A Fruit Fly Optimization Novel Algorithm to Plan a Power Distribution Network for Electric Vehicle Charging Stations

Dongxiao Niu, Tiannan Ma, Zongyun Song, Yali Huang*, Meiqiong Wu

School of Economic and Management Administration, North China Electric Power University, Beijing 102206, China.

***Abstract* — When massive Electric Vehicle (EV) charging stations are integrated into the power grid, the local distribution network will be dramatically affected. Therefore, a scientific and rational planning of the Power Distribution Network Structure (PDNS) should take full account of the integration of EV Charging Station (EVCS). In order to solve this problem, firstly, the objective function of PDNS is established considering the EVCS siting and sizing from the aspect of: i) minimizing the distribution network investment cost, ii) charging station investment and operation cost, and iii) the power loss cost. Secondly, we propose a new Quantum Fruit fly Optimization (QFOA) Algorithm to improve the optimization ability of the algorithm. Finally, two cases studies are carried out to verify the novel method. The results show that the proposed model converges faster and has better searching ability than that of the basic FFOA and other conventional algorithms.**

Keywords - Power Distribution Network Structure Planning; Quantum Fruit fly Algorithm (QFOA); Electric Vehicle Charging Station

I. INTRODUCTION

In recent years, with the deepening of the global energy crisis and the deterioration of the environment, the Electric Vehicle (EV), as a new energy consuming mode of transport, has gained widely attention around the world with broad development prospects, which is considered the best way to solve the energy conservation and emission reduction. Among all the types of EVs, the development of Pure Electric Vehicle (PEV) is recognized as the future of the automotive industry. As we all know, the normal use of electric vehicles need depend on the construction and operation of charging stations, charging piles, batteries and other infrastructure. When a large number of EV charging stations are integrated into the power grid, the network load burden will be increased, as well as the operation costs of the distribution network. Therefore, in the optimization of the Power Distribution Network Structure Planning (PDNSP), we should fully consider the impact of EV on the distribution network, and optimize the network structure in a scientific and rational way, which not only can reduce the power losses and the network construction cost, but also can improve the utilization efficiency of resources and bring economic benefits to society.

Currently, the optimization of the Power Distribution Network Structure Planning (PDNSP) mainly starts from two aspects: first, is to establish the objective function and constraints; and the second is to use the optimization model to solve the value of the objective function. In recent years, some paper have been published in the field of PDNSP, and various of methods have been used to solve the problem, such as Genetic Algorithm (GA), Ant Colony Optimization Algorithm (ACO), Particle Swarm Optimization algorithm (PSO) and so on. Paper [1] presented a non-dominated sorting genetic algorithm (NSGA) to solve the complex problem of multistage smart distribution network expansion planning; then the proposed method was applied to a distribution test system and the results showed an ideal improvement. Paper [2] modified the traditional ACO through optimizing its transition probability and volatile factor; the modified algorithm was applied into a specific example, and results showed that the proposed model was more feasible and effective compared with basic ACO. In paper [3], the well-known Teaching Learning Optimization Algorithm (TLO) was modified to solve the electrical and thermal distribution networks reinforcement planning considering cost and reliability; the paper used two test systems to evaluate the proposed algorithm and the simulation results revealed the feasibility and robustness of both modeling and solving technique. In paper [4], a modified particle swarm optimization algorithm (MPSO) was developed and used for distribution expansion planning problem which considers reliability and security; the effectiveness of the presented method was applied into the typical 33-bus test system and results showed that the proposed MPSO can efficiently generate optimal Pareto solutions.

In addition, only a few of literature has studied the siting and sizing of EVCS in the power distribution network. Most of them solve the proposed mathematics function by using swarm intelligent optimization algorithm. Such as paper[5] has studied the electric vehicles charging station planning problem, and proposed an mathematical problem with the minimization of total cost, then the problem was solved by a modified primal-dual interior point algorithm, the simulation results demonstrated that the proposed model can attain the reasonable planning and reduce the network loss. In paper [6], genetic algorithm(GA) has been successfully implemented to solve the layout planning of EVCS, which was based on quantity and power network distribution forecast of EV . Paper [7] established the mathematical model to formulate the optimal centralized charging station

(CCS) placement problem with minimum total transportation distance, then used proposed TM-BPSO to optimize the established CCS model; through the simulation of case studies, results showed that the derived distribution discipline of CCS was correct, and the TM-BPSO could achieve the optimal configuration of CCS with high reliability. Paper [8] applied modified primal-dual interior point algorithm as the main approach to solve the optimal planning problem of EVCS in power distribution systems and the paper [9] also used GA as optimal method to choose the best location of EV charging station in power distribution systems.

The above methods could find the optimal value and obtain a reasonable result. However, most of algorithms are difficult to reach the global optimal and to calculate the results; that's because too many parameters may lead the algorithm more complex and increase the amount of calculation work.

For the above issues, this paper adopts the Fruit Fly Optimization algorithm (FOA) for the PDNSP problem. FOA is inspired knowledge from the behavior of fruit flies. FOA is easy to understand and calculate, and its convergence speed is faster than other algorithms, therefore the global optimum is easier to reach. Because of its good performance, FOA has been applied to solve various optimization problems and has achieved a lot in very less time. However, some new problems have been found; for example, the algorithm appears premature phenomenon sometimes and also may be easy to fall into local optimum. To solve the emerging problems and get an better optimal result in PDNSP optimal problem, this paper modifies the basic FOA with quantum behavior and applies the improved method to optimize the PDNSP problem considering the siting and sizing of Electric Vehicle Charging Station (EVCS).

The rest of this paper is organized as follows: Section 2 presents the mathematical formulation of the objective functions of the PDNSP problem considering the siting and sizing of EVCS. In Section 3, the modified FOA for PDNSP is presented. Section 4 is devoted to present the numerical results. Two cases are used as a test to verify the applicability and validity of the modified FOA. Finally, some relevant conclusion are drawn in Section 5.

II. MATHEMATICS MODEL

Power distribution network structure planning is a nonlinear optimization problem with discrete as well as continuous parameters variables. Its purpose is to make the minimum cost of the grid planning through determining the number of lines in the planning period. The problem can be described by the function as follows [5-6]:

$$\min Z_{\cos t} = \lambda_1[\sum_{i=1}^{n}(\gamma_i + \partial_i)l_i a_i Z_i + \sum_{i=1}^{m}(\gamma_i + \partial_i)P_i Z_i] + \lambda_2 \sum_{i=1}^{n} C_0 T \Delta P_i \quad (1)$$

where $Z_{\cos t}$ is annual operating cost, n is the total number of power lines, m is the number of new substation, γ_i is the rate of return on investment, ∂_i is annual depreciation rate of equipment, l_i is the total length of line i , a_i is the total investment in the unit length, Z_i is whether to rebuild, Z_i will take 1 when newly built, otherwise 0. C_0 is unit power price, T is annual maximum load utilization hours, ΔP_i is the active power loss of line i , λ_1, λ_2 is weight coefficients, $0 \le \lambda_i \le 1, i = 1,2$, and $\lambda_1 + \lambda_2 = 1$.

The objective function must satisfy the following constraints:

①Load point voltage constraint:

$$U_{i\min} \le U_i \le U_{i\max} \quad (2)$$

where U_i is nodal voltage; $U_{i\max}$ is the upper bound of U_i ;$U_{i\min}$ is the lower bound of U_i .

② Branch current constraint: $I_{hi} > I_i$, where I_i is branch current; I_{hi} is the current-carrying capacity of branch current i .

③ Radiation type constraint: distribution network structure must be a radiation type network.

④Connectivity constraint: distribution network structure must meet the constraints that can provide electricity for all load points in the power supply area.

A. *The Objective Function of PDNS with EV Charging Station*

The load balance will be broken after the EV charging station being integrated into the network. When charging at the peak load, overload will happen because of the electric current generated by charging equipment [7], which can further raise the remaining power and reduce the network efficiency. Therefore, only by planning the distribution network structure can the problems above be avoided. In this paper, the model is established by minimizing the distribution network investment cost f_1 , charging station investment and operation cost f_2 and the loss cost f_3 :

$$\min Z_{\cos t} = \min\{f_1, f_2, f_3\} \quad (3)$$

$$f_1 = \sum_{i=1}^{N_l} l_i a_i \quad (4)$$

$$f_2 = \sum_{i=1}^{N_C} x_i \left[K_{i,f} + T\left(k_{i,v} + k_{i,o}\right)Q_i\right] \tag{5}$$

$$f_3 = T\tau\gamma \sum_{i=1}^{N_1} I_i^2 r_i \tag{6}$$

$$I_i = P_i / (\sqrt{3}U_N \cos\phi) \tag{7}$$

$$r_i = \rho_i l_i / o_i \tag{8}$$

where l_i and a_i are the length and unit length investment cost for line i, and N_1 is the number of line. x_i represents decision variable, which is equal to 1 when the station is new built, or equal to 0. $K_{i,f}$ is the fix cost for station i. T is the planning time. $k_{i,v}$ is the unit capacity variable investment for station i and the $k_{i,o}$ is the unit capacity operation cost for station i. Q_i represents the capacity of station i; τ is annual load maximum utilization hour; γ is the unit electricity cost. I_i is the electricity current for the i th line. r_i is the electrical resistance for the i th line. P_i is the annual peak load. U_N is the nominal voltage for the network., and $\cos\phi$ is the power factor. ρ_i and o_i represent resistivity and sectional area respectively.

Constraints:

①Node voltage constrains： $U_{i\min} \le U_i \le U_{i\max}$, $i = 1,2,\cdots,n$.

②Current constrains： $I_i \le I_{i\max}$, $i = 1,2,\cdots,n$.

③ Power balance constrains ： $\sum_{i=1}^{N} P_{ij} = P_{j,load} + P_{j,C} x_j$;

where P_{ij} is the active transmission power for line ij ; $P_{j,load}$ is the load in node j ； $P_{j,C}$ is charging station load; x_j is decision variable，which is set 1 when new built, or set 0.

④Radioactive constraint and connectivity constraint.

III. FRUIT FLY OPTIMIZATION ALGORITHM IN PDNS

A. Basic FFOA

Fruit fly optimization algorithms, proposed by professor Pan of national Taiwan University, are simulation of nature fruit flies for searching food. Fruit fly has a very sensitive sense of smell and sharp vision; those little things can smell the food source over than 40km away; then fly to the food nearby and use its visual system find the food location, finally obtain their final delicious meal. Figure 1 shows food finding process of fruit fly group.

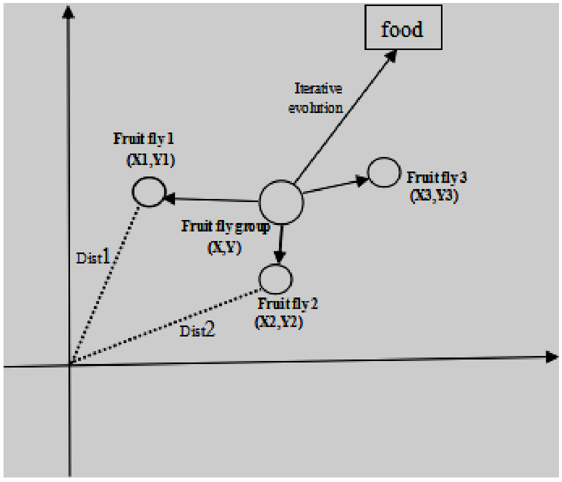


Fig1. Food Finding Process of Fruit Fly Group

Base on the food finding characteristics of the fruit fly, the optimization process of FOA can be divided into the following several aspects:

①Initialize the position of fruit fly group

$$InitX\_axis\,;InitY\_axis \tag{9}$$

② Initialize the random direction and distance for searching food using sense of smell by individual fruit fly

$$Xi = X\_axis + random() \tag{10}$$

$$Yi = Y\_axis + random() \tag{11}$$

③Estimate the distance between initialized individual fruit fly and original point; then calculate the concentration value of smell $S(i)$.

$$Dist = \sqrt{X(i)^2 + Y(i)^2} \tag{12}$$

$$S(i) = 1/Dist \tag{13}$$

④Subscribe the concentration value of smell into smell concentration judgment function, obtain the smell concentration $Smell(i)$ of each fruit fly location.

$$Smell(i) = Function(S(i)) \tag{14}$$

⑤Find out the best smell concentration value among fruit fly group.

$$[bestSmell \quad bestIndex] = \max[Smell(i)] \tag{15}$$

⑥ Keep the best smell concentration value and x, y coordinate, then using vision system of fruit fly to the target location.

$$Smellbest = bestSmell \tag{16}$$

$$X\_axis = X(bestIndex);$$
$$Y\_axis = Y(bestIndex)$$

⑦Enter the iterative optimization, repeat step②-⑤, and judge if the smell concentration is superior to the former iterative smell concentration, if so, execute step⑥.

B. *Steps for QFOA*

(1) Expression for quantum state information

The development of quantum mechanics impels quantum computing to be increasingly applied in various fields. In quantum computing, the expression of quantum state is quantum bit, and usually the quantum information is expressed by using 0 and 1 binary method. The basic quantum states are "0" state and "1" state. In addition, the state can be arbitrary linear superposition state between "0" and "1". That's to say, the two states can exist at the same time, which challenges the classic bit expression method in classical mechanics to a large extent. The superposition state of quantum state can be presented in Eq. (17).

$$|\psi> = \alpha|0> + \beta|1>, \quad |\alpha|^2 + |\beta|^2 = 1 \tag{17}$$

Where $|0>$ and $|1>$ are the two states of quantum, α and β are the probability amplitude. $|\alpha|^2$ represents the probability at quantum state of $|0>$ and $|\beta|^2$ represents the probability at quantum state of $|1>$ 。

In QFOA, the updating is proceeding by quantum rotating gate, and the adjustment is

$$\begin{pmatrix} \alpha_i' \\ \beta_i' \end{pmatrix} = \begin{pmatrix} \cos(\theta) & -\sin(\theta) \\ \sin(\theta) & \cos(\theta) \end{pmatrix} \begin{pmatrix} \alpha_i \\ \beta_i \end{pmatrix} \tag{18}$$

In Eq. (18), set $U = \begin{pmatrix} \cos(\theta) & -\sin(\theta) \\ \sin(\theta) & \cos(\theta) \end{pmatrix}$, where U is quantum rotating gate, θ is quantum rotating angle， and $\theta = \arctan(\alpha / \beta)$ 。

(2) Fruit fly position initialization

In QFOA, we code the individual current position by probability amplitude of quantum bit. Randomized strategy is applied here to initialize the fruit fly population, and the coding is as follows：

$$P_i = \begin{bmatrix} \cos(\theta_{i1})\cos(\theta_{i2})\cdots\cos(\theta_{in}) \\ \sin(\theta_{i1})\sin(\theta_{i2})\cdots\sin(\theta_{in}) \end{bmatrix} \tag{19}$$

Where $\theta_{ij} = 2\pi rand()$, $rand()$ is a random number between 0 and 1; $i = 1,2,\cdots,m$; $j = 1,2,\cdots,n$; m is the number of fruit fly， n is the number of space。

Therefore, the corresponding probability amplitude for the quantum state $|0>$ and $|1>$ are as follows:

$$P_{ic} = (\cos(\theta_{i1}), \cos(\theta_{i2})\cdots\cos(\theta_{in})) \tag{20}$$

$$P_{is} = (\sin(\theta_{i1}), \sin(\theta_{i2})\cdots\sin(\theta_{in})) \tag{21}$$

(3) Solution space conversion

The search process of QFOA proceeds in the actual parameter space $[a,b]$, but the position probability amplitude is in the range of $[0,1]$, which means the probability amplitude should be decoded into $[a,b]$. Assuming the j th quantum bit for the individual P_i is $[\alpha_i^j, \beta_i^j]^T$, the relevant solution space conversion equations are:

$$X_{ic}^j = \frac{1}{2}[b_i(1+\alpha_i^j) + a_i(1-\alpha_i^j)]$$
$$if \ rand() < P_{id} \tag{22}$$

$$X_{is}^j = \frac{1}{2}[b_i(1+\beta_i^j) + a_i(1-\beta_i^j)]$$
$$if \ rand() \geq P_{id} \tag{23}$$

Where $rand()$ is the random value between $[0,1]$, X_{ic}^j is the actual parameter value in j th dimension position when the quantum state of i th individual is $|0>$, X_{is}^j is the actual parameter value in j th dimension position when the quantum state of i th individual is $|1>$. b_i and a_i are the lower and upper limit.

Assuming the QFOA searching in two-dimensional space, that means $j=1,2$. Initialize the position: $InitX\_axis$, $InitY\_axis$, and the solution space can be determined as follows:

$if\ rand() < P_{id}$:

$$X(i) = X\_axis + \frac{1}{2}[b_i(1+\alpha_i^1) + a_i(1-\alpha_i^1)] \quad (24)$$

$$Y(i) = Y\_axis + \frac{1}{2}[b_i(1+\alpha_i^2) + a_i(1-\alpha_i^2)] \quad (25)$$

$if\ rand() \geq P_{id}$:

$$X(i) = X\_axis + \frac{1}{2}[b_i(1+\beta_i^2) + a_i(1-\beta_i^2)] \quad (26)$$

$$Y(i) = Y\_axis + \frac{1}{2}[b_i(1+\beta_i^2) + a_i(1-\beta_i^2)] \quad (27)$$

(4) Calculate the distance ($Dist$) between origin and the position , and gain the smell concentration discriminant value $S(i)$, where $Dist = \sqrt{X(i)\wedge 2 + Y(i)\wedge 2}$ and $S(i) = 1/Dist$.

(5) Take the $S(i)$ above into the smell concentration discriminant function, then obtain the smell concentration $Smell(i)$ for fruit fly individual position.

$$[bestSmell\ bestindex] = \min(Smell) \quad (28)$$

(6) Individual position update

The individual position update is operated by using quantum rotating gate in Eq. (29):

$$\begin{bmatrix} \alpha_{jd}^{k+1} \\ \beta_{jd}^{k+1} \end{bmatrix} = \begin{bmatrix} \cos\theta_{jd}^{k+1} & -\sin\theta_{jd}^{k+1} \\ \sin\theta_{jd}^{k+1} & \cos\theta_{jd}^{k+1} \end{bmatrix} \begin{bmatrix} \alpha_{jd}^{k} \\ \beta_{jd}^{k} \end{bmatrix} \quad (29)$$

where α_{jd}^{k+1} and β_{jd}^{k+1} are the probability amplitude of j th fruit fly in ($k+1$)th iteration for d dimension space; θ_{jd}^{k+1} is the rotating angle，which can be get from Eq.(30)：

$$\theta_{jd}^{k+1} = s(\alpha_{jd}^{k}, \beta_{jd}^{k})\Delta\theta_{jd}^{k+1} \quad (30)$$

Where $s(\alpha_{jd}^{k}, \beta_{jd}^{k})$ determines the rotating angle direction and $\Delta\theta_{jd}^{k+1}$ is the rotating angle increment.

In order to adapt to operation mechanism, we convert the updated α_{jd}^{k+1} and β_{jd}^{k+1} to solution space.

$$X_{jc}^{d} = \frac{1}{2}[b_j(1+\alpha_{jd}^{k+1}) + a_j(1-\alpha_{jd}^{k+1})] \quad if\ rand() < P_{id} \quad (31)$$

$$X_{js}^{d} = \frac{1}{2}[b_j(1+\beta_{jd}^{k+1}) + a_j(1-\beta_{jd}^{k+1})] \quad if\ rand() \geq P_{id} \quad (32)$$

$if\ rand() < P_{id}$, then $d=1$

$$X(j) = X\_axis + \frac{1}{2}[b_j(1+\alpha_{jd}^{k+1}) + a_j(1-\alpha_{jd}^{k+1})] \quad (33)$$

$$Y(j) = Y\_axis + \frac{1}{2}[b_j(1+\alpha_{jd}^{k+1}) + a_i(1-\alpha_{jd}^{k+1})] \quad (34)$$

$if\ rand() \geq P_{id}$: then $d=2$

$$X(j) = X\_axis + \frac{1}{2}[b_j(1+\beta_{jd}^{k+1}) + a_j(1-\beta_{jd}^{k+1})] \quad (35)$$

$$Y(j) = Y\_axis + \frac{1}{2}[b_j(1+\beta_{jd}^{k+1}) + a_j(1-\beta_{jd}^{k+1})] \quad (36)$$

(7) Individual mutation operation

The main reason for premature convergence and being trapped in local optimum is the loss of population diversity in searching process. However, QFOA can enrich the diversity by adding the individual mutation, which can avoid the problem above. The improvement can be realized by Eq. (37).

$$\begin{bmatrix} 01 \\ 10 \end{bmatrix} \begin{bmatrix} \cos(\theta_{ij}) \\ \sin(\theta_{ij}) \end{bmatrix} = \begin{bmatrix} \sin(\theta_{ij}) \\ \cos(\theta_{ij}) \end{bmatrix} = \begin{bmatrix} \cos(\frac{\pi}{2} - \theta_{ij}) \\ \sin(\frac{\pi}{2} - \theta_{ij}) \end{bmatrix} \quad (37)$$

where P_m is the mutation probability, $rand()$ is a random value in $[0,1]$. If $rand() < P_m$, the mutation can be operated and the probability amplitude in quantum bit is changed, and finally the mutated individual realizes the conversion to solution space.

(8) Retain the individual with the best smell concentration value and the corresponding coordinate values.

$$X\_axis = X(bestindex)$$

$$Y\_axis = Y(bestindex) \quad (38)$$

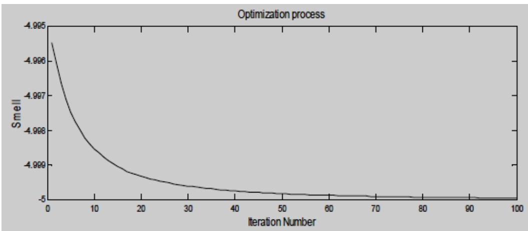
$$Smellbest = bestSmell \quad (39)$$

(9) Searching better individual. Repeat the steps (4)~(7). If the smell concentration value is better than that of the former iteration, go back to step(8).

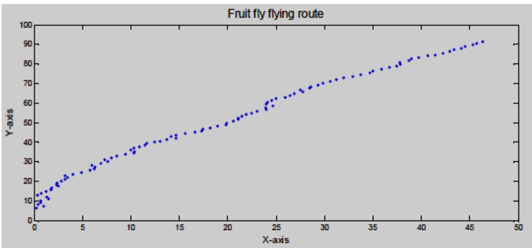
IV. CASE STUDY

A. *Case 1*

The purpose of this case is to examine the search ability of the proposed QFOA compared with the conventional FOA. The function $Y = -5 + X^2$ is employed as the optimal objective. The fruit fly position is in the interval of $[0,10]$, the random flying direction and distance is in the interval of $[-1,1]$, and the iteration number is 100. The testing function's minimum value is -5.

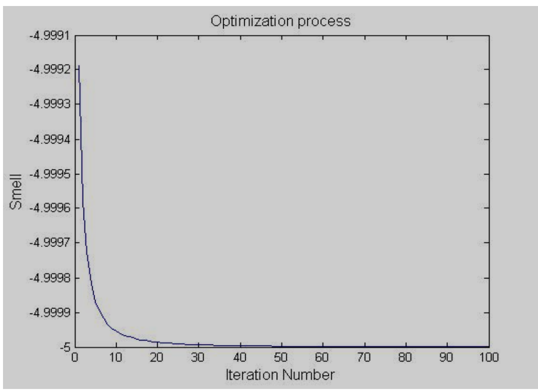


(a) Convergence characteristic

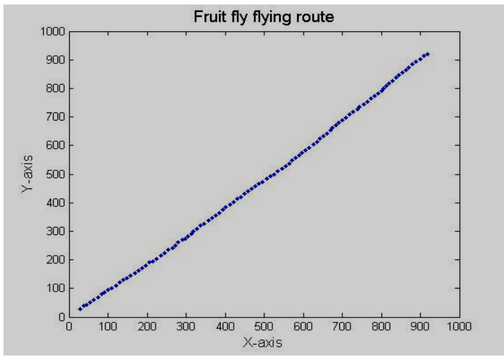


(b) Searching path of fruit flies

Fig2. The convergence characteristic and searching path of FOA.



(a) Convergence characteristic



(b) Searching path of fruit flies

Fig3. The convergence characteristic and searching path of QFOA

From the Fig2 (a) and Fig3 (a) above, we can see, QFOA converges to the minimum value at the iteration of 40, while that of FOA is 93. That means QFOA converges faster than FOA. The Fig2 (b) and Fig3 (b) show that, in QFOA the fruit flies' searching path is close to a straight line, yet in FOA the flying route disperses and is unsteady.

This result shows the faster convergence and stronger searching ability of QFOA, which can make it a good candidate as a powerful optimizer.

B. *Case 2*

The proposed algorithm of QFOA in this paper is applied in the optimization of power distribution network structure considering Electric Vehicle (EV) charging station siting and sizing, using the numerical example in paper [12] for empirical analysis, as shown in Figure 4. The total charging capacity demand for the system assumes 6MW, and the node 4~6 are the charging station alternative sites; the dotted lines in Figure 4 are the virtual links, which provide convenience for determining the capacity for the charging station alternative sites. The load information for each node is shown in Table 1, and the Table 2 describes the distance between every two nodes. Table 3 presents parameters for charging station. In addition, this example assumes that the planning period is 10 years, the annual maximum load utilization hours is 4000h, the rated voltage of the distribution network is 10kV, the power factor of each node $\cos\phi = 0.85$, and the line is single loop.

Initialize the parameters of QFOA, in which the maximum iteration: $Maxgen = 100$, the population: $Sizepop = 30$. When the quantum state for each fruit fly is $|0>$, the lower limit and the upper limit for the search range are $Varrange(1,1) = -10$ and $Varrange(1,2) = +10$ respectively. When the quantum state for each fruit fly is $|1>$, the lower limit and the upper

DOI 10.5013/ IJSSST.a.17.29.21 ISSN: 1473-804x online, 1473-8031 print

limit for the search range are $Varrange\ (2,1) = -10$ and $Varrange\ (2,2) = +10$ respectively.

Table 1 shows the power load of each node in the distribution network which contains 9 nodes in total.

TABLE 1. NODE LOAD FOR THE NETWORK

Node	Load/KW	Node	Load/KW	Node	Load/KW
1	350	4	350	7	350
2	350	5	350	8	350
3	350	6	350	9	350

Table 2 presents the length between the Start(S) node to the Finish (F) node, and there are 16 paths in the network. The structure is described in Fig4.

TABLE 2. LENGTH BETWEEN THE START(S) NODE TO THE FINISH (F) NODE

Path S-F	length/km	Path S-F	length/km
0-2	0.75	4-6	0.75
0-3	0.82	4-7	0.75
1-2	0.60	5-6	0.85
1-3	0.71	5-7	0.72
2-4	0.75	6-8	0.70
2-5	0.99	6-9	0.75
3-4	0.69	7-8	0.80
3-5	0.93	7-9	0.60

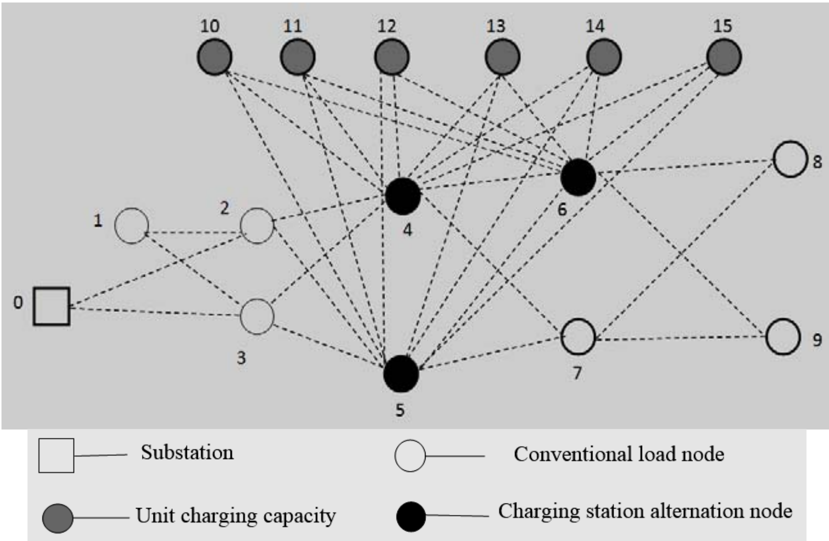


Fig4. Power distribution network structure for planning

The objective function for PDNSP problem is shown in the Eq. (3). In accordance with the optimization steps, the above parameters are put into the calculation using MATLAB2014ra. The planning result is shown in Fig.5.

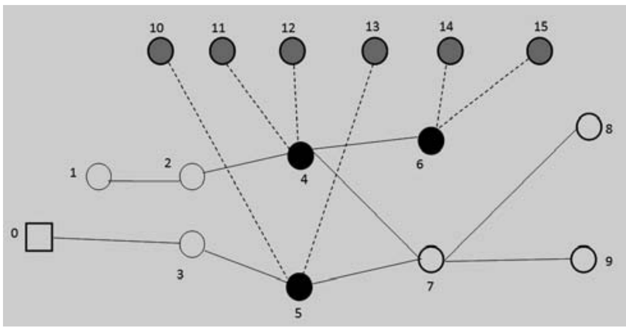


Fig5. Planning result

All the lines are LGJ-240 and assumed single loop. The line length and the construction cost are described in Table 3.

TABLE 3. LENGTH AND COST FOR THE NETWORK LINES

Start	Finish	Length (km)	Building Cost (Thousand dollars)	Operation Cost (Thousand dollars)	Total (Thousand dollars)
0	3	0.82	132.35	336.47	468.82
1	2	0.6	96.84	184.78	281.62
2	4	0.75	121.05	112.79	233.84
3	5	0.93	150.1	134.47	284.57
4	6	0.75	121.05	338.82	459.87
4	7	0.75	121.05	216.23	337.28
5	7	0.72	116.21	210.35	326.56
7	8	0.80	129.12	318.87	447.99
7	9	0.6	96.84	221.75	318.59

Table 4 presents the relative parameters, capacity, investment and operation cost for EV charging station.

TABLE 4. PARAMETERS FOR THE EV CHARGING STATION

Station site i	Fix Cost $K_{i,f}$	unit capacity investment $k_{i,v}$	Unit operation cost $k_{i,o}$	Station capacity MW	Total Cost (Thousand dollars)
4	50	7	10	2	3900
5	60	10	6	2	3800
6	45	9	9	2	4050

From Table 4 we can get, by using the proposed algorithm, the line construction cost for the power distribution network structure planning is 1084.61 thousand dollars, the lines operation cost is 2074.53 thousand dollars, the charging station construction and operation cost is 11750 thousand dollars, all of which are sum up to 14909 thousand dollars. For further comparison, this paper also uses FOA, GA and ACO to optimize the same problem, and the results are shown in Table 5 and Figure 6.

TABLE 5. COST OF NETWORK LINES AND CHARGING STATION BY DIFFERENT ALGORITHM

Algorithm	Lines construction cost (Thousand dollars)	Lines operation cost (Thousand dollars)	Charging station construction and operation cost (Thousand dollars)	Total cost (Thousand dollars)
QFOA	108.461	207.453	1175	1490.9
FOA	126.884	280.443	1195	1602.3
GA	125.641	275.63	1185	1586.3
ACO	131.225	271.238	1185	1587.5

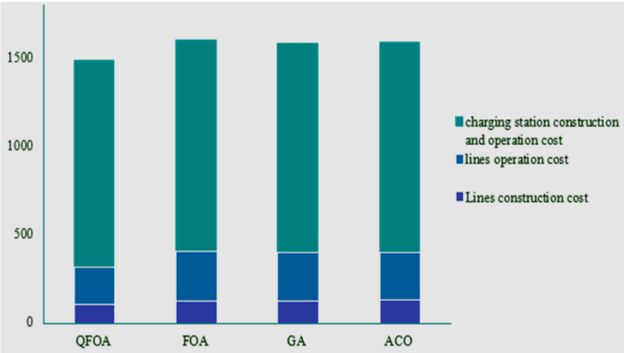


Fig6. Results comparison of four optimization algorithms

The above four kinds of costs for the problem by using QFOA are 1084.61, 2074.53, 11750, 14909 thousand dollars, and the costs by FOA are 1268.84, 2804.43, 11950, 16023 thousand dollars, which shows that the FOA improved by quantum strategy raises the optimization ability of FOA, and can be easier to find the global optimum. In addition, by comparing the results among QFOA, GA and ACO, the cost by QFOA are also lower than that of the other two methods, which proves that QFOA has better optimization ability and can produce more satisfactory results.

In order to present the superior ability of QFOA, the paper presents the convergence trend in Fig.7.

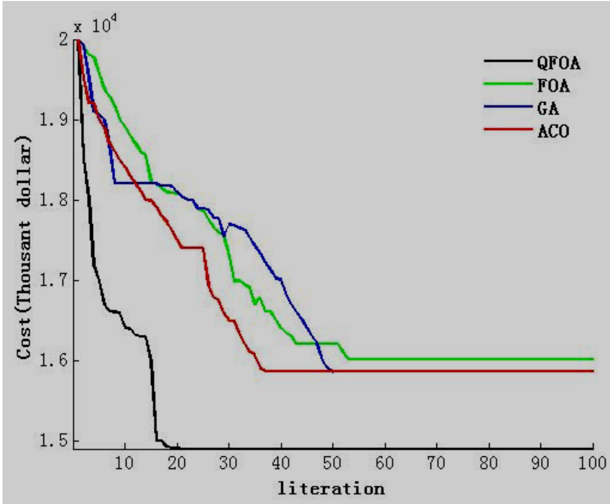


Fig7. Convergence characteristic of QFOA, FOA, GA and ACO

By comparing the convergence characteristic of the four algorithms we can see, QFOA converges to the lowest cost at the iteration of 21, while the convergence iteration for FOA, GA and ACO are 53, 50 and 37. That also means the algorithm proposed in this paper converge faster than other algorithms, and has the better optimization ability.

V. CONCLUSION

A more effective and efficient distribution network structure planning can decrease the cost of construction, operation and power loss. This paper introduced EV charging station siting and sizing into the network structure planning, and established proper objective functions and constraints based on the conventional planning. To improve the optimization ability of FOA, this paper proposed a new algorithm—QFOA, which was improved by quantum theory. The improvement contained two parts: (1) coding the fruit fly's current position using the probability of quantum bits, and (2) improving the position updating method with quantum rotating gate. Then, the proposed method was applied to Case 1 and Case 2 respectively. In Case 1, we used a simple function to test the performances of QFOA and FOA, and the result showed that the QFOA outperformed FOA with faster convergence and better searching ability. In Case 2, QFOA was used to solve the power distribution network structure planning problems, and compared with other algorithms such as FOA, GA and ACO. From the result of Case 2, we found the superiority of the proposed QFOA over the other well-known optimization algorithms.

REFERENCE

[1] Nejadfard-Jahromi S, Rashidinejad M, Abdollahi A. Multistage distribution network expansion planning under smart grids environment [J]. International Journal of Electrical Power & Energy Systems, 71: 222-230, 2015.

[2] Sun W, Ma T. The power distribution network structure optimization based on improved ant colony algorithm[J]. Journal of Intelligent and Fuzzy Systems, 26(6): 2799-2804. 2014.

[3] Abbasi A R, Seifi A R. Considering cost and reliability in electrical and thermal distribution networks reinforcement planning[J]. Energy, 84: 25-35, 2015.

[4] Aghaei J, Muttaqi K M, Azizivahed A, et al. Distribution expansion planning considering reliability and security of energy using modified PSO (Particle Swarm Optimization) algorithm[J]. Energy, 65: 398-411, 2014.

[5] Liu Z, Wen F, Ledwich G. Optimal planning of electric-vehicle charging stations in distribution systems[J]. Power Delivery, IEEE Transactions on, 28(1): 102-110, 2013.

[6] Li Y, Li L, Yong J, et al. Layout planning of electrical vehicle charging stations based on genetic algorithm[M]//Electrical Power Systems and Computers. Springer Berlin Heidelberg, 661-668,2011.

[7] Xu H, Miao S, Zhang C, et al. Optimal placement of charging infrastructures for large-scale integration of pure electric vehicles into grid[J]. International Journal of Electrical Power & Energy Systems, 53: 159-165, 2013.

[8] Liu Z, Wen F, Ledwich G. Optimal planning of electric-vehicle charging stations in distribution systems [J]. Power Delivery, IEEE Transactions on, 28(1): 102-110, 2013.

[9] Ge S, Feng L, Liu H. The planning of electric vehicle charging station based on Grid partition method[C]//Electrical and Control Engineering (ICECE), 2011 International Conference on. IEEE, 2726-2730, 2011.

[10] LIU Li, WANG Jian-xing, QIN Shu-shuo, MO Cheng-kai. A Kind of Application of Improve Ant Colonv Algorithm in Power Distribution Network Optimization Planning[J].Science Technology and Enguneering, 11(24):5801-5803, 2011.

[11] SUN Wei, SHANG Wei, NIU Dong-xiao. Application of Improve Ant Colony Optimization Algorithm in Distribution Network Planning [J]. Power System Technology, 30(15)：85-88, 2006.

[12] LI E-shou, WU Wen-min. Influence and Countermeasure of Electric Vehicle Battery Charging to Power Systems[J]. East China Electric Power, 38(1):109-113, 2010.