Particle Swarm Optimization with Constriction Factor for Optimal Reactive Power Dispatch

Vo Ngoc Dieu, Le Anh Dung, and Nguyen Phuc Khai

Abstract— *This paper proposes a simple particle swarm optimization with constriction factor (PSO-CF) method for solving optimal reactive power dispatch (ORPD) problem. The proposed PSO-CF is the conventional particle swarm optimization based on constriction factor which can deal with different objectives of the problem such as minimizing the real power losses, improving the voltage profile, and enhancing the voltage stability and properly handle various constraints for reactive power limits of generators and switchable capacitor banks, bus voltage limits, tap changer limits for transformers, and transmission line limits. The proposed method has been tested on the IEEE 30-bus and IEEE 118-bus systems and the obtained results are compared to those from other PSO variants and other methods in the literature. The result comparison has shown that the proposed method can obtain total power loss, voltage deviation or voltage stability index less than the others for the considered cases. Therefore, the proposed PSO-CF can be favorable solving the ORPD problem.*

Keywords— **Constriction factor, optimal reactive power dispatch, particle swarm optimization, voltage deviation, voltage stability index.**

NOMENCLATURE

G_{ij}, B_{ij}	Transfer conductance and susceptance between bus *i* and bus *j*, respectively
g_l	Conductance of branch *l* connecting between buses *i* and *j*
L_i	Voltage stability index at load bus *i*
N_b	Number of buses
N_d	Number of load buses
N_g	Number of generating units
N_l	Number of transmission lines
N_t	Number of transformer with tap changing
P_{di}, Q_{di}	Real and reactive load demand at bus *i*, respectively
P_{gi}, Q_{gi}	Real and reactive power outputs of generating unit *i*, respectively
Q_{ci}	Reactive power compensator at bus *i*
S_l	Apparent power flow in transmission line *l* connecting between bus *i* and bus *j*
T_k	Tap-setting of transformer branch *k*
V_{gi}	Voltage at generation bus *i*
V_{gi}, V_{li}	Voltage magnitude at generation bus *i* and load bus *i*, respectively
V_i, δ_i	Voltage magnitude and angle at bus *i*, respectively

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1. INTRODUCTION

Optimal reactive power dispatch (ORPD) is to determine the control variables such as generator voltage magnitudes, switchable VAR compensators, and transformer tap setting so that the objective function of the problem is minimized while satisfying the unit and system constraints [1]. In the ORPD problem, the objective can be total power loss, voltage deviation at load buses for voltage profile improvement [2], or voltage stability index for voltage stability enhancement [3]. ORPD is a complex and large-scale optimization problem with nonlinear objective and constraints. In power system operation, the major role of ORPD is to maintain the load bus voltages within their limits for providing high quality of services to consumers.

The problem has been solved by various techniques ranging from conventional methods to artificial intelligence based methods. Several conventional methods have been applied for solving the problem such as linear programming (LP) [4], mixed integer programming (MIP) [5], interior point method (IPM) [6], dynamic programming (DP) [7], and quadratic programming (QP) [8]. These methods are based on successive linearizations and use gradient as search directions. The conventional optimization methods can properly deal with the optimization problems of deterministic quadratic objective function and differential constraints. However, they can be trapped in local minima of the ORPD problem with multiple minima [9]. Recently, meta-heuristic search methods have become popular for solving the ORPD problem due to their advantages of simple implementation and ability to find near optimum solution for complex optimization problems. Various meta-heuristic methods have been applied for solving the problem such as evolutionary programming (EP) [9], genetic algorithm (GA) [3], ant colony optimization algorithm (ACOA) [10], differential evolution (DE) [11], harmony search (HS) [12], etc. These methods can improve optimal solutions for the ORPD problem compared to the conventional methods but with relatively slow performance. Among the meta-heuristic search methods, particle swarm optimization (PSO) is the most popular one for solving the ORPD problem including many variants such as multiagent-based PSO [13], enhanced PSO [2], parallel PSO [14], comprehensive learning PSO [15], etc. The PSO methods are generally simpler implementation, more powerful search ability, and faster performance than other meta-heuristic search methods, leading to solution quality for optimization problems considerably improved. In addition the single methods, hybrid methods have been also widely implemented for solving the problem such as hybrid GA [16], hybrid EP [17], hybrid PSO [18], etc to utilize the advantages of the single methods. The hybrid methods usually obtain better solution quality than the single methods but they also suffer longer computational time.

In this paper, a simple particle swarm optimization with constriction factor (PSO-CF) method is proposed for solving the ORPD problem. The proposed PSO-CF is the particle swarm optimization based on constriction factor which can deal with different objectives of the problem such as minimizing the real power losses, improving the voltage profile, and enhancing the voltage stability and properly handle various constraints for reactive power limits of generators and switchable capacitor banks, bus voltage limits, tap changer limits for transformers, and transmission line limits. The proposed method has been tested on the IEEE 30-bus and IEEE 118-bus systems and the obtained results are compared to those from other PSO variants and other methods in the literature.

The remaining organization of this paper is follows. Section 2 addresses the formulation of ORPD problem. A PSO-CF implementation for the problem is described in Section 3. Numerical results are presented in Section 4. Finally, the conclusion is given.

2. PROBLEM FORMULATION

The objective of the ORPD problem is to minimize is to optimize the objective functions while satisfying several equality and inequality constraints. Mathematically, the problem is formulated as follows:

$$\text{Min } F(x,u) \tag{1}$$

where the objective function *F(x,u)* can be expressed in one of the forms as follows:

- Real power loss:

$$F(x,u) = P_{loss} = \sum_{i=1}^{N_l} g_l \left[V_i^2 + V_j^2 - 2V_iV_j\cos(\delta_i - \delta_j)\right] \tag{2}$$

- Voltage deviation at load buses for voltage profile improvement [2]:

$$F(x,u) = VD = \sum_{i=1}^{N_d} \left|V_i - V_i^{sp}\right| \tag{3}$$

where V_i^{sp} is the pre-specified reference value at load bus *i*, which is usually set to 1.0 pu.

- Voltage stability index for voltage stability enhancement [3], [19]:

$$F(x,u) = L_{\max} = \max\{L_i\};\ i = 1,...,N_d \tag{4}$$

For all the considered objective functions, the vector of dependent variables *x* represented by:

$$x = [Q_{g1},...,\ Q_{gN_g},\ V_{l1},...,\ V_{lN_d},\ S_1,...,\ S_{N_l}]^T \tag{5}$$

and the vector of control variables *u* represented by:

$$u = [V_{g1},...,\ V_{gN_g},\ T_1,...,\ T_{N_t},\ Q_{c1},...,\ Q_{cN_c}]^T \tag{6}$$

The problem includes the equality and inequality constraints as follows:

a) Real and reactive power flow equations at each bus:

$$P_{gi} - P_{di} = V_i \sum_{j=1}^{N_b} V_j \left[G_{ij}\cos(\delta_i - \delta_j) + B_{ij}\sin(\delta_i - \delta_j)\right]$$
$$i = 1,...,N_b \tag{7}$$

$$Q_{gi} - Q_{di} = V_i \sum_{j=1}^{N_b} V_j \left[G_{ij}\sin(\delta_i - \delta_j) - B_{ij}\cos(\delta_i - \delta_j)\right]$$
$$i = 1,...,N_b \tag{8}$$

b) Voltage and reactive power limits at generation buses:

$$V_{gi,\min} \le V_{gi} \le V_{gi,\max};\ i = 1,...,N_g \tag{9}$$

$$Q_{gi,\min} \le Q_{gi} \le Q_{gi,\max};\ i = 1,...,N_g \tag{10}$$

c) Capacity limits for switchable shunt capacitor banks:

$$Q_{ci,\min} \le Q_{ci} \le Q_{ci,\max};\ i = 1,...,N_c \tag{11}$$

d) Transformer tap settings constraint:

$$T_{k,\min} \le T_k \le T_{k,\max};\ k = 1,...,N_t \tag{12}$$

e) Security constraints for voltages at load buses and transmission lines:

$$V_{li,\min} \le V_{li} \le V_{li,\max};\ i = 1,...,N_d \tag{13}$$

$$S_l \le S_{l,\max};\ l = 1,...,N_l \tag{14}$$

where the S_l is the maximum power flow between bus *i* and bus *j* determined as follows:

$$S_l = \max\{|S_{ij}|, |S_{ji}|\} \quad (15)$$

3. PARTICLE SWARM OPTIMIZATION WITH CONSTRICTION FACTOR

3.1 Basic particle swarm optimization

PSO is a population based evolutionary computation technique inspired from the social behaviors of bird flocking or fish schooling. Since the first invention in 1995 [20], PSO has become one of the most popular methods applied in various optimization problems due to its simplicity and ability to find near optimal solutions. In the conventional PSO, a population of particles moves in the search space of problem to approach to the global optima. The movement of each particle in the population is determined via its location and velocity. During the movement, the velocity of particles is changed over time and their position will be updated accordingly. For implementation in a n-dimension optimization problem, the position and velocity vectors of particle d are represented by $x_d = [x_{1d}, x_{2d}, \ldots, x_{nd}]$ and $v_d = [v_{1d}, v_{2d}, \ldots, v_{nd}]$, respectively, where $d = 1,\ldots, NP$ and NP is the number of particles. The best previous position of particle d is based on the valuation of fitness function represented by $pbest_d = [p_{1d}, p_{2d}, \ldots, p_{nd}]$ and the best particle among all particles represented by $gbest$. The velocity and position of each particle in the next iteration (k+1) for fitness function evaluation are calculated as follows:

$$v_{id}^{(k+1)} = w^{(k+1)} \times v_{id}^{(k)} + c_1 \times rand_1 \times \left(pbest_{id}^{(k)} - x_{id}^{(k)} \right) + c_1 \times rand_2 \times \left(gbest_i^{(k)} - x_{id}^{(k)} \right) \quad (16)$$

$$x_{id}^{(k+1)} = x_{id}^{(k)} + v_{id}^{(k+1)} \quad (17)$$

where the constants c_1 and c_2 are cognitive and social parameters, respectively and $rand_1$ and $rand_2$ are random values in [0, 1].

3.2 Implementation of constriction factor

The position and velocity for each particle have their own limits. For the position limits, the lower and upper bounds are from the limits of variables represented by the particle's position. However, the velocity limits for the particles can be defined by users. Generally, the solution quality of the PSO method for optimization problems is sensitive to the cognitive and social parameters and velocity limit of particles. Therefore, there have been several attempts to control the exploration and exploitation abilities of the PSO algorithm by adjusting the cognitive and social factors or to limit the range of velocity in the range [-$v_{id,max}$, $v_{id,max}$]. In this paper, the improved PSO with constriction factor proposed in [21] is implemented for solving the ORPD problem. The authors have claimed that the use of a constriction factor may be necessary to insure the stable convergence of the PSO algorithm. The modified velocity for the particles with constriction factor is expressed as follows:

$$v_{id}^{(k+1)} = C \times \left[v_{id}^{(k)} + c_1 \times rand_1 \times \left(pbest_{id}^{(k)} - x_{id}^{(k)} \right) + c_2 \times rand_2 \times \left(gbest_i^{(k)} - x_{id}^{(k)} \right) \right] \quad (18)$$

$$C = \frac{2}{\left| 2 - \varphi - \sqrt{\varphi^2 - 4\varphi} \right|}; \text{ where } \varphi = c_1 + c_2,\ \varphi > 4 \quad (19)$$

In the PSO-CF, the factor φ has an effect on the convergence characteristic of the system and must be greater than 4.0 to guarantee stability. However, as the value of φ increases, the constriction C decreases producing diversification which leads to slower response. The typical value of φ is 4.1 (i.e. c_1 = c_2 = 2.05) as proposed in [22]. When the constriction factor implemented in the PSO, the search procedure ensures the convergence for the method based on the mathematical theory. Consequently, the PSO-CF can obtain better quality solutions than the basic PSO approach.

3.3 PSO-CF for the ORPD problem

For implementation of the proposed PSO-CF to the problem, each particle position representing for control variables is defined as follows:

$$x_d = [V_{g1d}, \ldots, V_{gN_gd}, T_{1d}, \ldots, T_{N_td}, Q_{c1d}, \ldots, Q_{cN_cd}]^T \quad d = 1, \ldots, NP \quad (20)$$

The upper and lower limits for velocity of each particle are determined based on their lower and upper bounds of position:

$$v_{d,\max} = R \times (x_{d,\max} - x_{d,\min}) \quad (21)$$

$$v_{d,\min} = -v_{d,\max} \quad (22)$$

where R is the limit factor for particle velocity.

Both particle positions and velocities are initialized within their limits given by:

$$x_d^{(0)} = x_{d,\min} + rand_3 \times (x_{d,\max} - x_{d,\min}) \quad (23)$$

$$v_d^{(0)} = v_{d,\min} + rand_4 \times (v_{d,\max} - v_{d,\min}) \quad (24)$$

where $rand_3$ and $rand_4$ are random values in [0, 1].

During the iterative process, the positions and velocities of particles are always adjusted in their limits after being calculated in each iteration as follows:

$$v_d^{new} = \min\{v_{d,\max}, \max\{v_{d,\min}, v_d\}\} \quad (25)$$

$$x_d^{new} = \min\{x_{d,\max}, \max\{x_{d,\min}, x_d\}\} \quad (26)$$

The fitness function to be minimized is based on the problem objective function and dependent variables including reactive power generations, load bus voltages, and power flow in transmission lines. The fitness function is defined as follows:

$$FT = F(u,x) + K_q \sum_{i=1}^{N_g} \left(Q_{gi} - Q_{gi}^{\lim}\right)^2 + K_v \sum_{i=1}^{N_d} \left(V_{li} - V_{li}^{\lim}\right)^2 + K_s \sum_{l=1}^{N_l} \left(S_l - S_{l,\max}\right)^2 \quad (27)$$

where K_q, K_v, and K_s are penalty factors for reactive power generations, load bus voltages, and power flow in transmission lines, respectively.

The limits of the dependent variables in (25) are determined based on their calculated values as follows:

$$x^{\lim} = \begin{cases} x_{\max} & if\ x > x_{\max} \\ x_{\min} & f\ x < x_{\min} \end{cases} \quad (28)$$

whrere x and x^{lim} respectively represent for the calculated value and limits of Q_{gi}, V_{li}, or $S_{l,max}$.

The overall procedure of the proposed PSO-CF for solving the ORPD problem is addressed as follows:

Step 1: Choose the controlling parameters for PSO-CF including number of particle NP, maximum number of iterations IT_{max}, cognitive and social acceleration factors c_1 and c_2, limit factor for maximum velocity R, and penalty factors for constraints.

Step 2: Generate NP particles for control variables in their limits including initial particle position x_{id} representing vector of control variables in (5) and velocity v_{id} as in (23) and (24), where i = 1, …, $N_g + N_t + N_c$ and d = 1, …, NP.

Step 3: For each particle, calculate value of dependent variables based on power flow solution using Matpower toolbox and evaluate the fitness function F_{pbestd} in (27). Determine the global best value of fitness function F_{gbest} = min(F_{pbestd}).

Step 4: Set $pbest_{id}$ to x_{id} for each particle and $gbest_i$ to the position of the particle corresponding to F_{pbestd}. Set iteration counter k = 1.

Step 5: Calculate new velocity $v^{(k)}_{id}$ and update position $x^{(k)}_{id}$ for each particle using (18) and (17), respectively. Note that the obtained position and velocity of particles should be limited in their lower and upper bounds given by (25) and (26).

Step 6: Solve power flow using Matpower toolbox based on the newly obtained value of position for each particle.

Step 7: Evaluate fitness function FT_d in (27) for each particle with the newly obtained position. Compare the calculated FT_d to $F^{(k-1)}_{pbestd}$ to obtain the best fitness function up to the current iteration $F^{(k)}_{pbestd}$.

Step 8: Pick up the position $pbest^{(k)}_{id}$ corresponding to $F^{(k)}_{pbestd}$ for each particle and determine the new global best fitness function $F^{(k)}_{pbestd}$ and the corresponding position $gbest^{(k)}_{i}$.

Step 9: If $k < IT_{max}$, $k = k + 1$ and return to Step 5. Otherwise, stop.

4. NUMERICAL RESULTS

The proposed PSO-CF has been tested on the IEEE 30-bus and 118-bus systems with different objectives including power loss, voltage deviation, and voltage stability index. The data for these systems can be found in [23], [24]. The characteristics and the data for the base case of the test systems are given in Tables 1 and 2, respectively.

In this paper, the power flow solutions for the systems are obtained from Matpower toolbox [24]. For comparison, three other variants of PSO also implemented for solving the problem are PSO with time-varying inertia weight (PSO-TVIW) [25] and PSO with time-varying acceleration coefficients (PSO-TVAC) and self organizing hierarchical particle swarm optimizer with time-varying acceleration coefficients (HPSO-TVAC) in [26]. The algorithms of the PSO methods are coded in Matlab platform [27] and run on a 2.1 GHz with 2 GB of RAM PC. The parameters of the PSO methods for the test systems are given in Table 3. For stopping criteria, the maximum number of iterations for all PSO methods is set 200. For each test case, the PSO methods are performed 50 independent runs.

4.1 IEEE 30-bus system

In the test system, the generators are located at buses 1, 2, 5, 8, 11, and 13 and the available transformers are located on lines 6-9, 6-10, 4-12, and 27-28. The switchable capacitor banks will be installed at buses 10, 12, 15, 17, 20, 21, 23, 24, and 29 with the minimum and maximum values of 0 and 5 MVAR, respectively. The limits for control variables are given in [11], generation reactive power in [28], and power flow in transmission lines in [29]. The number of particles for the PSO methods in this case is set to 10.

The results obtained by the PSO methods for the system with different objectives including power loss, voltage deviation for voltage profile improvement, and voltage stability index for voltage enhancement are given in Tables 4, 5, and 6, respectively and the solutions for best results are given in Tables A1, A2, and A3 of Appendix.

The obtained best results from the proposed PSO-CF method are compared to those from DE [11], comprehensive learning particle swarm optimization (CLPSO) [15], and other PSO variants for different objectives as given in Table 7. For the objective of total power loss and voltage deviation, the optimal solutions by the proposed PSO-CF are less than those from the others while the best voltage stability index from the PSO-CF method is approximate to that from others and better than that of HPSO-TVAC. For computational time, the CLPSO method obtained its optimal solution for an average of 138 seconds which is vastly slower than that from the PSO-CF method. There is no report of computational time for the DE method.

Table 1. Characteristics of test systems

System	No. of branches	No. of generation buses	No. of transformers	No. of capacitor banks	No. of control variables
IEEE 30 bus	41	6	4	9	19
IEEE 118 bus	186	54	9	14	77

Table 2. Base case for test systems

System	ΣP_{di}	ΣQ_{di}	P_{loss}	Q_{loss}	ΣP_{gi}	ΣQ_{gi}
IEEE 30 bus	283.4	126.2	5.273	23.14	288.67	89.09
IEEE 118 bus	4242	1438	132.863	783.79	4374.86	795.68

Table 3. Parameters for PSO methods

Method	PSO-TVIW	PSO-TVAC	HPSO-TVAC	PSO-CF
w_{max}	0.9	-	-	-
w_{min}	0.4	-	-	-
c_1, c_2	2	-	-	2.05
c_{1i}, c_{2f}	-	2.5	2.5	-
c_{1f}, c_{2i}	-	0.2	0.2	-
R	0.15	0.15	0.15	0.15

Table 4. Results by PSO methods for the IEEE 30-bus system with power loss objective

Method	PSO-TVIW	PSO-TVAC	HPSO-TVAC	PSO-CF
Min P_{loss} (MW)	4.5129	4.5356	4.5283	4.5128
Avg. P_{loss} (MW)	4.5742	4.5912	4.5581	4.6313
Max P_{loss} (MW)	5.8204	4.9439	4.6112	5.7633
Std. dev. P_{loss} (MW)	0.1907	0.0592	0.0188	0.2678
VD	2.0540	1.9854	1.9315	2.0567
L_{max}	0.1255	0.1257	0.1269	0.1254
Avg. CPU time (s)	10.98	10.85	10.38	10.65

Table 5. Results by PSO methods for the IEEE 30-bus system with voltage deviation objective

Method	PSO-TVIW	PSO-TVAC	HPSO-TVAC	PSO-CF
Min VD	0.0922	0.1210	0.1136	0.0890
Avg. VD	0.1481	0.1529	0.1340	0.1160
Max VD	0.5675	0.1871	0.1615	0.3644
Std. dev. VD	0.1112	0.0153	0.0103	0.0404
P_{loss} (MW)	5.8452	5.3829	5.7269	5.8258
L_{max}	0.1481	0.1485	0.1484	0.1485
Avg. CPU time (s)	9.97	9.88	9.59	9.89

Table 6. Results by PSO methods for the IEEE 30-bus system with voltage stability index objective

Method	PSO-TVIW	PSO-TVAC	HPSO-TVAC	PSO-CF
Min L_{max}	0.1249	0.1248	0.1261	0.1247
Avg. L_{max}	0.1261	0.1262	0.1275	0.1265
Max L_{max}	0.1280	0.1293	0.1287	0.1281
Std. dev. L_{max}	0.0008	0.0009	0.0006	0.0008
P_{loss} (MW)	4.9186	4.8599	5.2558	5.0041
VD	1.9427	1.9174	1.6830	1.9429
Avg. CPU time (s)	13.42	13.39	13.05	13.39

Table 7. Comparison of best results for the IEEE 30-bus system

Method	Power loss (MW)	Voltage deviation (VD)	Stability index ($L_{i,max}$)
DE [11]	4.5550	0.0911	0.1246
CLPSO [15]	4.5615	-	-
PSO-TVIW	4.5129	0.0922	0.1249
PSO-TVAC	4.5356	0.1210	0.1248
HPSO-TVAC	4.5283	0.1136	0.1261
PSO-CF	4.5128	0.0890	0.1247

4.2 IEEE 118-bus system

In this system, the position and lower and upper limits for switchable capacitor banks, and lower and upper limits of control variables are given in [15]. The number of particles for the implemented PSO methods is set to 40.

The obtained results by the PSO methods for the system with different objectives similar to the case of IEEE 30 bus system are given in Tables 8, 9, and 10, respectively and the comparison of best results from methods for different objectives is given in Table 11. For the total power loss objective, the proposed PSO-CF can obtain less power loss than CLPSO and other PSO variants. For the voltage deviation, the PSO-CF method also obtains better optimal solution than that from other PSO variants while the best voltage stability index is nearly the same for PSO-CF and other PSO variants. For the computational time, the proposed PSO-CF is also vastly faster than that from CLPSO whose average computational time for this system is 1472 seconds.

5. CONCLUSION

In this paper, the PSO-CF method has been effectively and efficiently implemented for solving the ORPD problem. PSO-CF is a simple improvement of the conventional PSO method with convergence guaranteed for the method based on the mathematical theory. The proposed PSO-CF has been tested on the IEEE 30-bus and IEEE 118-bus systems with different objectives including power loss, voltage deviation, and voltage stability index. For the selected stopping criteria based on number of iterations, the obtained solutions by the proposed PSO-CF for test cases satisfy all constraints of the problem. Moreover, the convergence process of the PSO-CF method is also stable to the optimal solution of the problem. The test results have shown that proposed method can obtain total power loss, voltage deviation, or voltage stability index less than other PSO variants and other methods for the test cases. Therefore, the proposed PSO-CF could be a useful and powerful method for solving the ORPD problem.

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APPENDIX

The best solutions by PSO methods for the IEEE 30-bus system with different objectives are given in Tables A1, A2, and A3.

Table A1. Best solutions by PSO methods for the IEEE 30-bus system with power loss objective

Control variables	PSO-TVIW	PSO-TVAC	HPSO-TVAC	PSO-CF
V_{g1}	1.1000	1.1000	1.1000	1.1000
V_{g2}	1.0943	1.0957	1.0941	1.0944
V_{g5}	1.0748	1.0775	1.0745	1.0749
V_{g8}	1.0766	1.0792	1.0762	1.0767
V_{g11}	1.1000	1.1000	1.0996	1.1000
V_{g13}	1.1000	1.0970	1.1000	1.1000
T_{6-9}	1.0450	1.0199	1.0020	1.0435
T_{6-10}	0.9000	0.9401	0.9498	0.9000
T_{4-12}	0.9794	0.9764	0.9830	0.9794
T_{27-28}	0.9652	0.9643	0.9707	0.9647
Q_{c10}	5.0000	4.5982	2.3238	5.0000
Q_{c12}	4.9952	2.8184	2.8418	5.0000
Q_{c15}	5.0000	2.3724	3.6965	5.0000
Q_{c17}	5.0000	3.6676	4.9993	5.0000
Q_{c20}	4.0765	4.3809	3.1123	4.0041
Q_{c21}	5.0000	4.9146	4.9985	5.0000
Q_{c23}	2.5071	3.6527	3.5215	2.3834
Q_{c24}	5.0000	5.0000	4.9987	5.0000
Q_{c29}	2.2284	2.1226	2.3743	2.2176

Table A2. Best solutions by PSO methods for the IEEE 30-bus system with voltage deviation objective

Control variables	PSO-TVIW	PSO-TVAC	HPSO-TVAC	PSO-CF
V_{g1}	1.0090	1.0282	1.0117	1.0080
V_{g2}	1.0036	1.0256	1.0083	1.0030
V_{g5}	1.0184	1.0077	1.0169	1.0159
V_{g8}	1.0079	1.0014	1.0071	1.0078
V_{g11}	1.0240	1.0021	1.0707	1.0558
V_{g13}	1.0220	1.0046	1.0060	1.0059
T_{6-9}	1.0387	1.0125	1.0564	1.0780
T_{6-10}	0.9000	0.9118	0.9076	0.9000
T_{4-12}	0.9964	0.9617	0.9545	0.9799
T_{27-28}	0.9596	0.9663	0.9695	0.9654
Q_{c10}	3.1805	5.0000	1.5543	5.0000
Q_{c12}	0.0000	1.5065	1.4242	5.0000
Q_{c15}	4.9903	3.9931	2.5205	4.7892
Q_{c17}	1.5245	3.7785	1.6400	0.0000
Q_{c20}	5.0000	3.2593	5.0000	5.0000
Q_{c21}	5.0000	4.1425	1.8539	4.9069
Q_{c23}	5.0000	4.9820	3.3035	5.0000
Q_{c24}	4.1862	4.5450	4.5941	5.0000
Q_{c29}	1.6848	4.1272	3.5062	2.1107

Table A3. Best solutions by PSO methods for the IEEE 30-bus system with objective of stability index

Control variables	PSO-TVIW	PSO-TVAC	HPSO-TVAC	PSO-CF
V_{g1}	1.1000	1.1000	1.0979	1.1000
V_{g2}	1.0911	1.0934	1.0997	1.1000
V_{g5}	1.0440	1.0969	1.0500	1.1000
V_{g8}	1.0734	1.0970	1.0663	1.0766
V_{g11}	1.1000	1.1000	1.0561	1.1000
V_{g13}	1.1000	1.1000	1.0886	1.0834
$T_{6\text{-}9}$	0.9701	1.0935	0.9939	1.0040
$T_{6\text{-}10}$	0.9000	0.9000	1.0150	0.9000
$T_{4\text{-}12}$	0.9451	0.9579	0.9121	0.9182
$T_{27\text{-}28}$	0.9425	0.9651	0.9406	0.9414
Q_{c10}	3.7186	3.1409	3.7685	3.4792
Q_{c12}	2.2318	3.0186	4.6323	0.0000
Q_{c15}	0.5772	1.4347	2.6542	2.5747
Q_{c17}	0.0000	3.8498	2.6897	0.0061
Q_{c20}	2.3728	0.0000	2.8806	2.3822
Q_{c21}	2.6790	5.0000	2.1071	2.5272
Q_{c23}	0.1350	0.0000	3.1044	1.1154
Q_{c24}	1.2181	2.1733	2.1797	0.0000
Q_{c29}	1.3609	2.2708	3.5843	0.0000