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Research Article

Opposition-Based Improved PSO for Optimal Reactive Power Dispatch and Voltage Control

Shengrang Cao,[1,2] Xiaoqun Ding,[1] Qingyan Wang,[1] and Bingyan Chen[1,3,4]

[1] *College of Energy and Electrical Engineering, Hohai University, Nanjing 211100, China*
[2] *Jiangsu Union Technical Institute, Nanjing Branch, Nanjing 210019, China*
[3] *Hohai University, Nantong Institute of Marine and Offshore Engineering, Nantong 226000, China*
[4] *Jiangsu Province Key Laboratory of Environmental Engineering, Nanjing 210000, China*

Correspondence should be addressed to Shengrang Cao; csrhhu@foxmail.com

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An opposition-based improved particle swarm optimization algorithm (OIPSO) is presented for solving multiobjective reactive power optimization problem. OIPSO uses the opposition learning to improve search efficiency, adopts inertia weight factors to balance global and local exploration, and takes crossover and mutation and neighborhood model strategy to enhance population diversity. Then, a new multiobjective model is built, which includes system network loss, voltage dissatisfaction, and switching operation. Based on the market cost prices, objective functions are converted to least-cost model. In modeling process, switching operation cost is described according to the life cycle cost of transformer, and voltage dissatisfaction penalty is developed considering different voltage quality requirements of customers. The experiment is done on the new mathematical model. Through the simulation of IEEE 30-, 118-bus power systems, the results prove that OIPSO is more efficient to solve reactive power optimization problems and the model is more accurate to reflect the real power system operation.

1. Introduction

Particle swarm optimization (PSO) proposed by Dr. Eberhart and Dr. Kennedy in 1995 is a population-based evolutionary algorithm that emulates the social behavior of bird flocks in an attempt to optimally explore some given problem space. In the past decade, PSO has been studied and applied in many research and application areas. However, many experiments have shown that PSO converges too fast and easily falls into local optima especially when solving complex multimodal problems [1]. Many researchers have put forward improved programs. In general, there are three kinds of improved methods, that is, parameter factor [2, 3], neighborhood topology [4], and hybridization with other algorithms [5, 6]. Each of them has its own advantages but also has defects. The hybridization of PSO with other algorithms has been proved to be a promising technique. There are two ways to combine. One is with evolutionary algorithms, for instance, [5] is PSO combined with genetic algorithm, in which genetic algorithm was used to increase exploration ability of particles, [6] is the combination hybridized PSO with ant algorithm, and uses the characteristic of positive feedback to enhance the search ability of particles. The other is with nonevolutionary algorithms, such as hybridizing PSO with Filter [7], Cauchy mutation [8], and opposition-based learning [9], in which opposition-based learning has a good character; it can accelerate the convergence speed of the algorithm, and this concept was first proposed by Dr. Tizhoosh. When we seek the solution in a direction, it is beneficial to consider the opposite direction [10]. By comparison of fitness values of the two directions, the optimal candidate solution is chosen from them. For this reason, many algorithms were enhanced by opposition-based learning [11, 12].

In this paper, a new improved particle swarm optimization algorithm OIPSO is proposed, which makes some expansion and correction by inertia weight factors, crossover and mutation, neighborhood model, and opposition-based learning. Through these strategies, the new OIPSO algorithm can enhance population diversity and avoid premature convergence and stagnation.

The improved algorithm would be developed to multi-objective reactive power optimization. It is known that the purpose of power system reactive optimization is to find the best compensation methods to make the power system safe and economic under the demand of reactive load power system [13]. For that, we establish a mathematical model, including system network loss, voltage dissatisfaction, and switching operator. In the modeling process, introduce life cycle cost of the transformer, define switching operator cost, and also give descriptions of the customers' loss, voltage quality requirement, and dissatisfaction degree and then reactive power optimization tests through IEEE 30- and 118-bus systems.

The remaining of this paper is organized as follows: Section 2 provides an overview of PSO algorithm, opposition-based learning, and other improvement strategies. In Section 3, the multiobjective model of reactive power system is established. Combined with reactive power optimization, main steps of the improved OIPSO algorithm are given in Section 4. Then, the algorithm is applied to IEEE 30- and 118-bus systems in Section 5. Finally, Section 6 concludes the paper with a summary.

2. PSO Algorithm and Its Improvement

The essence of PSO algorithm is that by letting the information about good solutions spread out through the swarm, the particles would tend to move to good areas [14, 15]. At each iteration time t, particle i is moved to a new position by adding a velocity term to its current position according to formulas (1) and (2) as follows:

$$X_i(t+1) = X_i(t) + V_i(t+1), \tag{1}$$

$$\begin{aligned} V_i(t+1) = {} & \omega V_i(t) + c_1 \mathrm{rand}_1 \left(P_{\mathrm{best},i} - X_i(t)\right) \\ & + c_2 \mathrm{rand}_2 \left(G_{\mathrm{best}} - X_i(t)\right), \end{aligned} \tag{2}$$

where $i = 1, 2, \ldots, \mathrm{pop}$, pop is the size of swarm particles, $P_{\mathrm{best},i}$ is the best position of particle i, G_{best} is the global best position, ω is called inertia weight, and c_1 and c_2 are acceleration factors.

PSO algorithm converges fast, but it is also easy to fall into the local optimal. The reason is that, in the optimal process, all particles consider the global best position G_{best} as the goal and search directions run towards it. This situation worsens in the later process and leads to reduction of the ability to explore unknown area. Therefore, it is very important to enhance the diversity of particles. This paper makes some expansion and modification to the basic particle swarm algorithm. The main improvement measures are as follows.

2.1. Opposition-Based Learning. In PSO algorithm, starting points are given randomly. If the starting points are close to the optimal point, convergence speed would be faster. The opposite operation used in the selection of the starting points has proven that utilizing opposition in learning yields more efficient algorithms than using only pure randomness [10, 16]. Besides the opposition point used in the initial population, this paper would intersectionally use the opposition point and the following crossover and mutation to increase the diversity of particles. The definition of opposition is given as follows.

Definition 1 (opposite point). Let $X = (x_1, x_2, \ldots, x_n)$ be a point in n-dimensional space and let $x_i \in [a_i, b_i]$ be a real number, where $i = 1, 2, \ldots, n$. The opposite point $X' = (x'_1, x'_2, \ldots, x'_n)$ is defined by its components $x'_i = a_i + b_i - x_i$.

2.2. Inertia Weight Factor. Generally, for initial stage of search process, large inertia weight can enhance the global exploration and, for last stage, the small inertia weight is good for local exploration, so time-varying inertia weight, which typically decreases linearly from about 0.9 to 0.4 [17], can balance the global and local search; specific measures are as follows:

$$\omega = \omega_{\max} - \frac{t}{t_{\max}} \left(\omega_{\max} - \omega_{\min}\right), \tag{3}$$

where $\omega_{\max}$ and $\omega_{\min}$ are the maximum and minimum of ω, $t_{\max}$ is the maximum iterating times, and t is the current iteration.

2.3. Neighborhood Exchange. In particle swarm algorithm, each particle generally learns from its own best position and global best position. In social cognitive system, an individual, besides its own experience and excellent information obtained from the whole society, should exchange with other better individuals to improve itself [13, 18]. Based on this idea, PSO algorithm is modified as follows:

$$\begin{aligned} V_i(t+1) = {} & \omega V_i(t) + c_1 \mathrm{rand}_1 \left(P_{\mathrm{best},i} - X_i(t)\right) \\ & + c_2 \mathrm{rand}_2 \left(G_{\mathrm{best}} - X_i(t)\right) \\ & + c_3 \mathrm{rand}_3 \left(P_{\mathrm{best},n} - X_i(t)\right), \end{aligned} \tag{4}$$

where $P_{\mathrm{best},n}$ is position vector of the better individual in domain and c_3 is an accelerating constant. Larger c_3 can increase the ability of the individual to explore unknown better area, especially in the later process. In contrast, the set value of c_2 is related to convergence rate; based on their own characteristics, parameters c_2, c_3 are improved as follows:

$$\begin{aligned} c_3 &= c_{3\min} + \frac{t}{t_{\max}} \left(c_{3\max} - c_{3\min}\right), \\ c_2 &= c_{2\max} - \frac{t}{t_{\max}} \left(c_{2\max} - c_{2\min}\right), \end{aligned} \tag{5}$$

where $c_{2\max}$ and $c_{2\min}$ are the maximum and minimum of c_2 and $c_{3\max}$ and $c_{3\min}$ are the maximum and minimum of c_3.

2.4. Crossover and Mutation. Crossover and mutation operators are key technologies in genetic algorithm, which are used to enhance the diversity of the species. The particles of PSO

algorithm can be crossed and varied [13, 18]. For particle i, the crossover operation is described as follows:

$$V_i(t+1) = \frac{V_i(t) + V_n(t)}{\|V_i(t) + V_n(t)\|} \|V_i(t)\|,$$
$$X_i(t+1) = rX_i(t) + (1-r)X_n(t), \tag{6}$$

where r is a random variable in the range $[0, 1]$.

The method of mutation operator is

$$V_i(t+1) = \frac{V_i(t) + V_i(t+1)}{\|V_i(t) + V_i(t+1)\|} \|V_i(t)\|,$$
$$X_i(t+1) = \gamma X_i(t) + (1-r)\left(X_{i\max} - X_{i\min}\right), \tag{7}$$

where γ is a random coefficient in the range $[0, 1]$. $X_{i\max}$, $X_{i\min}$ are the maximum and minimum of X_i. A variable parameter P_m selected from $[0, 1]$ determines the mutation operator.

3. Mathematical Model of Power System Reactive Power Optimization

Objective function of reactive power optimization model is commonly the minimization of active power loss and ignores many security and economic factors. On security grounds, its optimal results often approach the upper limits of voltage level on load buses. Although the results satisfy equality and inequality constraints, it is not conducive to the safe operation of power system. In this paper, we introduce voltage dissatisfaction and use penalty to punish voltage dissatisfaction. And, in economic terms, transformer tap has mechanical life and the total number of switching times has a limit. Therefore, the switching operation cost should not be neglected. In this section, we present transformer operation cost by life cycle cost and use it as an objective function.

3.1. Active Power Loss. Reactive power is usually used as the objective function. Utilize the following equal to convert power loss into expense:

$$C_{P\text{loss}} = \lambda_1 \times P_{\text{loss}} = \lambda_1 \times \sum_{\substack{i\in N\\ j\in N_i}} G_{ij}\left(V_i^2 + V_j^2 - 2V_iV_j\cos\theta_{ij}\right), \tag{8}$$

where λ_1 is the unit price for system network loss and its value depends on market electricity prices, P_{loss} is system network loss, N is set of branches numbers, and N_i is the collection of nodes number associated with the node i (including i itself).

3.2. Voltage Dissatisfaction. The cost of voltage dissatisfaction describes the users' losses caused by overlimit voltages on the load buses. When the voltage amplitudes are far from the ideal range, the losses would become more heavy. Voltage dissatisfaction can be expressed by the following mathematical description [19]:

$$C_{\text{VVIO}} = \lambda_2 \times S_V = \lambda_2 \times \sum_{i=1}^{N_{\text{load}}} S_{Vi},$$
$$S_{Vi} = \begin{cases} a_i \times P_{Di} \times \left(V_i^{\min} - V_i\right)^{\theta} & V_i < V_i^{\min} \\ 0 & V_i^{\min} < V_i < V_i^{\max} \\ b_i \times P_{Di} \times \left(V_i - V_i^{\max}\right) & V_i^{\max} < V_i, \end{cases} \tag{9}$$

where λ_2 is the penalty for voltage dissatisfaction; S_V is the sum of nodal voltage dissatisfaction degree; P_{Di} is the active power load of node i; a_i, b_i are the voltage dissatisfaction degree when the voltage values overstep the lower or upper limit, which are declared by the relevant users; θ is the index parameter about the relationship of the losses and voltage deviation; we set $\theta = 1$ in this paper. In general, voltage range is $[0.94, 1.06]$, but some power consumption equipment needs high security and stability. It is obvious that the voltages are better to control in a satisfactory interval, instead of approaching upper limits, so we change voltage range into satisfactory interval. The satisfactory interval is set by users at different load buses. In this paper, we set satisfactory interval to be $[0.95, 1.05]$ if voltages satisfy equality and inequality constraints but overstep the satisfactory interval, and dissatisfactory penalty can be relatively small and can be set based on users' requirement of electricity quality.

3.3. Switching Operations. Transformer operation cost is mainly composed of construction, installation, equipment acquisition, maintenance, and so on. Define S_{Ti} as the change of the ratio at transformer i before and after optimization and it is described as

$$S_{Ti} = \frac{\left|T_i - T_{i0}\right|}{\Delta T_i}, \tag{10}$$

where T_i is the ratio of transformer i after optimization; T_{i0} is the ratio of transformer i before optimization; ΔT_i is the step of transformer i. After optimization, tap operation costs are

$$C_{\text{TC}} = \lambda_3 \times S_T = \lambda_3 \times \sum_{i=1}^{N_T} S_{Ti}, \tag{11}$$

where N_T is the total of transformers and λ_3 is the unit price of each action, which depends on the annual value of investment, operation, and maintenance cost, where each of them is described as follows.

3.3.1. Construction Cost. Construction cost of the transformer is composed of construction project cost, installation project cost, equipment acquisition cost, and other cost, called static investment [20, 21]. Generally, construction cost is expressed as

$$C_1 = V_1 \cdot \frac{\gamma \cdot (1+\gamma)^n}{(1+\gamma)^n - 1}, \tag{12}$$

where C_1 is the annual value of the lump-sum investment, V_1 is the lump-sum investment, and γ is the interest rate.

3.3.2. Scrap Value. Scrap value of the transformer can be divided into residual recovery income, early retirement loss cost, and disposal expenses. Its annual value is described as [19]

$$C_2 = -\rho \cdot C_1 + \frac{(n - n')}{n} \cdot C_1 + \mathrm{dc} \cdot \frac{\gamma \cdot (1+\gamma)^n}{(1+\gamma)^n - 1}. \quad (13)$$

ρ is the recovery factor, and we set it as 20%~30%. The minus sign expresses that the income is negative relative to the expenditure; dc is the current value of the disposal expense; n is the actual operating life; n' is the expected operating life. When the actual operating life is greater than or equal to the expected life, early retirement loss cost is 0.

3.3.3. Maintenance Cost. The maintenance method adopts scheduling repair; its model is described as

$$V_3 = \sum_{t=1}^{30} M_e \cdot \left(1 - \exp\left(-\left(\frac{t}{15.98}\right)^{1.35}\right)\right), \quad (14)$$

where M_e is early operation and maintenance cost; t is the year number; and V_3 is the total cost of maintenance in 30 years. Use the uniform annual value method for conversion; maintenance cost of each year can be expressed as

$$C_3 = V_3 \cdot \frac{\gamma \cdot (1+\gamma)^n}{(1+\gamma)^n - 1}. \quad (15)$$

Through the above models, the life cycle cost (LLC) is defined as

$$\mathrm{LCC} = C_1 + C_2 + C_3. \quad (16)$$

Take the 110 kv conventional substation [18]. For example, set the expected life of the transformer n' to be 30 years. γ is 8%, the mechanical life of tap is 10000 times, and average annual switching operations are 333 times. For transformer tap, its unit price of one action in the tth year is

$$C_{t\_\mathrm{avg}} = \frac{C_1 + C_2 + C_3}{333}. \quad (17)$$

In this paper, we set $\lambda_3 = C_{1\_\mathrm{avg}}$.

3.4. Objective Function and Constraints. To satisfy the cost savings and security purposes, this paper combines system network loss, voltage dissatisfaction, and switching operation as the optimization objective. Voltage dissatisfaction can be converted into economic cost, so the objective function can be expressed as

$$\min C_{\mathrm{tot}} = C_{P\mathrm{loss}} + C_{\mathrm{VVIO}} + C_{\mathrm{TC}}. \quad (18)$$

The function should satisfy the equality and inequality constraints, where equality constraints reflect the physics of the power system shown as

$$\begin{aligned} P_{Gi} - P_{Li} &= V_i \sum_{j=1}^{N} V_j \left(G_{ij} \cos\delta_{ij} + B_{ij} \sin\delta_{ij}\right), \\ Q_{Gi} - Q_{Li} + Q_{Ci} &= V_i \sum_{j=1}^{N} V_j \left(G_{ij} \sin\delta_{ij} - B_{ij} \cos\delta_{ij}\right), \end{aligned} \quad (19)$$

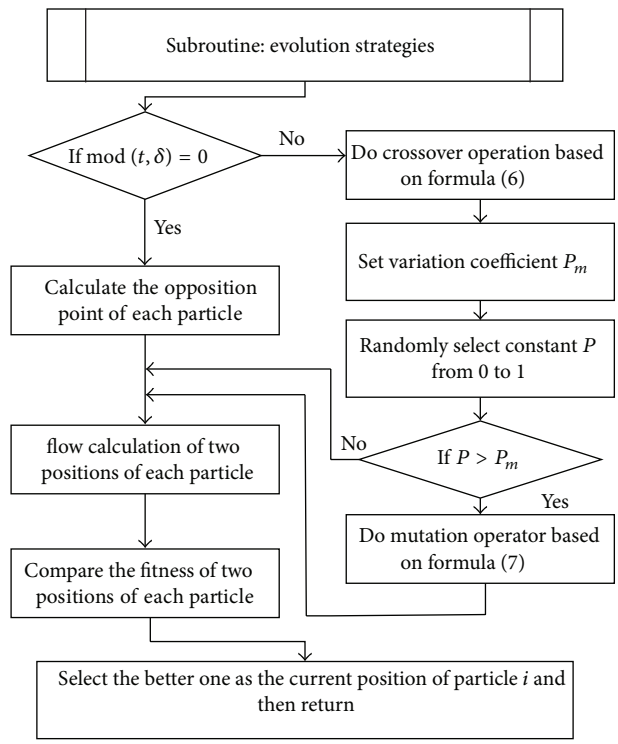

Figure 1: Subroutine of evolution strategies.

where N is node number; P_{Gi} and P_{Li} are generator active power output and active power of load at node i; and Q_{Gi}, Q_{Li}, and Q_{Ci} are generator reactive power input, load reactive power, and reactive power of the compensator capacitor at node i.

Inequality constraints are about the limits of active power, reactive power, voltage, capacitance, and the times of switching operations and are created to ensure system security [12] expressed as

$$\begin{aligned} P_{Gi\min} &\le P_{Gi} \le P_{Gi\max} \quad (i \in N_G), \\ Q_{Gi\min} &\le Q_{Gi} \le Q_{Gi\max} \quad (i \in N_G), \\ V_{i\min} &\le V_i \le V_{i\max} \quad (i \in N), \\ Q_{Ci\min} &\le Q_{Ci} \le Q_{Ci\max} \quad (i \in N_C), \\ T_{i\min} &\le T_i \le T_{i\max} \quad (i \in N_T), \end{aligned} \quad (20)$$

where N_G is the set of generation units; N_T is the set of tap transformers; and N_C is the set of compensator capacitors.

4. Reactive Power Optimization Using the Opposition-Based Improved PSO

Crossover and mutation operation and opposition-based learning are two improvement strategies. We combine and apply them to enhance diversity of particles. The specific process is shown in Figure 1. The main steps are as follows.

Step 1. Define the input data. The input data include the generator voltages and the transformer tap settings, reactive

power of switchable VAR sources, the population size of the particle swarm, the maximum number of iterations, and accelerated constants.

Step 2. Initialize the population. The initial population is generated randomly, which must meet the constraints. Calculate the opposition point $X_i'(t)$ of $X_i(t)$.

Step 3. Do flow calculation. Correct the system parameters for the flow calculation. Get the power system operation parameters, determine whether particles meet the bus voltage and generator reactive power and other constraints, modify the cross border values, and calculate their fitness.

Step 4. Compare the fitness of $X_i(t)$ and $X_i'(t)$; select the better one as the current generation.

Step 5. Record the individual optimal solution and the global optimal solution. For each particle, update the individual optimal solution. Then, select the best solution of the individual optimal solutions as the global optimal solution, $t = t + 1$.

Step 6. Calculate the current flight speed according to formula (4), and fix the particle position according to formula (1).

Step 7. Select the evolutionary strategies. Go into subroutine (see Figure 1); if $\mathrm{mod}(t, \delta) = 0$, calculate the opposition points as candidate solutions. Else, do crossover and mutation operations and generate candidate solutions according to formula (6) and (7).

Step 8. Update the particle position and modify the cross border values. After reactive compensation and transformer tap variables are discrete, do flow calculation (same as Step 3), compare the fitness of the candidate solution and contemporary individual, and select better one as the next generation.

Step 9. Determine whether it is under terminating condition. If the number of iterations at this time t is less than the maximum number of iterations, go to Step 5, or end the iteration and go to Step 10.

Step 10. Output the optimal solution. Optimal solution includes not only the control strategy of the control variables of each node but also the data of state variables, such as the system voltage of every node, system power loss, and generator reactive power output.

5. Results and Discussion

In order to validate the availability of the new opposition-based improved PSO (OIPSO) in solving power system reactive power optimization problems, IEEE 30- and IEEE 118-bus systems are employed to be the simulation studies. Two cases are presented in this section. In the first case, run with minimization of real power loss as the objective function and then compare the results with different methods. In the second case, take system network loss, voltage dissatisfaction, and switching operation as the optimization objective and give the optimal settings of control variables.

Table 1: Comparison of optimal results for different methods.

	Parameters	Losses (p.u.)
GA [22]	CR = 0.6; F = 0.01	0.04650
GSA [23]	G_0 = 100; α = 10	0.04617
DE [24]	F = 0.2; CR = 0.6	0.04550*
OGSA [25]	G_0 = 100; α = 10	0.04498*
PSO [26]	$w_{\max}$ = 0.9; $w_{\min}$ = 0.4; c_1 = 2	0.04814
CLPSO [26]	w_0 = 0.9; p_c = 0.4	0.04721
OIPSO	$w_{\max}$ = 0.9; $w_{\min}$ = 0.4; c_1 = 2; $c_{2\max}$ = 2.05; $c_{2\min}$ = 0.5; $c_{3\max}$ = 5; $c_{3\min}$ = 0.5	**0.04594**

CR is crossover rate; F is mutation rate; G_0 is the gravitational constant; p_c is learning probability, *The reactive compensation and transformer tap variables are continuous.

5.1. IEEE 30-Bus System. IEEE 30-bus system data and operating conditions are given in [21], which has 41 branches, 22 load buses, 6 generators (bus 1, bus 2, bus 5, bus 8, bus 11, and bus 13, while bus 1 is the slack bus and others are PV bus), 4 branches containing four adjustable transformers (branch 9-6, branch 10-6, branch 12-4, and branch 28-27, corresponding to transformers T1, T2, T3, and T4), and 2 shunt capacitors on buses 10 and 24, respectively. In the initial conditions, set the initial generator bus voltages and transformer taps to 1.0 and capacitor values to 0. The total power loss before optimization is 0.0537 p.u. In this paper, set the population size of particle swarm to be 36, and the number of iterations is 1000, $\delta = 2$. In case one, active power loss is studied, and the result is compared with genetic algorithm (GA) [22], gravitational search algorithm (GSA) [23], differential evolution approach (DE) [24], an opposition-based gravitational search algorithm (OGSA) [25], particle swarm optimization (PSO) [26], and comprehensive learning particle swarm optimization (CLPSO) [26]. Do 50 trials and choose the best one shown in Table 1.

Although DE [24] and OGSA [25] have obtained the optimal values 0.04550 and 0.4498, their reactive compensation and transformer tap variables are continuous, which could not satisfy actual operations. The best solution is 0.045936 calculated by the proposed OIPSO algorithm; its average consumption would be 135 s more than the CPU time of PSO (i.e., 130 s [26]), due to its discrete control variables and flow calculation of opposition point. And it improves 14.45%, more than 14% by GSA, and 10.35% by PSO.

In case two, apply OIPSO to the proposed multiobjective problem, which includes system network loss, voltage dissatisfaction of on-load nodes, and switching operations of adjustable transformer. All expenses involved are shown in Table 2. The results are shown in Table 3.

Table 3 shows the optimal value of the control variables of OIPSO solving reactive power optimization. Comparing with PSO, the OIPSO makes small changes in transformer tap and uses little reactive power compensation to improve voltage quality and increase economic efficiency. Meanwhile,

Table 2: All expenses of reactive power optimization.

Unit network loss convert expensed λ_1 (10000 RMB/MW)	Voltage dissatisfaction penalty λ_2 (10000 RMB)	Unit operation cost of transformer tap λ_3 (10000 RMB)
69	3	0.5

Table 3: The values of control variables after optimization.

Variables	Bus number	PSO [26]	OIPSO
V_1	1	1.0995	1.0995
V_2	2	1.0933	1.0945
V_5	5	1.0697	1.0747
V_8	8	1.0719	1.0764
V_{11}	11	1.0480	1.0945
V_{13}	13	1.0945	1.0989
Q_{10}	10	0.3000	0.2000
Q_{24}	24	0.0500	0.0500
T_1	9~6	0.9375	0.9500
T_2	6~10	1.0000	1.0000
T_3	12~4	1.0125	1.0000
T_4	28~27	0.9750	0.9875
P_{loss}	—	0.04702	0.04625
S_V	—	0.001355	0.00573
S_T	—	7	5

the results also reflect that satisfactory interval is necessary, if some voltage values exceed the satisfactory interval, but do not go beyond the constraints, the power system could give up a little of satisfactory degree in exchange for active power loss minimum. This situation would not cause security problems; the dissatisfactory penalty could arouse some attention of operators. The satisfactory interval has a function of forecast.

5.2. IEEE 118-Bus System. To test the potential of OIPSO algorithm in solving bigger systems, IEEE 118-bus system is considered, which has 54 generator buses, 64 load buses, 186 transmission lines, 9 transformer taps, and 14 reactive power sources. The system data and operating conditions are given in [26]. The total power loss before optimization is 1.3359 p.u. For case one, Table 4 shows the comparison of results obtained by GSA [23], DE [25], OGSA [25], PSO [26], CLPSO [26], and OIPSO.

OIPSO discovered the best solution, that is, 1.0518 p.u., in which the improvement is 21.27%, more than 4.36% by GSA, 3.95% by DE, 4.94% by OGSA, 1.26% by PSO, and 2% by CLPSO. Its success rate lags behind CLPSO by 3 points, and CPU process is 1.196 times as PSO does, but OIPSO has more than 20 times as improvement as CLPSO and PSO. The results in this table indicate the superiority of OIPSO. Comparative PSO- and OIPSO-based convergence profiles of power losses for this test system are presented in Figure 2.

Table 4: Comparison of optimal results for different methods.

	P_{loss} (p.u.)	CPU time (s)	Success rate (%)
GSA [23]	1.2776	1199	NR*
DE [25]	1.2832	NR*	NR*
OGSA [25]	1.2699	1101.3	NR*
PSO [26]	1.3191	1215	59
CLPSO [26]	1.3096	1472	73
OIPSO	**1.0518**	1453	70

NR*: not reported.

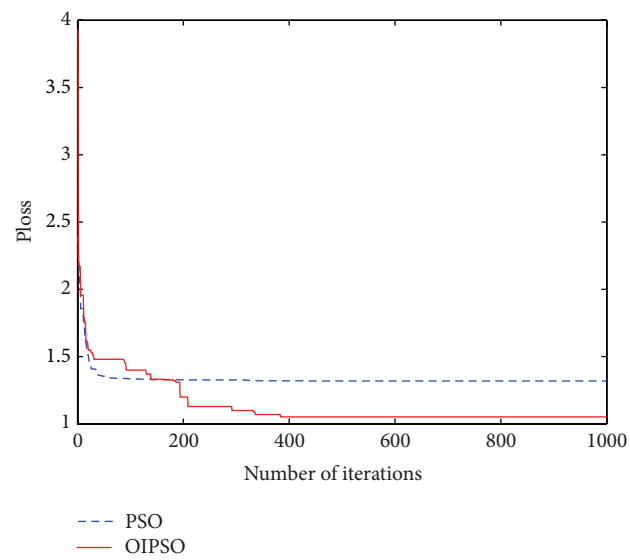

Figure 2: Comparative convergence profiles of power loss.

In case two, the multiobjective results of IEEE 118-bus system are given in Table 5; these values of the parameters provide actual operation variables, which is more effective and practical.

6. Conclusion

In this paper, we developed an opposition-based improved PSO for multiobjective reactive power optimization. The main novelty of the algorithm is the integration of the opposition-based computing into the basic PSO with inertia weight factors, crossover and mutation, and neighborhood model in order to enhance the diversity and produce some additional exploration ability of the population. The performance of the proposed OIPSO algorithm is demonstrated through its calculation on IEEE 30- and 118-bus systems; the comparison results with other algorithms show that OIPSO has better global search ability and fast searching speed. Meanwhile, when the new multiobjective model of reactive power optimization is being built, switching operation cost is defined by the life cycle cost and is emphasized to reflect the actual situation. So, the optimized results are more realistic and more reliable for practical operation.

Table 5: The values of control variables after optimization.

Variables	Bus number	PSO [26]	OIPSO
V_1	1	0.9736	1.0844
V_4	4	1.0145	1.0958
V_6	6	0.9969	1.0977
V_8	8	1.0169	1.0956
V_{10}	10	1.0344	1.0967
V_{12}	12	0.9868	1.0925
V_{15}	15	0.9867	1.0899
V_{18}	18	0.985	1.0929
V_{19}	19	0.9868	1.0893
V_{24}	24	0.9799	1.0917
V_{25}	25	1.0014	1.0981
V_{26}	26	1.0424	1.0955
V_{27}	27	1.002	1.0864
V_{31}	31	1.002	1.0855
V_{32}	32	1.001	1.0866
V_{34}	34	0.9964	1.097
V_{36}	36	0.9881	1.0932
V_{40}	40	0.9699	1.0731
V_{42}	42	1.0282	1.088
V_{46}	46	1.0165	1.0758
V_{49}	49	1.0213	1.0919
V_{54}	54	1.0147	1.081
V_{55}	55	1.0113	1.0819
V_{56}	56	1.0131	1.0814
V_{59}	59	1.0424	1.096
V_{61}	61	1.0252	1.0911
V_{62}	62	1.0284	1.0873
V_{65}	65	1.0377	1.0945
V_{66}	66	1.0381	1.0983
V_{69}	69	1.0161	1.0972
V_{70}	70	0.9551	1.0795
V_{72}	72	0.9793	1.087
V_{73}	73	0.9269	1.0852
V_{74}	74	0.9466	1.0593
V_{76}	76	0.938	1.0639
V_{77}	77	1.0049	1.0777
V_{80}	80	1.0194	1.0918
V_{85}	85	1.0303	1.095
V_{87}	87	1.09	1.0848
V_{89}	89	1.0361	1.0979
V_{90}	90	0.9907	1.0811
V_{91}	91	1.0087	1.0864
V_{92}	92	1.0183	1.0965
V_{99}	99	1.0311	1.084
V_{100}	100	1.0112	1.0975
V_{103}	103	1.0027	1.0885
V_{104}	104	1	1.091
V_{105}	105	1.0101	1.0829
V_{107}	107	0.9857	1.0867
V_{110}	110	0.9663	1.0647
V_{111}	111	0.972	1.0728
V_{112}	112	0.9529	1.0521
V_{113}	113	1.0241	1.0938
V_{116}	116	1.0285	1.0979
Q_5	5	0	−0.3
Q_{34}	34	0.1	0
Q_{37}	37	−0.25	−0.25
Q_{44}	44	0.1	0.05
Q_{45}	45	0.15	0.05
Q_{46}	46	0.2	0.1
Q_{48}	48	0.05	0.1
Q_{74}	74	0.1	0.05
Q_{79}	79	0.15	0.15
Q_{82}	82	0.2	0.2
Q_{83}	83	0.3	0
Q_{105}	105	1	1.05
Q_{107}	107	0.2	0.1
Q_{110}	110	0.05	0.05
T_1	5~8	1.025	1.0125
T_2	25~26	1.0125	1.0125
T_3	17~30	0.9875	0.975
T_4	37~38	0.9875	0.9875
T_5	59~63	1	1
T_6	61~64	1	0.9875
T_7	66~65	1	0.9875
T_8	69~68	0.975	1
T_9	80~81	1.025	0.9875
P_{loss}	—	1.2033	1.1605
S_V	—	0.000585	0.007313
S_T	—	18	8

Conflict of Interests

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

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