Reactive Power Optimization Algorithm to Distribution Network with Wind Power Integration

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Abstract. This paper discusses the reactive power optimization problem in distribution network with wind power integration and presents a new algorithm for it. In view of the uncertainty feature of wind power, mathematical model is built by the scenario analysis method and the improved particle swarm optimization algorithm (IPSO). Based on the Wasserstein distance, the optimal scenarios for wind power and the corresponding occurrence probability are deduced. By using the optimal scenario analysis results, the objective function is established according to the power loss and voltage stability margin. The optimization procedure is processed by the improved particle swarm optimization algorithm. The crossover and the mutation operator are added to the IPSO algorithm. In the beginning, classical PSO algorithm is carried out, and after 20 iterations, the crossover and the mutation operator begin to play a role. To ensure the diversity of particles, the mutation probability (P_m) is improved, and it can self-adjust the mutation operator based on the degree of convergence. By this way, the IPSO can both maintain rapid convergence speed and better global astringency. The IEEE 69-bus distribution system is used to the experiment, and test results show that the model and the algorithm are effective.

Keywords: reactive power optimization, wind power, scenario analysis, particle swarm optimization

1 Introduction

Affected by the factor of tight energy supply, the utilization of wind resources is receiving widespread attention across the globe [1]. But when the wind power is integrated into power grid, power grid becomes a grid system with multi-source power supply, and the network loss of power system and the voltage stability are greatly affected. A big part of the reason is that the reactive power distribution becomes unbalance, and the reactive power optimization is an effective way to improve voltage stability and enhance power quality.

Because of the intermittent and uncontrollability of wind, the conventional reactive power optimization method can not play a good role when wind farm connects to the power system. The traditional reactive power optimization scheme can not deal with the influence brought by the uncertain factor, and can not adapt to the changing condition. The [2] uses Monte-Carlo simulation to carry out the way for optimal reactive power planning, but it can not make response quickly and change with power grid. In [3], a reactive power optimization method is discussed, but the uncertainty of the wind turbine output is not taken into account; Based on stochastic simulation, the [4] put forwards the compensation of reactive power for wind farms, but the specific circumstances can not be considered. The [5] studied the reactive power optimization problem in distribution system with wind power generators based on scenario analysis, but the scenario analysis process is too simple and can not reflect the complicated conditions.

This paper presents a new algorithm for optimal reactive power that based on the probability of scenario occurrence. Multi-scenario technique is a method that forecasts the future situation based on the existing data. It transforms the uncertain factors into some certain scenarios problem so as to reduce the difficulty of processing. By scenario analysis, the uncertain scenario is decomposed into several certain scenarios, and each certain scenario usually is optimized respectively. Considering occurrence probability of each scenario, the final optimize result can be get by overlying the result of each scenario. By the division of multiple scenarios and the considering of each scenario occurrence probability, the high randomness of wind power can be weakened.

An improved particle swarm optimization algorithm (IPSO) is proposed to carry out the process of optimization. By improving the algorithm, the IPSO not only can avoid the premature phenomenon effectively, but also has faster convergence speed.

2 The Scenarios Division

This section discusses the method for getting the optimal scenario. First, the general calculating method for scenario selection is introduced. Next, the optimal scenario formula for wind farm is deduced.

2.1 The Method of Getting Optimal Scenario

The aim of optimization method based on scenario classification is transforming the uncertain random variable into some certain scenario so as to solve the question easily. The uncertain random variable is difficult to express by using the mathematical model. By scenario selection, a set of discrete probability distributions is adopted to replace the uncertainty. The probability distributions is (Z_k, P_k), $k=0,1,2,...,N$. Z_k is the kth scenario and P_k is its occurrence probability.

The scenario selection includes two steps: 1. determining the optimal quantiles (the scenario Z_k); 2. obtaining the P_k by estimating the Wasserstein distance metric [6].

The Wasserstein distance is given by following formula:

$$d_w(P,\widetilde{P}) = \sup\left\{\int x^m \bullet dP(x) - \int x^m \bullet d\widetilde{P}(x)\right\} \quad (1)$$

$P(\cdot)$ is the continuous probability distribution function of random variable and $\widetilde{P}(\cdot)$ is the discrete probability distribution function; $d_w(P, \widetilde{P})$ is the Wasserstein distance metric; $m \geqslant 1, m \in Z$; x is integration variable. When $m=1$, the formula can be obtained:

$$d_w(P,\widetilde{P}) = \sum_{n=1}^{N} \int_{(z_{n-1}+z_n)/2}^{(z_n+z_{n+1})/2} |x - z_n| \, dP(x) \quad (2)$$

$Z_1, Z_2, ..., Z_{N+1}$ are quantiles of $P(X)$.

The process of scenario selection is to determine $\widetilde{P}$ and $\widetilde{P}$ is represented by a set of discrete points. When P is known, $\widetilde{P}$ can be calculated on condition that $d_w(P, \widetilde{P})$ is close to minimum.

According to [6], to a single-dimensional random variable, the optimal quantiles Z_n $(n=1,2, ..., N)$ can be determined by the following formula:

$$\int_{-\infty}^{Z_n} \sqrt{p(x)}dx = \frac{2n-1}{2N} \bullet \int_{-\infty}^{+\infty} \sqrt{p(x)}dx \quad (3)$$

$p(x)$ is the probability density function. P_n is the occurrence probability of Z_n; P_n can be determined by means of following formula:

$$\begin{cases} p_n := \int_{(z_{n-1}+z_n)/2}^{(z_n+z_{n+1})/2} p(x)dx \qquad n = 2,..., N-1 \\ p_1 := \int_{z_0}^{(z_1+z_2)/2} p(x)dx \\ p_N := \int_{(z_{n-1}+z_n)/2}^{z_{N+1}} p(x)dx \end{cases} \quad (4)$$

2.2 The Optimal Scenario for Wind Power

The wind turbine generator's output power is related to the wind speed [5]. Fig. 1 presents the relationship between the output power and wind speed [7].

In Fig. 1, v_{in} , v_n , v_{out} represent the cut-in wind speed, the rated wind speed and the cut-out wind speed, respectively; ω_n is the wind turbine's rated output.

From [8][9], when the wind power $\omega \in (0, \omega_n)$, the probability density function of wind power is:

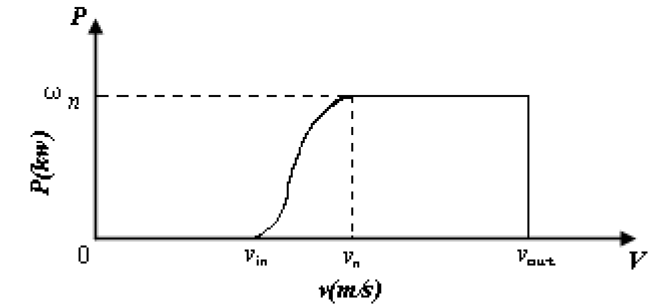

Fig. 1. Wind speed and output power

$$p(\omega)=p(v_{in}<V<v_n)=\frac{khv_n}{\omega_n c}\bullet[\frac{(1+h\omega/\omega_n)v_{in}}{c}]^{k-1}\bullet\exp\{-[\frac{(1+h\omega/\omega_n)v_{in}}{c}]^k\} \quad \textbf{(5)}$$

When the wind power $\omega=0$ or $\omega=\omega_n$, the corresponding expression is given respectively:

$$p(\omega=0)=p(V<v_{in})+p(V>v_{out})=1-\exp[-(v_{in}/c)^k]+\exp[-(v_{out}/c)^k] \quad \textbf{(6)}$$

$$p(\omega=\omega_n)=p(v_n<V<v_{out})=\exp[-(v_n\ /c)^k]-\exp[-(v_{out}/c)^k] \quad \textbf{(7)}$$

C and *k* represent the scale parameter and the shape parameter respectively. $C>0$, $k>0$. The scale parameter reflects the average wind speed. The Wind speed sequence samples can be acquired by anemometer, and the probability distribution model is built by parameter estimation method or nonparametric estimation method. When k=1, the probability distribution is exponential distribution, and when k=2, the probability distribution is rayleigh distribution [10]. Normally, k=2.

When $c_1 = v_{in}/c$, $c_2 =(v_{in}/c)\cdot(h/\omega_n)$ and $t=(t+h/\omega_n)(v_{in}/c)= c_2\cdot\omega+ c_1$, the $p(\omega)$ can be denoted as follow:

$$p(\omega)=c_2\bullet k\bullet t^{k-1}\bullet e^{-t^k} \quad \textbf{(8)}$$

Substituting $p(\omega)$ into the formula (3) , and the right of equals sign can be expressed:

$$(\frac{2n-1}{2N})\bullet\int_0^1\sqrt{p(\omega)}d\omega=(\frac{2n-1}{2N})\bullet\frac{(c_2\bullet k)^{1/2}}{c_2}\bullet\int_{c_1}^{c_1+c_2}t^{\frac{k-1}{2}}\bullet e^{-\frac{t^k}{2}}dt \quad \textbf{(9)}$$

When $x=t^k/2$ and $a=(k+1)/(2k)$:

$$(\frac{2n-1}{2N})\bullet\int_0^1\sqrt{p(\omega)}d\omega=(\frac{2n-1}{2N})\bullet 2^a\bullet(c_2k)^{1/2}\bullet\int_{c_1}^{c_1+c_2}x^{a-1}\bullet e^{-x}dx \quad \textbf{(10)}$$

Let $c_3=2^a\cdot(k\cdot c_2)^{-1/2}$ and the incomplete gamma function is $\Gamma(x,a)\bullet\Gamma(a)=\int_0^a x^{a-1}\bullet e^{-x}dx$, the next formula is obtained:

$$(\frac{2n-1}{2N})\bullet\int_0^1\sqrt{p(\omega)}d\omega=(\frac{2n-1}{2N})\bullet c_3\bullet\Gamma(a)\bullet[\Gamma(c_1+c_2,a)-\Gamma(c_1,a)] \quad \textbf{(11)}$$

Similarly, the left of equals sign of formula (3) can be expressed:

$$\int_0^{z_n}\sqrt{p(\omega)}d\omega=c_3\bullet\Gamma(a)\bullet[\Gamma(c_1+c_2z_n,a)-\Gamma(c_1,a)] \quad \textbf{(12)}$$

So, formula (3) can be represented as follow:

$$c_3\bullet\Gamma(a)\bullet[\Gamma(c_1+c_2z_n,a)-\Gamma(c_1,a)]=(\frac{2n-1}{2N})\bullet c_3\bullet\Gamma(a)\bullet[\Gamma(c_1+c_2,a)-\Gamma(c_1,a)] \quad \textbf{(13)}$$

The optimal quantiles Z_n ($n=1,2, \ldots, N$), that is, the wind power scenario can be determined by above formula. The probability of Z_n occurrence can be calculated by formula (4).

According Fig. 1, three kinds of scenarios can be divided: the rated output scenario ($v_n<v<v_{out}$), the owe rated output scenario ($v_{in}<v<v_n$) and the zero output scenario ($v<v_{in}$ or $v>v_{out}$). The output power of wind turbine for the rated output scenario and the zero output scenario, separately, is rated output power and zero. The owe rated output scenario is divided four scenarios in this paper. Each quantile (Z_n) can be determined by formula (13), and by formula (4), the occurrence probability of Z_n can be obtained.

3 The Objective Function

This section introduces the objective function for the improved particle swarm optimization algorithm.

The power losses (P_{loss}) and the stability margin of static voltage (δ) are two aspects that the objective function represents. The power loss (k_1) and the stability margin of static voltage (k_2) are redfined according to the occurrence probability of scenario:

$$k_1 = \sum_{k=1}^{n} p_k \bullet p_{loss}^k \tag{14}$$

$$k_2 = \sum_{k=1}^{n} p_k \bullet \delta_k \tag{15}$$

where n is the number of scenarios. P_k represents the kth occurrence probability of scenario; P^k_{loss} represents the power loss of kth scenario and δ_k represents the voltage stability margin of kth scenario.

Further, we get the normalized expressions as follow:

$$P_{loss}^* = (k_1 - k_{1\min})/(k_{1\max} - k_{1\min}) \tag{16}$$

$$\delta^* = (k_{2\max} - k_2)/(k_{2\max} - k_{2\min}) \tag{17}$$

Following formula gives the final objective function:

$$\min F = \alpha_1 \bullet P_{loss}^* + \alpha_2 \bullet \delta^* \tag{18}$$

Here, α_1 and α_2 represent the weight coefficient.

4 The Constraints

This section introduces the constraints for the improved particle swarm optimization algorithm.

The power flow equation of each scenario is used to define the equality constraints, and according to [11], the power flow equation in a scenario of node i can be represented by following formulas:

$$P_i = V_i \bullet \sum_{j \in i} V_j \bullet (G_{ij} \bullet \cos\theta_{ij} + B_{ij} \bullet \sin\theta_{ij}) \tag{19}$$

$$Q_i = V_i \bullet \sum_{j \in i} V_j \bullet (G_{ij} \bullet \sin\theta_{ij} - B_{ij} \bullet \cos\theta_{ij}) \tag{20}$$

where the voltage of node i is V_i; P_i is the active power of the ith generator and Q_i is the reactive power of the ith generator; θ_{ij} , G_{ij}, B_{ij} are respectively represent the angular phase difference and admittance between node i and node j.

The wind speed of each scenario determines the value of P_i, and the generator voltage determines the value of Q_i.

The inequality constraints of each scenario are defined by the following formulas:

$$Q_{g\min} \le Q_g \le Q_{g\max} \tag{21}$$

$$T_{\min} \le T \le T_{\max} \tag{22}$$

$$V_{i\min} \le V_i \le V_{i\max} \tag{23}$$

$$V_{g\min} \le V_g \le V_{g\max} \tag{24}$$

$$C_{\min} \le C \le C_{\max} \tag{25}$$

Here, Q_g are generator reactive power and V_i are node voltage; Q_g and V_i are called state variables. V_g and T represent the generator terminal voltage and the ratio of variable-voltage transformer respectively; C represents the susceptance value for capacitance compensation. V_g , T and C are called control variables.

5 The Improved Particle Swarm Optimization Algorithm (IPSO)

This section introduces the specific implementation process for IPSO. The IPSO is put forward based on the particle swarm optimization algorithm (PSO). The improved ways in IPSO is discussed. The crossover operator, the mutation operator, and the improved mutation probability (P_m) are introduced concretely.

5.1 Introduction of PSO

PSO has already been applied to the reactive power optimization of power grid [12][13]. Particle swarm optimization algorithm, as the genetic algorithm (GA), is also an iterative optimization algorithm. It can search the optimum by iterating. The particle updates the velocities and the positions during each iteration by following formulas:

$$v_{ik}^{n+1} = v_{ik}^{n} + c_1 \bullet r_1 \bullet (p_{bestik}^{n} - x_{ik}^{n}) + c_2 \bullet r_2 \bullet (g_{bestk} - x_{ik}^{n}) \quad \textbf{(26)}$$

$$x_{ik}^{n+1} = x_{ik}^{n} + v_{ik}^{n+1} \quad \textbf{(27)}$$

where X_i is a particle of the particle swarm, and it is an n-dimensional vector $X_i=(x_{i1} ,x_{i2} ,x_{i3} ,\ldots, x_{ik})^T$. C_1 and c_2 are accelerated factors ; v_{ik} is the running speed of x_{ik}; g_{bestk} is the global best value and P_{bestik} is the local best value of x_{ik}; N is iterations; $r_1$and r_2 are the random numbers between [0,1].

From above formulas, we can see that, by each iteration, X_i is updated toward the global optimum value g_{bestk} with speed V_i . C_1 and c_2 adjust the direction of X_i in order to make it toward g_{bestk}.

In comparison with the GA, PSO algorithm has a high speed of convergence, but PSO algorithm usually plunges into the local optima. The reason is that the evolution pattern of PSO algorithm is simpler than that of GA [14] and the crossover operator and mutation operator of GA can guarantee the multiplicity of the population.

In this paper an improved particle swarm algorithm (IPSO) is presented. Compared with PSO algorithm, the mutation operator and the crossover operator are added to IPSO. The specific strategies are introduced as follows.

5.2 Strategies of IPSO

The strategies of IPSO can be illustrated by Fig. 2. In order to ensure the fast convergence of PSO, In the beginning, classical PSO algorithm play a role, the particles of the particle swarm are updated according to formula (26)(27). When the result tends to convergence in a few iterations, the crossover operator and the mutation operator are added to classical PSO. To the rest of the iterative process, optimization algorithm is carried out based on the new running process. From the Fig. 2 we can see, most of particles are proceeded the crossover operator and mutation operator except from some excellent particles, and the multiplicity of the population is insured.

The flow chart of IPSO is presented by Fig. 3. From Fig. 3 and Fig. 2 we can see that in order to maintain the quick convergence speed, the classical PSO optimization at initial phase and the optimal particles reserving are adopted. In IPSO algorithm, the crossover and mutation operator also are introduced. That can enable the diversity of the swarm, and avoid falling into premature convergence.

5.3 Coding Format

Next formula gives the coding format, and integer coding is adopted. The capacitor set numbers and adjustable transformer tap values are coded as below:

$$x = [T_1 T_2 \ldots T_{NT} \mid C_1 C_2 \ldots C_{NC}] \quad \textbf{(28)}$$

The x is a particle for particle swarm. T and C represent the adjustable transformer tap value and capacitor set number respectively. NC and NT represent the total numbers of the capacitance bank and the total numbers of the adjustable transformer.

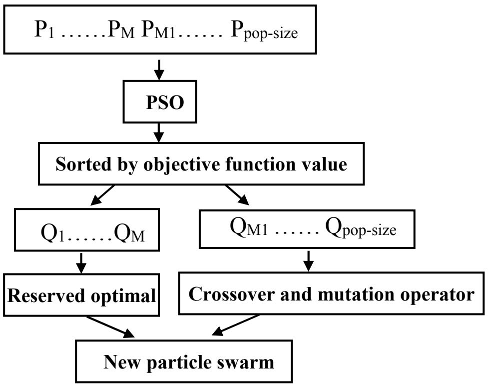

Fig. 2. Generation process of particle

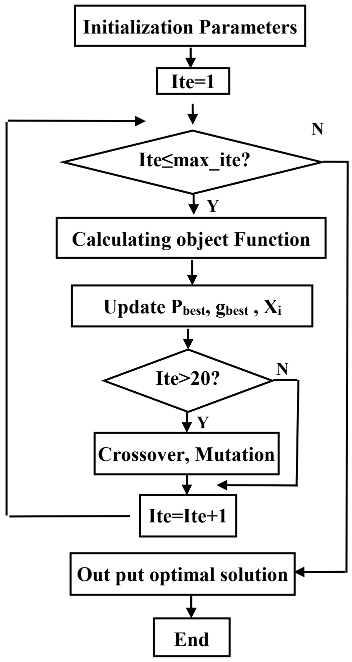

Fig. 3. Flow based on IPSO

5.4 Implementation Process of IPSO

Fig. 3 shows the implementation process of IPSO. The initialization parameters part in Fig. 3 includes the parameters of IPSO, the power network parameters and each scenario parameters (number of scenarios and scenario probability). *Ite* represents the number of iterations, and *max_Ite* represents the maximum number of iterations.

Usually, the classical PSO algorithm tends to convergence after 20 iterations in reactive power optimization. So, from Fig. 3 we can see when *Ite* is bigger than 20 iterations, crossover operator and mutation operator are added to the IPSO.

Fig. 5 gives the optimization analysis example of IPSO, we can find that after the area S, the curve of PSO tends to be parallel, and this means the object function tends to be a fixed value. The situation can easily lead to local optimum. So, in order to acquire the preferable result, when the *Ite* is between 20 and 30, the crossover and mutation operators should be added to the IPSO. So, in the example, after *Ite* is bigger than 20, the crossover operator and mutation operator come into play.

5.5 The Crossover Operator and Mutation Operator in IPSO

The algorithm of intermediate recombination is used to process crossover operator. According to the crossover probability (P_c), two particles are randomly selected out, and the operation is performed by the next formula:

$$x_i' = u*(x_j - x_i) + x_i \tag{29}$$

$$x_j' = u*(x_i - x_j) + x_j \tag{30}$$

Here x_i' and x_j' are new particles after crossover operator; u is a random parameter, $u \in (0, 1)$; x_i and x_j are the particles which will carry out crossover operator.

A random number between (0, 1) is generated at first, and if the number is less than P_c, the crossover operator will be performed according to above formulas. When each crossover operator is processed, u needs to be regenerated randomly.

The mutation operator is an important process to keep the difference for the particle swarm. By keeping the difference, IPSO can avoid local convergence. The operator need not be carried out in every iteration, and the mutation probability (P_m) is used to determine if the mutation operator is processed. By P_m, the mutation operator is processed as the follow formula:

$$x_{t\,new} = \theta * (x_{t\max} - x_{told}) + x_{t\,old} \quad \theta > 0.5 \tag{31}$$

$$x_{tnew} = \theta * (x_{t\,old} - x_{t\min}) + x_{told} \quad \theta \le 0.5 \tag{32}$$

The x_t is a component of particle swarm X, and $X=(X_1,X_2,...X_t)$. $\theta \in (0, 1)$, it is generated randomly; x_{tmax} , x_{tmin} represents the x_t that with the maximum norm and the minimum norm respectively; x_{told} , x_{tnew} respectively represents the particle before or after mutation operator.

The process by above formulas is called uniform mutation. A random number between (0, 1) is generated at first, and when the number is less than P_m , the mutation operator will be processed. From above formulas we can see that the value of x_{tnew} will be changed up and down depending on x_{told} , and that can limit the value of x_{tnew} in a suitable range. θ should be regenerated randomly when each mutation operator is processed.

5.6 The Improvement of P_m in IPSO

By the crossover operator and mutation operator, GA ensures the dispersibility of the population. But GA may still be trapped in local optimum. The adaptive genetic algorithm (AGA) improves the crossover probability (P_c) and the mutation probability (P_m) to avoid this situation. With the process of algorithm, P_c and P_m can alterable automatically. When the individual's fitness is lower or higher than average level, the P_c and P_m will become bigger or smaller. This variation can determine if an individual can enter the next generation in the operation of algorithm, and can guarantee the convergence speed of the algorithm. But, the optimization procedure AGA is too complex to IPSO. In this paper, only the P_m is redesigned, and the new adaptive P_m can adjust the mutation operator based on the degree of convergence. The P_c and the new adaptive P_m are given as follows:

$$P_c = \begin{cases} \dfrac{k_1 \bullet (f_{\max} - f')}{f_{\max} - f_{avg}} & (f' \ge f_{avg}) \\ k_2 & (f' < f_{avg}) \end{cases} \tag{33}$$

$$P_m = \begin{cases} \dfrac{k_3 \bullet (f_{\max} - f)}{f_{\max} - f_{avg}} + \eta \bullet \dfrac{f_{\min}}{f_{\max}} & (f \ge f_{avg}) \\ k_4 + \eta \bullet \dfrac{f_{\min}}{f_{\max}} & (f < f_{avg}) \end{cases} \tag{34}$$

where, f and f' respectively represent objective function value of crossover particle and mutation particle; the average objective function value of particle swarm is f_{avg}; similarly, f_{max} is the maximum value and f_{min} is the minimum value of objective function. k_1, k_2, k_3, k_4, η are constants.

In the formula (34), $\eta \bullet (f_{min}/f_{max})$ can ensure the adaptation of P_m. When the value of objective function tends to be constant, $\eta \bullet (f_{min}/f_{max})$ become bigger. This can let more particles to carry out mutation operator. In this paper, $\eta=0.05$.

6 Experiment and Analysis

This section introduces the experiment program for IPSO, and presents the concerning data. The experimental conditions are shown, and the comparison of two algorithms is given. By the analysis of experimental data, the result is obtained.

Fig. 4 is the IEEE 69-bus distribution system, and this system is adopted to verify the effectiveness for the model of IPSO. The branch parameters and node data for IEEE 69-bus are provided in [5]. The node12, 22, 35, 47, 54, 69 are used for cutting and throwing capacitor banks; every capacitor bank's capacity is 50kvar, and the every capacitor bank number that used for cutting and throwing is 10. The size of particle swarm is 20 and the maximum iteration (*max_Ite*) is 100; $c_1=c_2=2$.

At the node of 54, a wind generator is integrated, and the rated voltage of it is 690v. The wind generator rated capacity is 600kw. The Weibull model for wind speed is adopted [5]. The shape parameter is 2, and the scale parameter is 15. Some parameters for wind farm are shown in Table 1. The X_1 is the stator leakage reactance; X_2 is the rotor leakage reactance; r_2 is the rotor resistance; X_m is the magnetizing reactance.

According to the concepts described in section 2.2, the owe rated output scenario is divided four scenarios. The scenarios is represented by Z_n $(n=2,..., 5)$, and the corresponding probability is P_n $(n=2,...,5)$. The zero output scenario and probability are Z_1, P_1. The rated output scenario and probability are Z_6, P_6. By the formula (13) and formula (4), we can get the results given by Table 2.

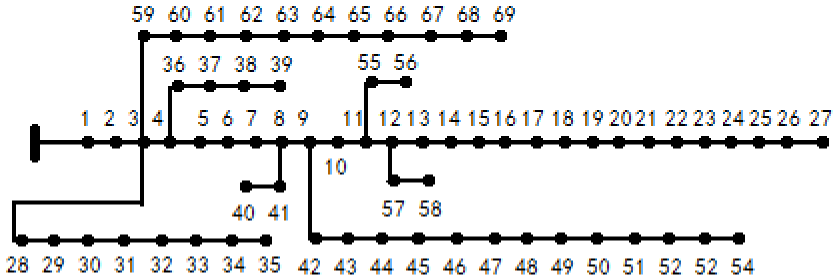

Fig. 4. IEEE 69-bus distribution system

Table 1. Parameters of wind farm

Wind speed			Parameters of single induction generator			
cut-in speed	cut-out peed	rated wind speed	X_1	X_2	r_2	X_m
5 m/s	45 m/s	15m/s	0.0762Ω	0.2329Ω	0.0759Ω	3.44797Ω

Table 2. The scenarios division and their probability

	n=1	n=2	n=3	n=4	n=5	n=6
Z_n	0.0000	0.0770	0.2657	0.49889	0.8075	1.0000
P_n	0.1052	0.0771	0.1104	0.1538	0.1858	0.3678

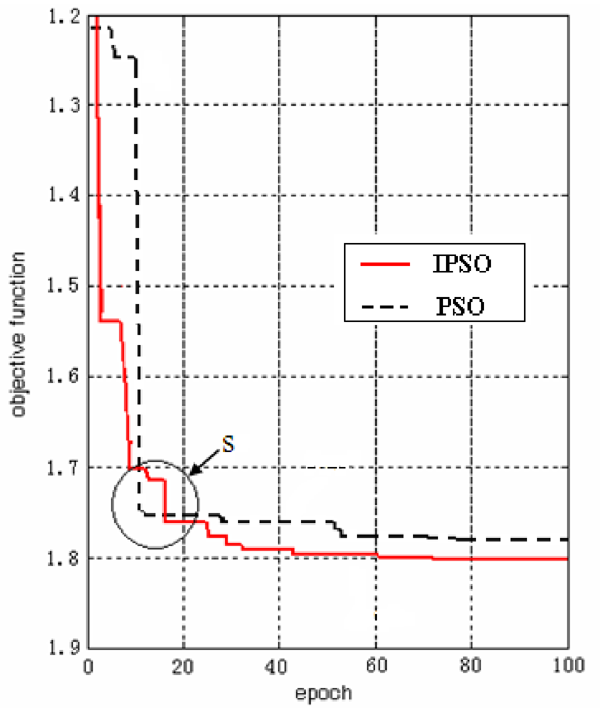

Fig. 5. Comparison of two algorithms

Fig. 5 gives the curve of IPSO algorithm. By comparison, the curve of PSO is also shown. From Fig. 5, we can see that both the two algorithms can converge rapidly at the beginning. After 20 epochs, the PSO has plunged into a local optimal solution, but the IPSO has an excellent performance.

The optimize results are presented in Table 3 and Table 4. In Table3, the capacitor set numbers are given in the brackets, and the figure that outside the brackets are node numbering. The optimization schemes of all scenarios are given by Table 4. The opt is the final optimum result, for that the occurrence probability for each scenario is taken into account.

Table 3. Optimization scheme

	Optimization scheme					
Scenario **1**	12(8)	22(7)	35(2)	47(6)	54(8)	69(7)
Scenario **2**	12(8)	22(7)	35(2)	47(6)	54(8)	69(8)
Scenario **3**	12(9)	22(9)	35(3)	47(7)	54(10)	69(7)
Scenario **4**	12(9)	22(10)	35(5)	47(7)	54(10)	69(7)
Scenario **5**	12(8)	22(9)	35(5)	47(8)	54(9)	69(6)
Scenario **6**	12(10)	22(10)	35(4)	47(6)	54(10)	69(5)
Opt	12(10)	22(9)	35(3)	47(7)	54(10)	69(6)

The power loss and stability margin of static voltage for all scenarios and opt are given by Table 4. As can be seen that though compare with the other scenarios, the results of opt are not the optimum value of power loss or stability margin of static voltage but they are the excellent results for synthetically evaluation.

Table 4. Result of optimal schemes

	Power loss(kw)	Stability margin of static voltage
Scenario **1**	83.27	0.01282
Scenario **2**	96.16	0.01281
Scenario **3**	114.73	0.01290
Scenario **4**	125..46	0.01295
Scenario **5**	115.39	0.01290
Scenario **6**	107.43	0.01293
Opt	106.40	0.01289

7 Conclusions

In this paper, the reactive power optimization in distribution network with wind farm is discussed. The mathematical model based on scenario classification and the improved particle swarm optimization is studied. The reactive power optimization model considering wind power is established; the method of getting optimal scenario based on Wasserstein distance is given. The relevant formula about the optimal quantiles and the occurrence probability of scenario is deduced. In the IPSO, the crossover operator and mutation operator are added to, and the mutation probability (P_m) is improved. Experimental results have shown that the algorithm not only can weaken the randomness of wind power, but also have rapid convergence speed and global astringency.

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