# Reactive power optimizational configuration of wind farms on the distribution network based on improved random black hole particle swarm optimization algorithm

## Chaofan Zong, Zhongxiao Cong and Zhigang Lu

The Electrical Engineering College, Guizhou University, Guiyang, 550000, China

**Keywords:** wind farms of the distribution network; Weibull model; reactive power limit; optimal installation location; optimal reactive power generation; improved random black hole particle swarm optimization algorithm

**Abstract.** At present, the reactive power compensation devices of the distribution network can't compensate reactive power smoothly. To solve this problem, this paper studys reactive power optimizational generation of wind farms on the distribution network. First of all, in order to reflect the wind property, We adopt Weibull wind farm probabilistic model. Thus, the mathematical expected power of the model is the active power of double-fed induction wind turbine(DFIG) .In addition, we take the DFIG reactive power limit into account. Last but no least, we present a improved random black hole particle swarm optimization algorithm(IRBHPSO) which is faster convergence, better global searching. Using this algorithm, we can easily solve the optimal installation location and the optimal reactive power generation capacity of wind farms. We do a simulation on the IEEE33 system which has the same wind conditions on every node and compare IRBHPSO with other four algorithms. Finally, the result shows that the proposed algorithm is effective and feasible, and the installation of wind farms can enhance the power quality of the distribution network.

## Introduction

Among the distrubuted generations, wind power generation has the advantages of its high efficiency, good controllability, appropriate cost and so on. Unlike the traditional reactive power compensation devices by switching capacitors, wind power generation can generate reactive power smoothly. Besides, the grid loss of the distribution network has a large proportion on the power system. Therefore, in order to decrease the grid loss and improve the voltage level effectively, it's necessary to install the wind farms on the distribution network. However, the wind is random and intermittent. So the output of wind power generation turbine is random and uncertain. Thus, the DFIGs on the grid have a serious impact on the grid flow, node voltage level, grid loss and power supply reliability[1].

Swarm intelligence algorithms are widely used in solving nonlinear, discrete, non-convex problems, such as the distribution network wind farm optimization configuration problem[2]. Swarm intelligence algorithms which include particle swarm optimization, fish swarm algorithm, bacterial foraging algorithm, etc are always premature. And they always fall into local optimum but global optimal solution. the results are random. Based on a random black hole particle swarm algorithm, this paper solve the optimal installation location and the optimal reactive power generation capacity of wind farm on the distribution network. Considering the randomness of the wind and taking full advantages of the wind farm reactive power optimization capabilities, the distribution network optimizes the reactive power compensation by istalling wind farms. Finally, we do a simulation of IEEE33 system and it's result that the proposed mathod and algorithm is effective and feasible.

### **Power properties of DFIG**

## Active power properties of DFIG

Active power of DFIG is related to wind speed. Active power formula of a 1.5MW double-fed induction wind turbine is Eq. (1) as follows[3]:

$$\begin{cases} 0 & v < v_i or v > v_o \\ k1v + k2 & v_i \le v \le v_n \\ P_n & v_n \le v < v_o \end{cases}$$
(1)

Among them,  $v_i, v_n, v_o$  Were the cut in wind speed, rated wind speed and the cut out wind speed. Eq. (1) shows the three operating states: Stop operating, under rated operating and rated operating. Its output active power has three states: zero(when it stops.), a linear function of wind speed(when it is under rated operating.) and rated active power(when it is rated operating).

For fitting the wind characteristics, there are Weibull model, Rayleigh model and so on. We adopt the two-parameter Weibull model which is widely used and has a more accurate fitting of wind characteristics[4].Weibull model distribution function and the probability density function is written as Eq. (2), Eq. (3)below:

$$F(v) = 1 - e^{-\frac{(v)^{k}}{c}^{k}}.$$
(2)
$$f(v) = \frac{k}{c} \times (\frac{v}{c})^{k-1} e^{-\frac{(v)^{k}}{c}}.$$
(3)

Among them, v is the wind speed, k is the shape parameter, c is the scale parameter.

By Weibull probability distribution model, we can get the probability of three operating states: p1,p2,p3. Its expression formula is Eq. (4):

$$\begin{cases} p1 = p\{v \le v_i\} + p\{v > v_o\} = 1 - [F(v_o) - F(v_i)] \\ p2 = p\{v_i \le v < v_n\} = F(v_r) - F(v_i) \\ p3 = p\{v_n \le v < v_o\} = F(v_o) - F(v_r) \end{cases}$$
(4)

Among them, p1 is the probability of stop operation and its output active power is 0; p3 is the probability of rated operation and its output active power is Pn; p2 is the probability of under-rated operating state and its output active power is the mathematical expected power as the Eq. (5) below:

$$P_{w2} = E(P_w) = \int_{v_n}^{v_0} p_w f(v) dv = \int_{0}^{p_n} p_w \frac{k}{klc} \left(\frac{p_w - k2}{klc}\right) e^{-\left(\frac{p_w - k2}{klc}\right)^k} dp_w.$$
 (5)

#### **Reactive power property of DFIG**

DFIG consists of an induction generator, wind turbine, rotor excitation controller and other components. Its output reactive power is determined by the stator and grid converters. And its output reactive power is limited by the converters. So there is a reactive power limit[5,6]. As Eq.(6), Eq. (7) shows:

$$\left(\frac{P_T}{1-s}\right)^2 + Q_s^2 = (3U_s I_s)^2.$$
(6)

$$\left(\frac{P_T}{1-s}\right)^2 + \left(Q_s + 3\frac{U_s^2}{X_{ss}}\right)^2 = \left(3\frac{X_M}{X_{ss}}U_sI_R\right)^2.$$
(7)

Among them,  $X_{ss} = X_s + X_M$ ; Us, Is are stator voltage and stator current respectively;  $I_R$  is the current of rator converters;  $X_s, X_M$  is namely stator leakage reactance and excitation reactance; s is slip.

As we can see from Eq.(7) and Eq.(6), the reactive power limit is mainly determined by the

stator current Is and the rotor converter  $I_R$ . And  $I_R$  plays a major role[7].

The output reactive power of DFIG:

$$Q_T = Q_c + Q_s. \tag{8}$$

Among them,  $Q_T$  is the reactive power flowing into the power system, which is generated by DFIG.Qc is the the reactive power which is generated by the grid converter. When the power factor is adjusted closly to 1, Qc  $\approx$  0. Therefore, by the Eq. (7) to Eq.(8), the reactive power limit expression of DFIG can be described as Eq.(9):

$$\begin{cases} Q_{T\min} = -3\frac{U_s^2}{X_s} - \sqrt{(3\frac{X_M}{X_s}U_sI_{r\max})^2 - (\frac{P_T}{1-s})^2} \\ Q_{T\max} = -3\frac{U_s^2}{X_s} + \sqrt{(3\frac{X_M}{X_s}U_sI_{r\max})^2 - (\frac{P_T}{1-s})^2} \end{cases}$$
(9)

Among them,  $I_{R_{max}}$  is the maximum rotor converter current.

#### Multi-objective reactive power optimization mathematical model

#### The objective function

In this paper, multi-objective reactive power optimization includes grid loss, the node voltage deviation and voltage stability index, which is considerated as economical efficiency, safety and reliability. The objective functions consist of grid loss  $P_{loss}$ , the node voltage deviation  $\Delta U$  and the voltage stability index  $U_{stable}$ . The objective functions show as Eq. (10):

$$\begin{cases} F1 = \min P_{loss} = \sum_{b \in N_b} G_{ij} [U_i^2 + U_j^2 - 2U_i U_j \cos \delta_{ij}] \\ F2 = \min \Delta U = \sum_{i \in N_p} (\frac{U_i - U_i^N}{\Delta U_i^{\max}}) \\ F3 = \min(\max U_{stable.i}) = \frac{4[(X_{ij}P_j - R_{ij}Q_j)^2 + (X_{ij}Q_j + R_{ij}P_j)U_i^2]}{U_i^4} \end{cases}$$
(10)

Among them, Nb is the system branch number, Np is the number of nodes;  $G_{ij}$  is the admittance between node i, and node j; Ui, Uj are the voltage of node i and node j;  $U_i^N$  is the rated voltage of node i;  $U_{stable.i}$  is the voltage stability index of the node i;  $\delta_{ij}$  is the phase angle difference of node i and j; Rij and Xij is the resistance and reactance between nodes i and j; Pj and Qj are the active power and reactive power which inject the node j.

## **Constraints**

Constraint conditions contain equality constraints of active power and reactive power and inequality constraints, such as the Eq. (11) presents.

$$\begin{cases} P_i = U_i \sum_{j \in H} U_j (G_{ij} \cos \delta_{ij} + B_{ij} \sin \delta_{ij}) \\ Q_i = U_i \sum_{j \in H} U_j (G_{ij} \sin \delta_{ij} - B_{ij} \cos \delta_{ij}) \end{cases}$$
(11)

Inequality constraints such as Eq.(12), Eq.(13) are written.

$$T_{i.\min} < T_i < T_{i.\max}.$$
 (12)

$$Q_{DGi.min} < Q_{DGi} < Q_{DGi.max}.$$
(13)

Among them, Bij is the susceptance of branch ij; Ti is transformer ratio at node i;  $Q_{DGi}$  is the output reactive power of DFIG if there is a wind farm at node i.

## Normalization and weighting preferences

To make the different objective functions in the same dimension, We should normalize the different objective functions and show the preference of the three objective functions. the objective functions are processed as following .

$$F = k_1 F_1^* + k_2 F_2^* + k_3 F_3^* + k \sum_{i=1}^{n} (\Delta U_i)^2.$$

$$F_1^* = \frac{F_1 - F_{1\min}}{F_{1\max} - F_{1\min}} (15), \quad F_2^* = \frac{F_2 - F_{2\min}}{F_{2\max} - F_{2\min}} (16), \quad F_3^* = \frac{F_3 - F_{3\min}}{F_{3\max} - F_{3\min}} (17)$$

Among them, k1, k2, k3 are the weighting preferences of the grid loss, voltage deviation and the voltage stability index[8]. Satisfy k1 + k2 + k3 = 1, k1, k2, k3  $\ge 0$ .  $F_{1\min}$ ,  $F_{2\min}$ ,  $F_{3\min}$  are the optimums when it is single-objective optimization.  $F_{1\max}$ ,  $F_{2\max}$ ,  $F_{3\max}$  are the initial solutions before optimization.

#### **Random black PSO**

#### Fundamental

Standard particle swarm optimization algorithm(PSO) has the advantages of simple parameters, fast convergence, quickly getting the ideal solution and so on[9]. Literature[2] proposed a new space PSO(SPSO) idea that there is a height variable adding to the original two-dimensional varibles position and velocity. When fitness are equal in the iteration process, We can update the height dimension to prevent falling into local optimum. By this way, It can find the global optimum.

In this paper, We propose a improved random black hole particle swarm optimization algorithm(IRBHPSO) which is using the black hole strategy based on PSO[10]. The Fundamental of IRBHPSO algorithm is shown in the following figure.



Fig.1: illustration of the IRBH Fundamental

In the each generation and dimension, we randomly propose a particle close to the current optimal particle as a black hole.Set a threshold p which means the magnetism of the black hole,  $p \in [0,1]$ . In each dimension of every particle, set a value 1 which is a random number,  $1 \in [0,1]$ . If l < p, let the black hole capture the particle. Otherwise, update the position and velocity in the PSO way.

Its position and velocity updating formulas are shown below. And the updating formulas are improved.

When 
$$l_{id}^{k} \ge p$$
 ,  $v_{id}^{k+1} = \omega v_{id}^{k} + c[r1(x_{pid}^{k} - x_{id}^{k}) + r2(x_{gid}^{k} - x_{id}^{k})];$ 

(18)

$$x_{id}^{k+1} = x_{id}^k + v_{id}^{k+1}$$

(19)

When

$$l_{id}^k < p$$
 ,  $x_{id}^{k+1} = x_{gd}^k + 2R(r3 - 0.5).$ 

(20)

Among them, r1, r2, r3 are the random numbers which belong to [0,1].  $l_{id}^{\kappa}$  is the probability of

i\_th particle on the d-th dimension when it is the k-th iteration. It means the probability that particles escape from the black hole. R is the radius of the black hole.

Inertia weight  $^{(0)}$  and learning factor c update themselves dynamically. The following Eq.(21), Eq.(22) are given.

$$\omega = \omega_0 + r4(1 - \omega_0). \tag{21}$$

$$c = c_0 + \frac{\iota}{Mt}.$$
(22)

Among them, r4 is a random number,  $r4 \in [0,1]$ ;  $\omega 0$  is a constant,  $\omega 0 \in [0, 0.5]$ ; c0 is a constant,  $c0 \in [0.5, 1]$ ; t is the number of iterations; Mt is the maximum number of iterations. Large inertia weight enhances global searching capability, and small inertia weight strengthen the capacity of local searching. The update method of learning factor improve the capacity of the global searching in the later searching period.

### The simulation results and analysis

## Simulation parameters setting

In this paper, we do a reactive power optimization simulation on IEEE33 system by installing wind farms. IEEE33 system detailed parameters can refer to the literature[11]. Set the number of IRBHPSO iterations is 100; the population of particle is 100; the initial inertia weight w0 = 0.3; initial learning factor c0 = 0.9; black hole radius R = 8; black hole magnetism probability p = 0.3.

1.5MW DFIG: cut-in wind speed is  $3^{m/s}$ , rated wind speed is  $12^{m/s}$ , cut-out wind speed is  $25^{m/s}$ . The shape parameter k =1.93, and the scale parameter c=9.19. The probability of Stop operating state, under rated operating state and rated operating state are 0.1099,0.7035 and 0.1866. Their active power is 0MW, 0.2839MW and 1.5MW. Hence, the mathematical expected output active power: E (p) = 0.4796MW. Its reactive power limit is (-3.554,06237).

The simulation projects: the wind farms could be installed on the node 2 to node 33 in the IEEE33 system and the wind resources of every node are the same. Option One: optimal installing only one wind farm in the IEEE33 system; Option Two: optimal installing two wind farms in the IEEE33 system. A 1.5MW DFIG simulates a wind farm.

### Example calculation results and analysis

In order to verify that the installation of wind farms in the distribution network can optimize reactive power, we compare the affects on the distribution network system when it is the the optimal location and capacity of installation of one wind farm, the optimal location and capacity of the installation of two wind farms and without installing any wind farm. Cite the grid losse, voltage deviation and voltage stability index to measure the impact of the wind farm reactive power optimization on the distribution network. As it is shown in Table 1.

Objects	No wind farm	One wind farm	Two wind farms				
Grid loss(kW)	203.8930	134.081	67.3656				
Voltage deviation	17.0498	11.8955	8.3381				
Voltage stability index	85.7845	63.2073	43.4063				
Percentage of grid loss decrease (%)		34.2395	66.9603				

Table 1: Comparison of optimizational results of IEEE33 system

As we can see from Table 1, in the IEEE33 system, when there is no installing wind farm, the grid loss is 203.8930kW, voltage deviation is 17.0498; voltage stability index is 85.7845. And the IRBHPSO algorithm can find the optimal installing position and the compension capacity of reactive power. Comparing with the relations of the three situations, we can see that the installation of wind farms can improve the power quality greatly. Because of the reactive power of wind farms,

the grid losse, voltage deviation and voltage stability index is smaller. So the effect of intalling two wind farms is better than one. The following figure is the comparison of each node voltage (pu).



Fig.2:Comparison of optimizational voltage level

From the above figure, we know that the node voltage level has been improved greatly by the installation of wind farm.

The IRBHPSO algorithm can find the optimal location and optimal capacity of wind farms within the constraints. It can account grid loss, voltage deviation and voltage stability index comprehensively to find the compromised solution. Detailed optimal configuration is shown in Table 2.

Objects	1	No wind farm	One wind f	arm Two	wind farms		
Optimal installing location			Node 16	ó No	de 16 & 32		
Optimal read power gener capacity (k	ctive ation Var)	0 359.40 248.78 & 52		78 & 528.27			
Table 3: Comparison of single object optimum and compromised optimization							
Objects	No wind farm	Single object optimum of one wind farm	Compromis ed optimizatio n of one wind farm	Single object optimum of two wind farms	Compromis ed optimizatio n of two wind farms		
Grid loss(kW)	203.8930	113.8328	134.081	60.5389	67.3656		
Voltage deviation	17.0498	10.5076	11.8955	6.0683	8.3381		
Voltage stability index	85.7845	60.6821	63.2073	40.9403	43.4063		

Table 2: The optimizational reactive power capacity

We can know from the table3 that this IRBHPSO algorithm can get the promising compromised solutions. And its compromised solution is closed to the single objective optimum.

In order to verify the advantages of the proposed IRBHPSO algorithm, we compare IRBHPSO with PSO, SPSO and RBHPSO. Calculate this example 30 times with the four algorithms respectively. The average time of PSO example calculation is 11.57171s; the average time of SPSO is 11.7771s; The average time of RBHPSO is 11.59234s; The average time of IRBHPSO is 11.51702s. Most of the calculation time is consumed in the iterative flow calculation, and all the four algorithms can calculate the optimum solutions.

To fully testify the advantages of this IRBHPSO algorithm, we try to calculate more complex multimodal function. Its function expression Eq.(23) is below.

$$y = \sum_{i=1}^{N} x_i - 10\cos(2\pi x_i + 10).$$
(23)

N = 20(the dimension is 20), solve the multi-modal function minimum. The results of the four algorithms calculation are shown in figure 3. The IRBHPSO algorithm iterate faster and can find the global optimum.



Fig.3:The iterative process of four algorithms

Figure 4 and figure 5 are the calculating the function minimum and the calculation time of the four algorithms. The four algorithms run on the same computer on the same conditions for 30 times.



Fig.4:Calculating function minimum by four algorithms Fig.5:Calculation time of four algorithms

The above two figures show that, compared with the other three algorithms, the IRBHPSO algorithm iterates faster, is less prone to premature phenomenon and is able to find the global optimum.

#### Summary

For the sake of reflecting the characteristics of the wind, This paper bases on the weibull probability model of wind farms. Use the model mathematical expected power to fit the active power of wind farms and take the reactive power limit which is the ability of reactive power compensation into account. Wind farms can generate the reactive power smoothly. And adopt the IRBHPSO algorithm which is faster iteration, faster convergence and able to find the the global optimum. Calculate the optimal installation location of wind farms and the best configuration reactive power capacity of the wind farms to verify the proposed algorithm is effective and feasible, and the installation of wind farms can enhance the power quality of the distribution network.

### References

[1] Chen Shu-yang, Dai Hui-zhu, etc. Reliability model of wind power plants and its application. *Proceedings of the CSEE*, 20(3), pp. 26-29, 2000.

- [2] Zhou Ren-jun, Li Shao-jin, etc. Space particle swarm optimization algorithm and its application in environmental & economic load distribution of power system. *Electric Power Automation Equipment*, 34(9), pp. 7-12, 2014.
- [3] He Yu-qing, Peng Jian-chun, etc. Reactive power optimization in distribution system with multiple wind power generators. *Automation of Electric Power Systems*, 34(19), pp. 37-41,2010.
- [4] Ding Ming, Wu Wei, etc. Research on forecasting of probabilistic distribution parameters of wind speed and its application. *Power System Technology*, 32(14), pp. 10-14,2008.
- [5] Wang Rui, You Xiao-jie etc. Research on the reactive power control of distributed generation system based on genetic algorithm. *Power System Protection and Control*, 37(2), pp. 24-27,2009.
- [6] Shen Hong, Wang Wei-sheng, etc. Reactive power limit of variable-speed constant-frequency wind turbine. *Power System Technology*, 27(11), pp. 60-63,2003.
- [7] Datta R, Ranganathan V T. Variable-speed power generation using doubly fed wound rotor induction machine-a comparison with alternative schemes. *IEEE Trans on Energy Conversion*, 17(3), pp. 414-421,2002.
- [8] Li Jun, Feng Bin, etc. Particle swarm optimization with particles having quantum behavior. *Proceedings of 2004 Congress on Evolutionary Computation.* 2004: 325-331.
- [9] Kennedy J, Eberhaart R. Particle swarm optimization. *Proceedings of IEEE Conference on Neural Networks*. Perth(Australia)1995: 1942-1948.
- [10] Zhang Jun-qi, Liu Kun, etc. Random black hole particle swarm optimization and its application. *Proceedings of IEEE Conference on Neural & Signal Processing*. Zhenjiang(China)2008: 359-365.
- [11] Li Jiang, Li Hong-lu, etc. *The simplify analysis and optimization of the complicated distribution network*. Beijing:China Electric Power Press,2002.