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Comparative analysis of PSO variants for Voltage control and Loss minimization

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Abstract— **In this paper, two variants of particle swarm optimization (PSO) algorithms namely Coordinated Aggregation PSO (CAPSO) and Adaptive PSO (APSO) are compared with the conventional PSO algorithms for the optimal steady-state performance of power system. The proposed methods are used for loss minimization and voltage control. Simulation results of standard IEEE 30 test system is presented to illustrate the effectiveness of the proposed approaches under simulated conditions.**

Index Terms— **Coordinated aggregation (CA), particle swarm optimization (PSO), Adaptive particle swarm optimization (APSO).**

I. INTRODUCTION

The Optimal Power Flow (OPF) is an important criterion in today's power system operation and control due to scarcity of energy resources, increasing power generation cost and ever growing demand for electric energy. As the size of the power system increases, load may be varying. The generators should share the total demand plus losses among themselves. The sharing should be based on the fuel cost of the total generation with respect to some security constraints. The security constraints are real and reactive power generation limits, tap changing transformers line flow limits. Since the dependence each generator fuel cost on the load it supplies, the objective of the OPF algorithm is to allocate the total electric power demand and losses among the available generators in such a manner, that it minimizes the electric utility's total fuel cost while satisfying the security constraints. But it is very difficult task considering all the constraints.

Natural creatures sometimes behave as a swarm. One of the main streams of artificial life research is to examine how natural creatures behave as a swarm and reconfigure the swarm models inside a computer. Reynolds developed boid as a swarm model with simple rules and generated complicated swarm behavior by computer graphic animation. Boyd and Richerson examined the decision process of human beings and developed the concept of individual learning and cultural transmission. According to their examination, human beings make decisions using their own experiences and other persons' experiences [1].

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A new optimization technique using an analogy of swarm behavior of natural creatures was started in the beginning of the 1990s. Dorigo developed ant colony optimization (ACO) based mainly on the social insect, especially ant, metaphor [2]. Each individual exchanges information through pheromones implicitly in ACO. Eberhart and Kennedy developed particle swarm optimization (PSO) based on the analogy of swarms of birds and fish schooling. Each individual exchanges previous experiences in PSO. These research efforts are called swarm intelligence [1].

In the recent years, the effort is continued by the same and other researchers [3-5] generating more effective EAs. The reason for the growing development of EA is that conventional optimization methods have failed in handling non-convexities and non-smoothness in engineering optimization problems [6]. However, their main problem remains the same, achieving the global best solution in the possible shortest time.

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 non-linear optimization problems faster and with better accuracy in detecting the global best solution. In this paper, the APSO, and CA are applied in two nonlinear optimization problems of power systems, namely, the loss minimization and voltage control problems. The results obtained are compared with conventional PSO algorithm for demonstrating improved performance of the proposed algorithms.

II. PARTICLE SWARM OPTIMIZATION

Swarm behavior can be modeled with a few simple rules. Schools of fishes and swarms of birds can be modeled with such simple models. Namely, even if the behavior rules of each individual (agent) are simple, the behavior of the swarm can be complicated. Reynolds utilized the following three vectors as simple rules in the researches on boid.

- Step away from the nearest agent
- Go toward the destination
- Go to the center of the swarm

The behavior of each agent inside the swarm can be modeled with simple vectors. The research results are one of the basic backgrounds of PSO.

Each agent decides its decision using its own experiences and the experiences of others. The research results are also one of the basic background elements of PSO. According to the above background of PSO, Kennedy and Eberhart developed PSO through simulation of bird flocking in a two-dimensional space. The position of each agent is represented by its x, y axis position and also its velocity is expressed by vx (the velocity of x axis) and vy (the velocity of y axis). Modification of the agent position is realized by the position and velocity information.

Bird flocking optimizes a certain objective function. Each agent knows its best value so far (pbest) and its x, y position. This information is an analogy of the personal experiences of each agent. Moreover, each agent knows the best value so far in the group (gbest) among pbests. This information is an analogy of the knowledge of how the other agents around them have performed. Each agent tries to modify its position using the following information:

- The current positions (x, y)
- The current velocities (vx, vy),
- The distance between the current position and pbest
- The distance between the current position and gbest
- This modification can be represented by the concept of velocity (modified value for the current positions). Velocity of each agent can be modified by the following equation:

$$v_i^{k+1} = wv_i^k + c_1 rand_1 * (pbest_i - s_i^k) + c_2 rand_2 * (gbest - s_i^k) \quad (1)$$

where v_i^k is velocity of agent i at iteration k, w is weighting function, c1 and c2 are weighting factors, rand1 and rand2 are random numbers between 0 and 1, s_i^k is current position of agent i at iteration k, $pbest_i$ is the pbest of agent i, and gbest is gbest of the group. Namely, velocity of an agent can be changed using three vectors such like boid. The velocity is usually limited to a certain maximum value. PSO using (1) is called the Gbest model.

$$w = w_{max} - ((w_{max} - w_{min})/(iter_{max})) * iter \quad (2)$$

The following weighting function is usually utilized in (1): Where w_{max} is the initial weight, w_{min} is the final weight, $iter_{max}$ is maximum iteration number and iter is current iteration number.

The RHS of (1) consists of three terms (vectors). The first term is the previous velocity of the agent. The second and third terms are utilized to change the velocity of the agent. Without the second and third terms, the agent will keep on "flying" in the same direction until it hits the boundary. As shown below, for example, w_{max} and w_{min} are set to 0.9 and 0.4. Therefore, at the beginning of the search procedure, diversification is heavily weighted, while intensification is heavily weighted at the end of the search procedure such like simulated annealing (SA). Namely, a certain velocity, which gradually gets close to pbests and gbest, can be calculated. PSO using (1), (2) is called inertia weights approach (IWA).

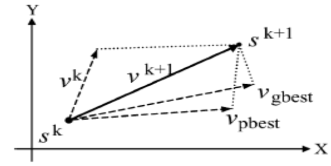


Figure 1: concept of modifications of a searching point by PSO

s^k : current searching point

s^{k+1} : modified searching point

v^k : current velocity

v^{k+1} : modified velocity

v_{pbest} : velocity based on pbest

v_{gbest} : velocity based on gbest

The current position (searching point in the solution space) can be modified by the following equation:

$$s_i^{k+1} = s_i^k + v_i^{k+1} \quad (3)$$

Figure 1 shows a concept of modification of a searching point by PSO, and Fig. 1 shows a searching concept with agents in a solution space. Each agent changes its current position using the integration of vectors as shown in Fig. 1.

III. PSO VARIANTS

A. *Coordinated Aggregation-based PSO*

The basic system equation of PSO [(1), (2), and (3)] can be considered as a kind of difference equation. Therefore, the system dynamics, that is, the search procedure, can be analyzed using eigen values of the difference equation. Actually, using a simplified state equation of PSO, Clerc and Kennedy developed CA of PSO by eigen values [8, 14]. The velocity of the constriction factor approach (simplest constriction) can be expressed as follows instead of (1) and (2):

$$v_i^{k+1} = K[v_i^k + c_1 * rand_1 * (pbest_i - s_i^k) + c_2 * rand_2 (gbest - s_i^k)] \quad (4)$$

Where

$$K = \frac{2}{2 - \varphi - \sqrt{\varphi^2 - 4\varphi}}, \text{ where } \varphi = c_1 + c_2, \varphi > 4 \ldots\ldots (5)$$

where φ and K are coefficients.

For example, if φ =4.1, then K = 0.73. As w increases above 4.0, K gets smaller.For example, if φ=5.0, then K =0.38, and the damping effect is even more pronounced. The convergence characteristic of the system can be controlled by w. The whole PSO algorithms by IWA and CA are the same except that CA utilizes a different equation for calculation of velocity [(4) and (5)]. Unlike other EC methods, PSO with CA ensures the convergence of the search procedures based on mathematical theory. PSO with CA can generate higher-quality solutions for some problems than PSO with IWA. However, CA only considers dynamic behavior of only one agent and studies on the effect of the interaction among agents.

B. *Adaptive PSO*

The following points are improved to the original PSO with IWA.

- The search trajectory of PSO can be controlled by introducing the new parameters (P1, P2) based on the probability to move close to the position of (pbest, gbest) at the following iteration.
- The wv_i^k term of (1) is modified as (7). Using the equation, the center of the range of particle movements can be equal to gbest.
- When the agent becomes gbest, it is perturbed. The new parameters (P1, P2) of the agent are adjusted so that the agent may move away from the position of (pbest, gbest).
- When the agent is moved beyond the boundary of feasible regions, pbests and gbest cannot be modified.
- When the agent is moved beyond the boundary of feasible regions, the new parameters (P1, P2) of the agent are adjusted so that the agent may move close to the position of (pbest, gbest).

The new parameters are set to each agent. The weighting coefficients are calculated as follows:

$$c_2 = \frac{2}{P_1}, \quad c_1 = \frac{2}{P_2} - c_2 \qquad (6)$$

The search trajectory of PSO can be controlled by the parameters (P_1, P_2). Concretely, when the value is enlarged more than 0.5, the agent may move close to the position of pbest/gbest.

$$w = gbest - \left(\{c_1(pbest - x) + c_2(gbest - x)\}/2 + x\right) \quad (7)$$

Namely, the velocity of the improved PSO can be expressed as follows:

$$v_i^{k+1} = w_i + c_1 rand_1 * (pbest_i - s_i^k) \quad + c_2 rand_2 * (gbest - s_i^k) \qquad (8)$$

The improved PSO can be expressed as follows (steps 1 and 5 are the same as PSO):

- ***Generation of initial searching points***: Basic procedures are the same as PSO. In addition, the parameters (P1, P2) of each agent are set to 0.5 or higher. Then, each agent may move close to the position of (pbest, gbest) at the following iteration.
- ***Evaluation of searching points***: The procedure is the same as PSO. In addition, when the agent becomes gbest, it is perturbed. The parameters (P_1, P_2) of the agent are adjusted to 0.5 or lower so that the agent may move away from the position of (pbest, gbest).
- ***Modification of searching points***: The current searching points are modified using the state equations (7), (3) of adaptive PSO.

IV. PROBLEM FORMULATION

The OPF problem is to optimize the steady state performance of a power system in terms of an objective function while satisfying several equality and inequality constraints. Mathematically, the OPF problem can be formulated as given

$$\text{Min } F(x,u) \qquad (9)$$

$$\text{Subject to } g(x,u) = 0 \qquad (10)$$

$$h(x,u) \le 0 \qquad (11)$$

where *x* is a vector of dependent variables consisting of slack bus power P_{G_1}, load bus voltages V_L, generator reactive power outputs Q_G, and the transmission line loadings S_l, Hence, *x* can be expressed as given

$$x^T = [P_{G_1}, V_{L_1} ... V_{L_{NL}}, Q_{G_1} ... Q_{G_{NG}}, S_l ... S_{l_{nl}}] \quad (12)$$

where *NL, NG* and *nl* are number of load buses, number of generators and number of transmission line respectively.

u is the vector of independent variables consisting of generator voltages V_G, generator real power outputs P_G except at the slack bus P_{G_1}, transformer tap settings *T*, and shunt VAR compensations Q_C. Hence *u* can be expressed as given

$$u^T = [V_{G_1} ... V_{G_{NG}}, P_{G_2} ... P_{G_{NG}}, T_1 ... T_{NT}, Q_{C_1} ... Q_{C_{NC}}] \quad (13)$$

Where *NT* and *NC* are the number of the regulating transformers and shunt compensators, respectively. *F* is the objective function to be minimized. g is the equality constraints that represents typical load flow equations and *h* is the system operating constraints

1) Objective functions

In this paper, the objective(s)(J) is the objective function to be minimized, which is one of the following:

(i) Objective function-1 (Loss Minimization)

The optimal reactive power flow problem to minimize active losses can be formulated as

$$J_1 = P_{Loss}(x,u) = \sum_{i=1}^{nl} P_l \qquad (14)$$

where x is the vector of depended variables, 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.

(ii) Objective function-2 (Voltage Control)

Voltage profile is one of the quality measures for power system. It can be improved by minimizing the load bus voltage deviations from 1.0 per unit. The objective function can be expressed as

$$J_2 = \sum_{i=1}^{NL} \left| V_i - V_i^{sp} \right| \qquad (15)$$

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 NL is the number of load buses.

2) Equality constraints

The equality constraints of the OPF reflect the physics of the Power System as well as the desired voltage set points throughout the system. The physics of the Power System are enforced through the power flow equations which require that the net injection of real and reactive power at each bus sum to zero

$$P_{Gi} - P_{Di} - \sum_{j=1}^{n} |V_i||V_j||Y_{ij}| \cos(\theta_{ij} - \delta_i + \delta_j) = 0$$

$$Q_{Gi} - Q_{Di} + \sum_{j=1}^{n} |V_i||V_j||Y_{ij}| \sin(\theta_{ij} - \delta_i + \delta_j) = 0 \qquad (16)$$

where P_{Gi} and Q_{Gi} are the real and reactive power outputs injected at bus- i respectively, the load demand at the same bus is represented by P_{Di} and Q_{Di}, and elements of the bus admittance matrix are represented by $|Y_{ij}|$ and θ_{ij}.

3) Inequality constraints

The inequality constraints of the OPF reflect the limits on physical devices in the Power System as well as the limits created to ensure system security. This section will lay out all the necessary inequality constraints needed for the OPF implemented in this thesis.

1) Generators real and reactive power outputs

$$P_{Gi}^{\min} \le P_{Gi} \le P_{Gi}^{\max}, i = 1, \ldots, N_G$$
$$Q_{Gi}^{\min} \le Q_{Gi} \le Q_{Gi}^{\max}, i = 1, \ldots, N_G \quad (17)$$

2) Voltage magnitudes at each bus in the network

$$V_i^{\min} \le V_i \le V_i^{\max}, i = 1, \ldots, NL \quad (18)$$

3) Transformer tap settings

$$T_i^{\min} \le T_i \le T_i^{\max}, i = 1, \ldots, N \quad (19)$$

4) Reactive power injections due to capacitor banks

$$Q_{Ci}^{\min} \le Q_{Ci} \le Q_{Ci}^{\max}, i = 1, \ldots, S \quad (20)$$

5) Transmission lines loading

$$S_i \le S_i^{\max}, i = 1, \ldots, N \quad (21)$$

V. PERFORMANCE EVALUATION

The main focus of this paper is the comparison of the two alternative PSO algorithms with the conventional PSO algorithm. Specifically, they need to handle two optimization problems, namely, minimization of 1) real power losses in transmission lines (Reactive Power Control) and 2) voltage deviation on load buses (Voltage control). 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.

To verify the feasibility of the proposed PSO algorithms (PSO, CAPSO and APSO) in the Loss minimization and voltage control, they are applied on the IEEE 30-bus system. The results are also compared with conventional PSO algorithm. All PSO algorithms are simply called competitors. The topology and the complete data of this network can be found in [20]. 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]. Voltages are considered within the range of [0.95,1.1].

C. *Results with Loss minimization objective*

TABLE -I Optimal control variable setting for Loss minimization objective

Control Variables	Min	Max	PSO	CAPSO	APSO
P_1	50	200	80.69	77.33	77.16
P_2	20	80	80.00	80.00	80.00
P_5	15	50	50.00	50.00	50.00
P_8	10	30	30.00	30.00	30.00
P_{11}	12	40	12.00	40.00	40.00
P_{13}	10	35	35.00	10.00	10.00
V_1	0.95	1.10	1.0673	1.0593	1.0681
V_2	0.95	1.10	1.0599	1.0528	1.0641
V_5	0.95	1.10	1.0383	1.0321	1.0453
V_8	0.95	1.10	1.0409	1.0357	1.0672
V_{11}	0.95	1.10	1.0456	0.9728	1.0409
V_{13}	0.95	1.10	1.0332	1.0609	1.0323
T_{11}	0.90	1.10	0.9661	0.9750	1.0111
T_{12}	0.90	1.10	1.1000	1.0116	0.9841
T_{15}	0.90	1.10	0.9739	1.1000	0.9595
T_{36}	0.90	1.10	1.0117	0.9863	0.9809
Q_{C10}	0.00	0.10	0.1000	0.0596	0.0176
Q_{C12}	0.00	0.10	0.1000	0.0319	0.0596
Q_{C15}	0.00	0.10	0.0577	0.0532	0.0552
Q_{C17}	0.00	0.10	0.0677	0.0733	0.0705
Q_{C20}	0.00	0.10	0.0368	0.0440	0.0414
Q_{C21}	0.00	0.10	0.0978	0.1000	0.1000
Q_{C23}	0.00	0.10	0.0179	0.0000	0.0254
Q_{C24}	0.00	0.10	0.0663	0.0873	0.0662
Q_{C29}	0.00	0.10	0.1000	0.0000	0.0314
Cost($/h)			924.2717	932.8452	932.4037
Voltage Deviation			0.8649	0.4042	0.9952
Ploss (MW)			**4.29**	**3.93**	**3.76**

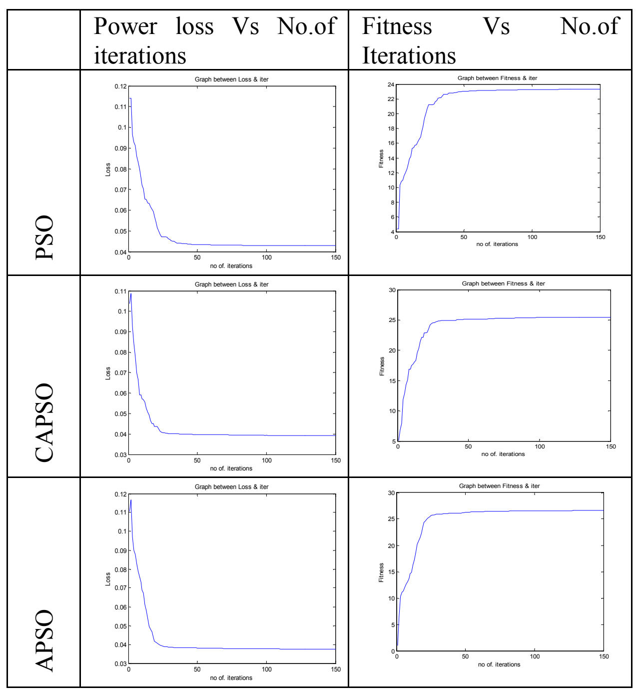


Figure 2 Convergence characteristics of PSO, CAPSO

Table 1 shows the optimal setting of control variables for loss minimization objective. From Table 1, Power loss using APSO is 3.76MW which is less than 3.93MW using CAPSO and 4.29MW using conventional PSO.

Figure 2 shows the graphs plotted between Power loss vs iterations and Fitness variation for PSO, CAPSO and APSO algorithms for IEEE-30 bus system respectively.

D. *Results for Voltage Control objective*

Table 2 shows the optimal setting of control variables for voltage deviation minimization objective. From Table 2, Voltage deviation using APSO is 0.0745 p.u which is less than 0.0764 p.u. using CAPSO and 0.0794 p.u. using conventional PSO.

Figure 3 shows the graphs plotted between Voltage deviation Vs iterations and Fitness variation for PSO, CAPSO and APSO algorithms for IEEE-30 bus system respectively.

Table 2 shows the optimal setting of control variables for voltage deviation minimization objective. From Table 2, Voltage deviation using APSO is 0.0745 p.u which is less than 0.0764 p.u. using CAPSO and 0.0794 p.u. using conventional PSO.

Figure 3 shows the graphs plotted between Voltage deviation Vs iterations and Fitness variation for PSO, CAPSO and APSO algorithms for IEEE-30 bus system respectively

TABLE –II
OPTIMAL CONTROL VARIABLE SETTING FOR VOLTAGE DEVIATION MINIMIZATION OBJECTIVE

Control Variables	**Min Limit**	**Max Limit**	**PSO**	**CAPSO**	**APSO**
P_1	50	200	150.31	177.86	144.90
P_2	20	80	47.94	57.27	61.28
P_5	15	50	19.72	17.09	30.61
P_8	10	30	24.82	20.98	30.00
P_{11}	12	40	23.35	12.00	12.00
P_{13}	10	35	26.03	17.09	13.34
V_1	0.95	1.10	1.0089	0.9945	0.9978
V_2	0.95	1.10	1.0126	1.0041	0.9982
V_5	0.95	1.10	1.0171	1.0165	1.0155
V_8	0.95	1.10	0.9977	1.0025	1.0053
V_{11}	0.95	1.10	1.0323	1.0109	1.0221
V_{13}	0.95	1.10	0.9847	1.0271	1.0232
T_{11}	0.90	1.10	1.0422	1.0155	1.0334
T_{12}	0.90	1.10	0.9960	0.9842	0.9831
T_{15}	0.90	1.10	0.9504	1.0238	1.0083
T_{36}	0.90	1.10	0.9701	0.9853	0.9748
Q_{C10}	0.00	0.10	0.0657	0.0548	0.0542
Q_{C12}	0.00	0.10	0.0394	0.0495	0.0109
Q_{C15}	0.00	0.10	0.0443	0.0561	0.0421
Q_{C17}	0.00	0.10	0.0382	0.0315	0.0291
Q_{C20}	0.00	0.10	0.1000	0.0780	0.1000
Q_{C21}	0.00	0.10	0.1000	0.0896	0.0893
Q_{C23}	0.00	0.10	0.0484	0.0372	0.0411
Q_{C24}	0.00	0.10	0.0861	0.1000	0.0999
Q_{C29}	0.00	0.10	0.0282	0.0449	0.0263
Cost($/h)			818.0057	811.2806	819.7407
Voltage Deviation			**0.0794**	**0.0761**	**0.0745**
Ploss (MW)			0.1229	0.0847	0.1158

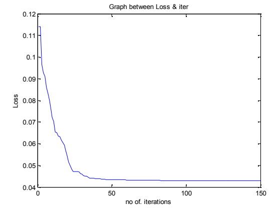
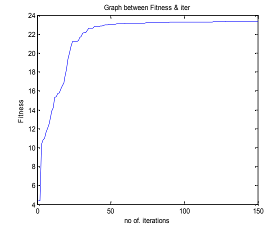
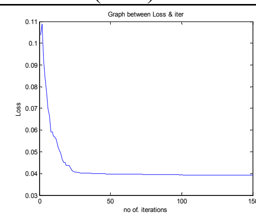
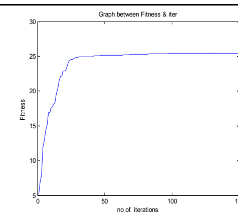
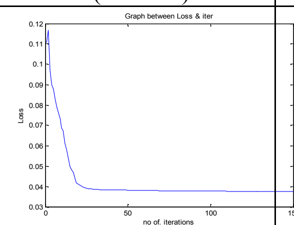
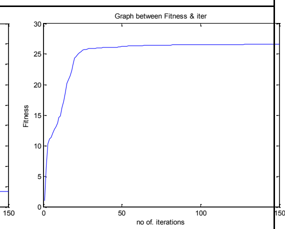
	Voltage Deviation Vs No.of iterations	Fitness Vs No.of Iterations
PSO	 Voltage Deviation variation(PSO)	
CAPSO	 Voltage Deviation variation(CAPSO)	
APSO	 Voltage Deviation variation(APSO)	

Figure 3 Convergence characteristics of PSO, CAPSO and APSO for Voltage control objective

CONCLUSIONS

This paper proposed PSO variants such as Coordinated Aggregation PSO (CAPSO) and Adaptive PSO (APSO) The proposed PSO algorithms competed in the optimization problems of Power loss minimization and Voltage control problems. The results of the proposed CAPSO and APSO methods for different objective functions are compared with conventional PSO method to show the effectiveness of the proposed algorithms. Proposed algorithms been applied to IEEE-30 bus system and observed APSO outperforms the CA and Conventional PSO.

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