of the competing algorithms. In all case studies, as decision variables, generator voltages, transformers tap settings, and reactive power compensators are chosen. In this paper, these variables are considered to be continuous. Nevertheless, in the case of reactive compensation, modern silicon controlled rectified (SCR) power controllers may handle continuous values of reactive power compensation [9]. Moreover, PSO algorithms can handle topological changes easily in power systems due to the particles "flight" on the space of decision variables, and there is no need to "know" the special topology given by Jacobian or a similar matrix.

A. IEEE 30-Bus System

To verify the feasibility of the proposed PSO algorithms (enhanced GPAC, LPAC, and CA) in the reactive power and voltage control, they are applied on the IEEE 30-bus system. The results are also compared with those given by a conventional PSO algorithm [8], [9], as well as by the IP-OPF algorithm [23] and an EA [24] on the same system. All PSO algorithms are simply called competitors. The topology and the complete data of this network can be found in [34]. The network consists of 6 generators, 41 lines, 4 transformers, and 2 capacitor banks. In the transformer tests, tap settings are considered within the interval $[0.9, 1.1]$. The available reactive powers of capacitor banks are within the interval $[0, 30]$ MVAr, and they are connected to buses 10 and 24. Voltages are considered within the range of $[0.95, 1.1]$. In this case, the decision space has 12 dimensions, namely, the 6 generator voltages, 4 transformer taps, and 2 capacitor banks. The parameters of PSO algorithms are those, which lead them faster in convergence and were selected after many runs on the test system. All parameters were selected by means of sensitivity analysis tables.

Sensitivity analysis was performed with the parameters Nr, $c_1, c_2, c_3, w_{\min}$, and $w_{\max}$ following our earlier work [25]. The average and minimum of objective functions was estimated with up to 1500 iterations in 100 trials for each competitor. The sensitivity analysis yielded the parameters in Table I as best values of random parameters for each competitor. The number of particles is 30 for all competitors.

Fig. 2 gives the convergence iterations of the competitors. The conventional PSO converges in 93 iterations, achieving the least power loss of 5.09219 MW (see Table II). The total CPU time is 3.72 s. The enhanced GPAC converges faster than the conventional PSO (in 68 iterations), achieving sub-optimal loss of 5.09226 MW (see Table II). The total CPU time of the enhanced GPAC is 3.434 s. However, LPAC and CA algorithms converge very fast in 25 and 27 iterations, respectively. The total CPU time of LPAC and CA are 1.262 and 1.365 s, respectively. Although LPAC is faster than CA, it fails in finding the global best solution achieved by CA (5.09209 MW). The IP-OPF is the fastest among all competitors (total CPU time at 0.636 s) but fails to achieve the global best. The EA in [24] converges in about 70 iterations, and its optimum solution is 5.1065 MW. The IP-OPF and EA achieve approximately the same solution. Table II gives the optimal settings of decision variables in p.u. for the reactive control of IEEE 30-bus system as proposed by competitors and the IP-OPF.

The feasibility of voltage control is also tested for the competitors. In this case, conventional PSO converges in 92 iterations (see Fig. 3), achieving voltage deviation of 0.13029 p.u.

TABLE I
Parameters of PSO Algorithms on IEEE 30-Bus System

Parameter	Conventional PSO	GPAC	LPAC	CA
c_1	2.05	2.10	2.10	-
c_2	2.00	2.05	2.10	-
c_3	-	1.10	2.00	-
w_{min}	0.1	0.7	0.1	0.1
w_{max}	1.0	0.9	0.9	1.0
Nr	15	15	15	15

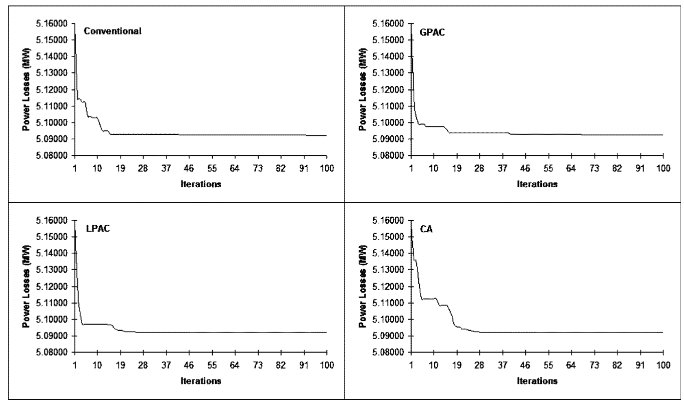

Fig. 2. PSO algorithms for reactive power control of IEEE 30-bus system.

TABLE II
Results of PSO and IP-OPF Algorithms in Reactive Power Control of IEEE 30-Bus System

Decision / Objective	Conventional PSO	GPAC	LPAC	CA	IP-OPF
V_{G1}	1.01775	1.02942	1.02342	1.02282	1.10000
V_{G2}	1.02458	1.00645	0.99893	1.09093	1.05414
V_{G5}	1.02466	1.01692	0.99469	1.03008	1.10000
V_{G8}	1.01421	1.03798	1.01364	0.95000	1.03348
V_{G11}	1.01717	1.03952	1.01647	1.04289	1.10000
V_{G13}	0.99613	1.04870	1.01101	1.03921	1.01497
T_{6-9}	1.09699	1.04225	1.04247	1.07894	0.99334
T_{6-10}	0.92509	0.99417	0.99432	0.94276	1.05938
T_{4-12}	1.00048	1.00218	1.00061	1.00064	1.00879
T_{27-28}	1.00714	1.00751	1.00694	1.00693	0.99712
Q_{C10}	0.15365	0.17267	0.17737	0.15232	0.15253
Q_{C24}	0.06220	0.06539	0.06172	0.06249	0.08926
P_{Loss} (MW)	5.09219	5.09226	5.09212	5.09209	5.10091
Achieved iteration	93	68	25	27	5
Total CPU time (s)	3.720	3.434	1.262	1.365	0.636

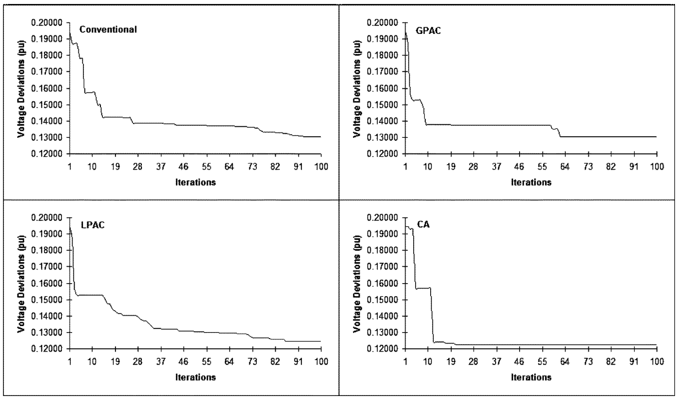

Fig. 3. PSO algorithms for voltage control of IEEE 30-bus system.

TABLE III
RESULTS OF PSO AND IP-OPF ALGORITHMS IN VOLTAGE CONTROL OF IEEE 30-BUS SYSTEM

Decision/ Objective	Conventional PSO	GPAC	LPAC	CA	IP-OPF
V_{G1}	0.98482	1.00963	1.03879	1.0890	1.10000
V_{G2}	0.97057	1.00984	1.01776	0.9500	0.99100
V_{G5}	1.07144	1.01000	1.04863	1.0860	0.96145
V_{G8}	1.03448	1.03516	1.04993	1.1000	0.95986
V_{G11}	0.96837	1.03000	0.98373	1.0021	1.10000
V_{G13}	0.99586	1.00274	1.00524	1.0279	0.95000
T_{6-9}	1.03287	1.02139	1.03054	1.0287	0.99734
T_{6-10}	0.95369	0.93327	0.91429	0.9000	1.08595
T_{4-12}	0.99560	0.99338	0.99469	0.9929	1.00087
T_{27-28}	1.01759	1.02729	1.02078	1.0248	1.00482
Q_{C10}	0.06750	0.04348	0.00000	0.0000	0.11072
Q_{C24}	0.04729	0.00000	0.03586	0.0000	0.15928
VD	0.13029	0.12737	0.12401	0.12252	0.17328
Achieved iteration	92	79	98	21	7
Total CPU time (s)	3.680	3.989	4.949	1.064	0.890

(see Table III). The total CPU time is 3.68 s. GPAC and LPAC converge in 79 and 98 iterations, respectively (see Fig. 3). The total CPU time of the enhanced GPAC and LPAC are 3.989 and 4.949 s, respectively. Although their convergence time is bigger than the conventional PSO, they find better results, achieving 0.12737 and 0.12401 p.u., respectively.

Comparing these results, LPAC finds better results than the conventional PSO and the enhanced GPAC but takes more time to converge. On the contrary, CA finds the global optimum solution achieving 0.12252 p.u. (see Table III) in a very short time (only 21 iterations). The total CPU time of CA is 1.064 s. The IP-OPF is the fastest of all competitors (total CPU time at 0.89 s) but fails to achieve the global best solution. It actually achieves the worst solution of 0.17328 p.u. The EA in [24] converges in about 110 iterations, and its optimum solution is 0.1477 p.u., which is much better than the classical IP-OPF. The final optimal settings of decision variables in p.u. as proposed by competitors are given in Table III.

Comparing the results given in the reactive power control problem as well as in the voltage control problem, the best performance of the CA is concluded among all competitors. In both problems, CA achieves the global optimal solution in a very few iterations, up to 30 within a total CPU time of 1.365 and 1.064 s, respectively.

TABLE IV
PARAMETERS OF PSO ALGORITHMS ON IEEE 118-BUS SYSTEM

Parameter	Conventional PSO	GPAC	LPAC	CA
c_1	2.10	2.05	2.05	-
c_2	2.10	2.05	2.05	-
c_3	-	1.20	2.00	-
w_{min}	0.1	0.1	0.1	0.1
w_{max}	1.0	0.9	1.0	1.0
Nr	20	20	20	20

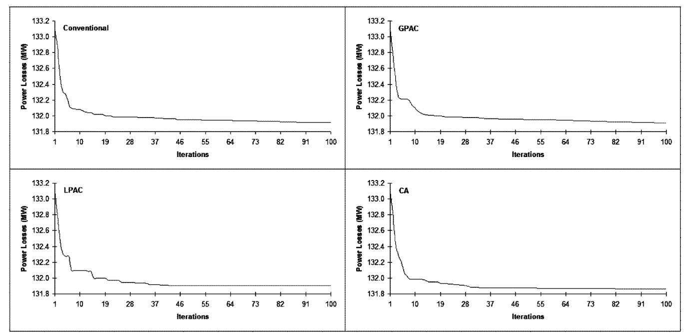

Fig. 4. PSO algorithms for reactive power control of IEEE 118-bus system.

B. IEEE 118-Bus System

In this section, the competition of PSO algorithms is moved to a larger test system such as the IEEE 118-bus [35]. In this case, the decision space has 75 dimensions. The network consists of 54 generators, 9 transformers, 12 capacitor banks, and 186 lines. In the transformer tests, tap settings are considered within the interval $[0.9, 1.1]$. The available reactive powers of capacitor banks are within the range of $[0, 30]$ MVAr. Voltages are considered within the range of $[0.95, 1.1]$. The parameters of competitors are given in Table IV. The number of particles is 30 for all competitors. The sensitivity analysis is performed for each one of the competitors on the IEEE 118-bus system.

In the case study for reactive power control, Fig. 4 gives the convergence iterations of competitors. Conventional PSO and the enhanced GPAC converge in 93 and 89 iterations achieving 131.91469 and 131.90834 MW, respectively. The total CPU time of the conventional PSO and the enhanced GPAC are 26.04 and 28.09 s, respectively. However, LPAC and CA converge faster: in 43 and 71 iterations, respectively, achieving better results. The total CPU time of LPAC and CA are 13.572 and 22.453 s, respectively. Although LPAC is faster than CA, it achieves sub-optimal solution of 131.90104 MW while CA achieves the global optimal solution of 131.86385 MW. The IP-OPF is the fastest algorithm since it converges within 11.873 s. However, it gives the worst solution of 132.1097 MW. So, the difference in power losses between IP-OPF and CA (the best of the proposed competitors) is about 0.25 MW and with GPAC (the worst of the proposed competitors) is 0.20 MW (see Table V). So the proposed PSO offers an improvement of 0.15% higher than the widely recognized IP-OPF. Due to the space limitation, Table V presents the final optimal settings

TABLE V
RESULTS OF PSO AND IP-OPF ALGORITHMS IN REACTIVE POWER CONTROL OF IEEE 118-BUS SYSTEM

Decision / Objective	Conventional PSO	GPAC	LPAC	CA	IP-OPF
V_{G1}	1.00997	1.07183	1.01687	1.02433	0.95500
V_{G4}	1.03899	0.99734	1.05270	1.01117	0.99800
V_{G34}	1.03325	1.03031	1.01955	1.01595	0.98400
V_{G65}	1.02210	1.02626	1.04786	1.00494	1.00500
V_{G92}	1.05364	1.02712	1.04645	1.05149	0.99000
V_{G113}	0.99132	1.07186	0.99906	1.03860	0.99300
T_{8-5}	0.99786	0.99561	0.99133	0.99435	0.99726
T_{26-25}	1.09041	1.09048	1.10000	1.10000	1.02806
T_{30-17}	1.01243	1.01258	1.01476	1.01238	1.01440
T_{68-69}	0.92064	0.93099	0.91905	0.93057	0.92988
T_{81-80}	0.95415	0.95940	0.95797	0.95945	1.00317
Q_{C34}	0.18757	0.23130	0.20304	0.26978	0.18699
Q_{C48}	0.14560	0.22609	0.13747	0.10773	0.15299
Q_{C74}	0.17504	0.20603	0.26237	0.30000	0.20441
Q_{C110}	0.14891	0.23381	0.13298	0.15823	0.16283
P_{Loss} (MW)	131.9146	131.9083	131.9010	131.8638	132.1097
Achieved iteration	93	89	43	71	8
Total CPU time (s)	26.040	28.090	13.572	22.453	11.873

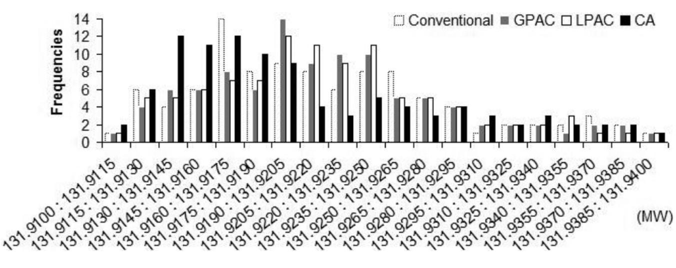

Fig. 5. Statistical results of competitors (100 trials) for power losses on IEEE 118-bus system.

TABLE VI
MINIMUM, AVERAGE, AND MAXIMUM VALUES OF OBJECTIVE FUNCTION (J_1) ON IEEE 118-BUS SYSTEM (100 TRIALS)

J_1 (MW)	Conventional PSO	GPAC	LPAC	CA
Minimum	131.91469	131.90834	131.90104	131.86385
Average	131.91783	131.91448	131.90876	131.86669
Maximum	131.93974	131.92726	131.92112	131.88209

of 15 out of 75 decision variables in p.u. as proposed by the competitors.

Fig. 5 shows the statistical evaluation of results of competitors in 100 trials. The spectrum of Fig. 5 reveals that most of the obtained results are close to the minimum value of the objective function J_1 (1) for CA, while the plethora of results are close to the average values for other competitors. The maximum, average, and minimum values of the objective function J_1 (1) are shown in Table VI.

PSO algorithms are also competed in the minimization of voltage deviations on load buses of the IEEE 118-bus system. In this case study, competitors converge between 85 and 95 iterations (see Fig. 6) within the total CPU time between 25.48 and 29.984 s (see Table VII).

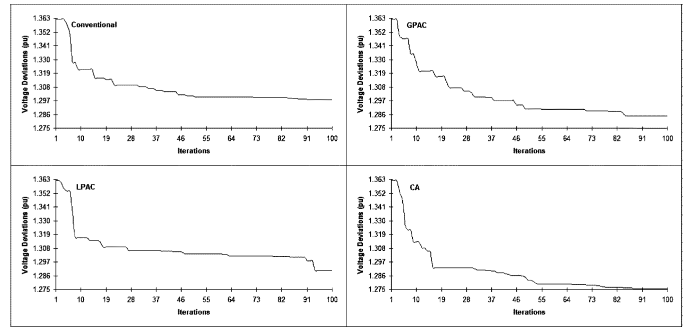

Fig. 6. PSO algorithms for voltage control of IEEE 118-bus system.

TABLE VII
RESULTS OF PSO AND IP-OPF ALGORITHMS IN VOLTAGE CONTROL OF IEEE 118-BUS SYSTEM

Decision / Objective	Conventional PSO	GPAC	LPAC	CA	IP-OPF
V_{G1}	1.00607	1.04261	1.06480	1.08477	1.04292
V_{G4}	0.99380	0.95000	1.04374	1.01488	0.99948
V_{G34}	1.04010	1.05522	1.00416	1.01101	1.01500
V_{G65}	1.07434	1.07772	1.01818	0.95000	0.98968
V_{G92}	1.03054	1.05265	1.05754	1.10000	0.98540
V_{G113}	0.98768	1.02342	0.96913	0.97463	0.98000
T_{8-5}	0.98273	0.99738	0.97877	0.98634	1.01205
T_{26-25}	0.94625	0.95184	0.98998	0.92555	0.96345
T_{30-17}	0.97344	0.96860	0.96746	0.97947	0.99290
T_{68-69}	0.94614	0.93147	0.91404	0.90000	0.94491
T_{81-80}	0.94051	0.95095	0.94855	0.94696	0.96677
Q_{C34}	0.21290	0.25216	0.18419	0.23172	0.19144
Q_{C48}	0.30000	0.21317	0.17862	0.21554	0.19588
Q_{C74}	0.10367	0.10721	0.07908	0.00000	0.14417
Q_{C110}	0.12998	0.14607	0.06590	0.25232	0.15323
VD	1.29768	1.28499	1.28891	1.27558	1.32235
Achieved iteration	91	95	85	85	11
Total CPU time (s)	25.480	29.984	26.828	26.881	16.325

The CA achieves voltage deviation of 1.27558 p.u., which is the global best, while the enhanced GPAC and LPAC achieve near optimum voltage deviations of 1.28499 and 1.28891 p.u., respectively. Although the IP-OPF is the fastest of all competitors, it achieves the worst voltage deviation of 1.32235 p.u. In all cases, the total CPU time is calculated in a 1.4-GHz Pentium-IV PC. Due to the space limitation, Table VII presents the final optimal settings of 15 out of 75 decision variables in p.u. as proposed by the competitors.

Fig. 7 shows the statistical evaluation of results of competitors in 100 trials. The spectrum of Fig. 7 reveals that most of the obtained results are close to the minimum value of the objective function J_2 (2) for CA, in contrast to other competitors where they are close to their average values. In this case study, the maximum, average, and minimum values of the objective functions J_2 (2) are shown in Table VIII.

Fig. 8 shows the compromise between the number of particles and the number of iterations for the CA algorithm for the last case study. It is concluded that the number of iterations decreases as the number of particles varies from 20 to 40. However, the rate of decrease is not appreciable when the number of particles exceeds 30. Further, the number of load flow computations

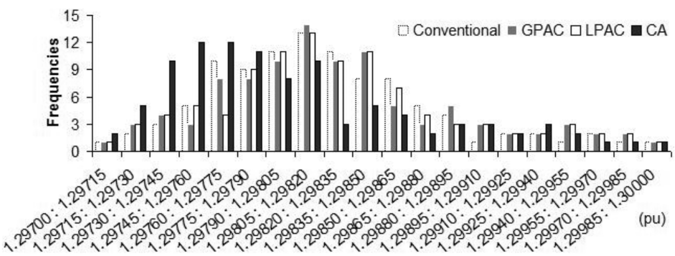

Fig. 7. Statistical results of competitors (100 trials) for voltage deviation on IEEE 118-bus system.

TABLE VIII
MINIMUM, AVERAGE, AND MAXIMUM VALUES OF OBJECTIVE FUNCTION (J_2) ON IEEE 118-BUS SYSTEM

J_2 (pu)	Conventional PSO	GPAC	LPAC	CA
Minimum	1.29768	1.28499	1.28891	1.27558
Average	1.29803	1.28854	1.29231	1.27592
Maximum	1.29988	1.29412	1.29823	1.27741

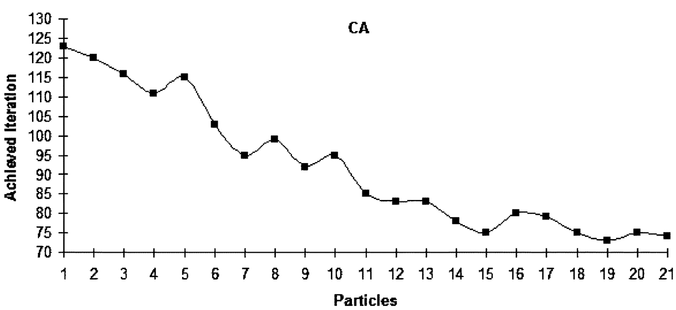

Fig. 8. Compromise between the number of particles and the number of iterations of the CA for IEEE 118-bus system.

is easily provided if the number of particles (horizontal axis) multiplied with number of achieved iteration (vertical axis).

Finally, in order to verify the achievements of competitors, in both cases, we run them over 100 iterations (say, for 1500 iterations), and we obtain an improvement over their achievements only in less than 0.01%.

VII. DISCUSSION

A comparison between the competitors was presented as well as with conventional IP-OPF. A fair comparison of competitors with IP-OPF could be done in optimization problems where their solution space is semi-smooth, such as reactive power and voltage control. The final results indicated that, even in "easy" spaces for IP-OPF, the competitors have better performance. Finally, we note that competitors are more attractive on problems with more complexities, where conventional IP-OPF fails.

The objective functions, power loss (1), and voltage deviations (2) are functions of many decision (control) variables (12 decision variables for the 30-bus system and 75 for the 118-bus system). Therefore, there are many possible combinations of decision variables that will yield almost the same values of the objective functions, yielding many local minima. Furthermore, evolutionary algorithms that are compared here are all generated by pseudo random numbers, which are different for different algorithms. The difference in control variables among algorithms is not significant in the case of loss minimization (see Tables II and V and Figs. 2 and 4) due to the possible flat nature of the objective function (1). However, it is noticeable in the case of minimization of voltage deviations (see Tables III and VII and Figs. 3 and 6) since this objective function (2) is very sensitive to the control variables.

Further, comparing all results obtained in both IEEE 30-bus and IEEE 118-bus systems, a general conclusion can be drawn that all competitors are much better in achieving better solutions than conventional IP-OPF [23] and an EA algorithm [24]. However, the main drawbacks of competitors compared to the conventional IP-OPF [23] are the computing time and the handling of discrete variables. Fortunately, the rapid progress of computer systems will soon overcome the issue of convergence time. In addition, recent studies have attempted to enforce PSO to discrete optimization problems [36]–[38].

Obviously, the two examined problems, though different, have several local minima, much more for the voltage deviation minimization. In such complex problems, the conventional OPF techniques are susceptible to be trapped in local minima, and the solution obtained will not be the optimal one. In general, the IP-OPF techniques suffer from bad initial condition, termination condition, and optimality criteria, and in most cases are unable to solve nonlinear quadratic objective functions [13], [39].

Observing the results given in this paper, the conventional PSO algorithm [8], [9] is shown to be more efficient than the IP-OPF [23] in finding optimal solutions. This is also confirmed by a recent work, presented in [9], where the IP-OPF technique [23] and a genetic algorithm were compared with a hybrid PSO algorithm (called the conventional PSO in this paper).

In addition, the comparison between all competitors demonstrates the improved performance of LPAC over the enhanced GPAC. However, in most of the cases, the enhanced GPAC is much better than the conventional PSO. Regarding CA, it has an excellent performance in finding the global best solution in a comparable computing time with other competitors. The main advantages of the CA over all other competitors are: 1) it optimally manipulates the swarm by regulating only three empirical parameters, namely, the limits of inertia weighting factor $(w_{\max}, w_{\min})$ and the chosen number of search intervals Nr. The enhanced GPAC and LPAC regulate six empirical parameters ($w_{\min}$, $w_{\max}$, Nr, c_1, c_2, and c_3), and the conventional PSO regulates five ($w_{\min}$, $w_{\max}$, Nr, c_1, and c_2), and 2) it takes into account much more coordinators for the swarm's manipulation than the conventional PSO and the enhanced GPAC and LPAC (to be specific, the conventional PSO considers only two coordinators, namely, the best position a particle has ever encountered and the global/local best in the swarm, while in the enhanced GPAC and LPAC, only one more, namely, the passive congregator, is added), and 3) it adopts a stochastic coordination for the manipulation of swarm similar to the craziness concept [1]. These advantages provide the CA more possibilities than the conventional and passive congregated PSO, in exploring the decision space around local minima and escaping from them.

VIII. Conclusions

This paper proposed three types of PSO algorithms: the enhanced GPAC and LPAC with constriction factor approach based on the passive congregation operator and the CA based on the coordinated aggregation operator. The proposed PSO algorithms as well as the state-of-the-art PSO and the conventional interior-point OPF-based algorithm competed in the optimization problems of reactive power and voltage control. The results obtained in IEEE 30-bus and IEEE 118-bus systems indicated an improved performance of LPAC and an excellent performance of CA. The CA achieves the global optimum solution and exhibits better convergence characteristics, regulating the fewest random parameters than others. However, its main drawback remains the computing time. For future research, the feasibility of the enhanced GPAC, LPAC, and CA in more nonlinear optimization problems in power systems with harder constraints, non-differentiable functions, and non-convex decision space can be studied. Moreover, other types of CA can be implemented, where, for instance, the number of leader particles, which move randomly, could be more than one. Other more optimal processes can be used in choosing the number of coordinators for each particle in CA, such as resemblance coefficients process, in order to reduce the computing time.

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