İSTANBUL UNIVERSITY CERRAHPAŞA

ORIGINAL ARTICLE
Electrica 2023; 23(2): 222-230

Research on Multi-Objective Optimization of Smart Grid Based on Particle Swarm Optimization

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Cite this article as: F. Long, et al. "Research on multi-objective optimization of smart grid based on particle swarm optimization," *Electrica*, 23(2), 222-230, 2023.

ABSTRACT

Microgrids can benefit from multi-objective optimization dispatch in several ways, including reduced operation costs and improved service dependability. While using the traditional power network optimization method to solve power network planning, the algorithm mostly falls into the local optimal solution, rendering the global optimal solution intractable. In this research, multi-objective power grid planning is applied to an eight-bus system using a multi-objective optimization technique, such as reducing distribution network building costs and losses, planning distribution network growth and fixed capacity, and distributed generation (DG) addressing planning. Improvements are made to the quantum particle swarm optimization algorithm so that it can be applied to solving discrete problems. This report also employs a binary-coded quantum particle swarm optimization technique to design the distribution network without DG and runs the debugged program in MATLAB to compare the final optimization results. Finally, MATLAB software is used to simulate the example, and the corresponding planning results are obtained. From the model verification results, it can be observed that the quantum particle swarm optimization algorithm applied in this research can complete the task of power grid planning well under the premise of ensuring the calculation speed in the multi-objective design of a smart grid.

***Index Terms*—**Multi-objective optimization, smart grid, quantum particle swarm optimization

I. INTRODUCTION

The power grid is the basic concept and public utility related to the lifeline of the national economy. The development of the modern power grid has reached a critical period, and global resources and the environment are facing enormous pressure, forcing society to pay recognition to environmental protection, energy conservation, emission reduction, and sustainable development. At the same time, users' requirements for power quality and reliability are constantly improving. In the future, the power grid must provide users with safer, more reliable, cleaner, and better power [1]. Commercial and industrial buildings, which consume roughly one-third of all energy in cities, play an important role in the expanding electricity network by offering energy flexibility [2, 3]. It can be seen from Fig. 1 that the development of new energy sources provides possibilities for the realization of power generation forms from various energy sources. Under the influence of this series, the coordination and information exchange between power companies and users become more frequent. The traditional power system has been difficult to adapt to the new situation [4]. There is, however, a lack of functional interplay between the smart grid and the energy management system (SG-EMS) to completely elicit flexibility from the built environment to satisfy energy savings and environmental policy [5, 6]. In order to upgrade the conventional electrical system, people proposed the notion of creating a "Smart Grid."

Mirrors are used for concentrating solar-thermal power systems to reflect and focus daylight onto receptors, which then collect the solar energy and convert it to heat that may either be utilized immediately or saved for later use. It is typically employed in very big power plants. Electricity production by photovoltaics (PV) or Concentrated Solar Power (CSP) systems is only the beginning of solar energy technology. These solar energy systems must be used in conjunction with various ratios of traditional and alternative renewable energy sources in residential and commercial structures as well as with the current electrical grid. When combined with storage, solar energy may supply backup power during nights and outages, lower electricity costs, help build a more robust

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Received: May 8, 2022

Revised: August 3, 2022

Accepted: September 8, 2022

Publication Date: November 10, 2022

DOI: 10.5152/electrica.2022.22047

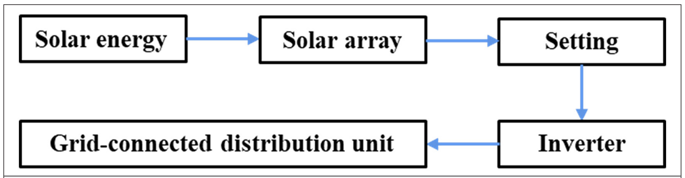

Fig. 1. New energy power generation process.

electrical grid, promote economic growth, create employment, and operate at equivalent performance on both small and big sizes.

II. LITERATURE REVIEW

Buildings with an adequate energy management system (EMS) can improve energy efficiency, reduce capital expenditure, and improve grid operation by incorporating alternative energy sources through appropriate information programs without jeopardizing demand-side operations [7, 8]. Meng et al. explained that the particle optimization technique's capacity to search globally is improved by sub-population hybridization operations, and the modified approach can be used to address a variety of multi-objective issues [9]. Li et al. applied genetic algorithm (GA) to solve the power grid planning problem and achieved good results [10]. Gabbar et al. used a parthenogenetic algorithm to obtain the optimal grid structure. However, in the process of GA optimization, there were some shortcomings [11], such as slow optimization speed and convergence to local optimum in some optimization problems. Shen and Ge made some improvements to the algorithm and achieved a better optimization effect [12]. Several attempts have been made to enable these extremely complex systems to interact with each other. Buildings, on the other hand, have been thought of as independent and different controls, each acting on its data and overblowing connection with the other [13, 14]. According to Indragandhi et al., the multi-objective particle swarm optimization (MOPSO) method produces positive results, and the suggested system is recommended as the best solution to increase electric energy usage in distant places [15]. Soares proposed that the genetic algorithm was applied to expand the distribution network with distributed generation and to determine the location and capacity of distributed generation in the distribution network. Compared with GA, evolutionary programming (EP) was more suitable for continuous optimization problems because it did not need to encode and decode decision variables [16]. Li et al. studied the relationship and differences between EP and GA and used the P algorithm for power grid planning. The effectiveness of this algorithm in power grid planning was verified [17]. Li et al. derived that to achieve multi-objective optimization, the total economic and environmental benefits of operation included in the benefit–cost analysis can be minimized using an upgraded particle swarm method. The outcomes show how well the suggested strategy can meet the load while cutting down on operating expenses and emissions [18]. The metropolis acceptability criterion, which Swarm Algorithm (SA) uses to avoid the best solution from falling into local optimum, was then utilized to resolve the issue and each cooling step of SA was very time-consuming and belonged to single-point optimization, and the optimization speed was inherently slow. Hu et al. used a hybrid algorithm based on chain genetic-simulated annealing for a power grid plan to suppress the instability and local convergence of the genitive algorithm [19]. Lu et al. applied the combination of Prufer number and algorithm for fuzzy discrete particle swarm optimization in the distribution network optimization planning (as shown in Fig. 2) so that the optimal solution finally obtained was feasible [20]. Qi et al. introduced the crossover operation between dynamic neighborhoods into the basic PSO algorithm and posed an improved hybrid particle swarm optimization algorithm (IHPSO) [21]. Khan thought

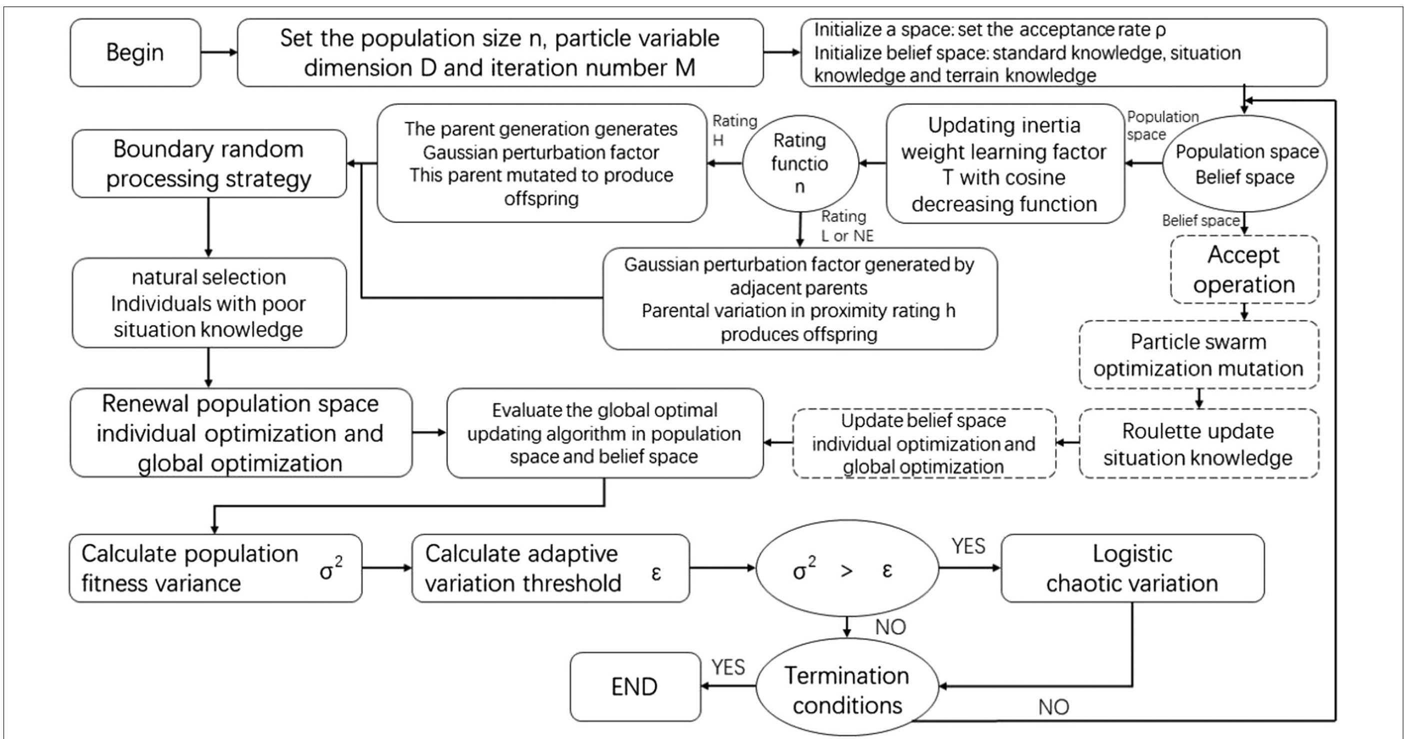

Fig. 2. Microgrid capacity optimization based on improved hybrid particle swarm optimization algorithm.

that equal SA algorithm with PSO algorithm increased the global searching ability and convergence speed of the algorithm and put forward the Btheoid model to simulate the movement behavior and law of birds [22]. The artificial fish swarm algorithm proposed by Liu had a strong global searching ability, and the well has the advantages of universality, simplicity, par, allele, sm, and stability [23, 24].

To deal with the complexity of these interface specifications, a change from centralized smart metering to a decentralized manner is noticeable with the development of computational and distributed intelligence [25, 26]. This work suggests an enhanced quantum PSO algorithm based on the fundamental principles of PSO and quantum theory and applies it to the grid planning of transmission networks and multi-objective optimization planning of smart grids with a distributed generation [27, 28]. The research shows that the algorithm is effective for multi-objective optimization planning for smart grids.

III. PARTICLE SWARM OPTIMIZATION

Particle swarm optimization can simulate the foraging process of birds to solve the optimization problem. Imagine a picture where a flock of birds is looking for food in a limited area, but there is only one piece of food in this area, and all the birds do not know the exact location of the food. The only thing they know is the distance between their position and food, so these birds will fly to the area around the nearest bird to find food [29, 30]. After a long time of joint efforts, one bird will eventually find food. Particle swarm optimization algorithm is inspired by this. If the wellness value is higher and the optimization problem is a minimization problem, the objective function value should be lower. Individual best position $P_i(t)$ of particle 1 is determined by (1):

$$P_i(t)=\begin{cases} X_i(t) & f\left[X_i(t)\right]<f\left[P_i(t-1)\right] \\ P_i(t-1) & f\left[X_i(t)\right]>f\left[P_i(t-1)\right] \end{cases} \tag{1}$$

The global best position Pg(t) of the population is determined by the following formula:

$$P_g(t)=\operatorname{argmin}\left\{f\left[P_i(t)\right]\right\} \tag{2}$$

Then, the speed and position evolution process of the basic PSO algorithm can be described by the following formula:

$$\begin{aligned} v_{i,j}(t+1)&=wv_{i,j}(t)+c_1r_1\left[P_{i,j}(t)-x_{i,j}(t)\right] \\ x_{i,j}(t+1)&=x_{i,j}(t)+v_{i,j}(t+1) \qquad j=1,2,\cdots d \end{aligned} \tag{3}$$

$$\begin{cases} V_{i,j}=V_{\max} & V_{i,j}>V_{\max} \\ V_{i,j}=-V_{\max} & V_{i,j}<V_{\max} \end{cases} \tag{4}$$

Where is the inertia weight factor? c_1 and c_2 are learning the F factor which is a constant greater than 0. r_1 and r_2 is a random number, and its value range is between 0 and 1. $V_{\max}$ is the maximum limit velocity of particles.

It can be seen from (3) that the particle velocity consists of three parts. The position of particles is updated in steps of speed. It can be seen from (4) that the velocity V_{ij} of particles is given in a specific area, and if the searching accuracy of a particle by the PSO algorithm is determined to some extent as too high, particles may fly over the optimal solution. If too small, particles are easily trapped in the local search space and cannot be searched globally.

The performance of the PSO algorithm is determined by parameters such as current population, learned variables, weight of inertia, maximal speed, and population topology. The final result will be very different with different parameters. Therefore, the improvement of the PSO algorithm is mainly realized by improving these parameters.

A. Particle Swarm Optimization Algorithm

The optimization steps of PSO and the algorithm are as follows:

1) Initialization design of parameters. Design the initial parameters of the algorithm, including the number of particles, iteration times, termination conditions, etc., and randomly generate the initial positions of each particle in the target space to form the initial population [31, 32];
2) Determining every molecule's current fitness value in the population fitness evaluation function;
3) Collecting all the particle's function values and comparing these values with individual optimal values. If the current position value is better than the individual optimal value, set the individual optimal value as the current position;
4) Comparing the particle solo optimal position with the population optimal position. The population's worldwide optimal location is set as the position of the current particle if the current value is superior to it, and the adapted value of the current particle is given to the global optimal particle [33, 34];
5) Updating the position and velocity of the particles in the particle swarm;
6) Judging whether the ending condition is met and if so, ending the optimization process. If not, return to (2) to cycle until the end. The optimization methodology of Fig. 3 displays the PSO method.

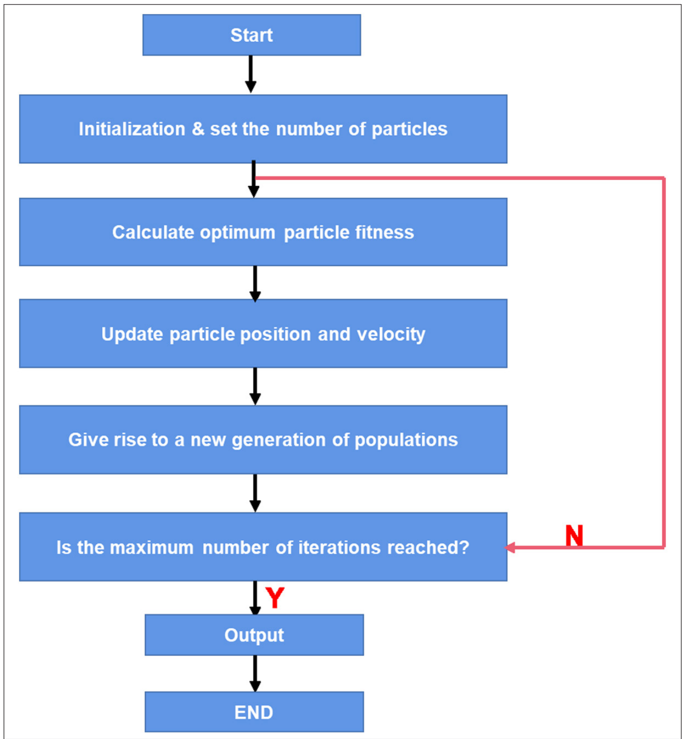

Fig. 3. Flow chart of particle swarm optimization algorithm.

B. Multi-Objective Optimization of Smart Grid

The mathematical model of multi-objective planning of the power grid can be expressed by the optimization model, and its simple form is shown in the following formula:

$$f=\min \begin{array}{l}(f_1,f_2\cdots f_n)\\ g_i(x)=o\\ h_k(x)\geq 0\end{array} \tag{5}$$

where f is the objective function after multi-objective processing, x is the decision vector of the model, and $g_i(x)=0$, $h_k(x)=0$ are equality constraint and inequality constraint.

The hierarchical multi-objective optimization model can be expressed by the following mathematical model:

$$A-\min\left[B_s f_s(x)\right]_{s=1}^{A} \tag{6}$$

where $B_s(s=1,\cdots A)$. The second pair is the label of the priority level, indicating the corresponding objective function. $f_s(x)(s=1,2\cdots A)$ belongs to s Priority, and for each B_s, there is a relationship between them.

Hierarchical optimization method can be applied to multi-objective optimization planning of power grid because although other objectives are transformed in multi-objective planning to make them have the same dimensions as another optimization objective, it does not mean that their values can fully reflect their importance in this planning. In actual power grid planning, some planning objectives are often the most important constraints, the degree of which is greater than that of other objective function constraints [35, 36]. The idea of stratification here already implies that the priority layer is paid more attention to, which is also in line with reality, and it avoids the difficulty of weighing the weights of the two layers from a practical point of view. This process is shown in Fig. 4.

In Fig. 4, a hierarchical optimization framework is used to solve the developed multi-objective model, which redesigns the multi-objective model into a multi-layer optimization model by rebuilding additional constraints. The linearization approach is used to linearize the nonlinear element of the optimization model. Finally, the branch and bound approach is used to solve the optimization model. The optimization of power generation for sustainable growth has gained significance in light of developing countries' urgent need to combat climate change. The reality of emerging countries is not fully represented by current models. The application of dynamic programming's optimality concept is made easier by this design. The best policy portfolios are produced through synchronized optimization of strategies with regard to the shared objectives at each level.

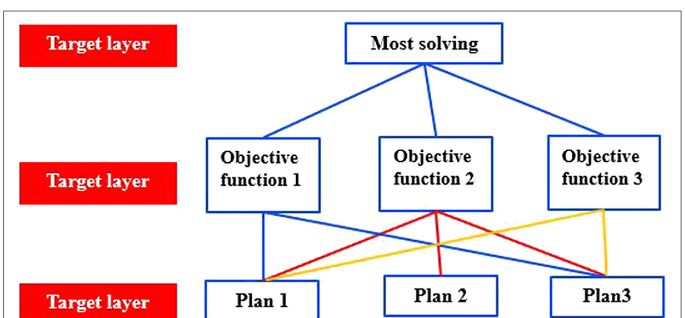

Fig. 4. Hierarchical analysis structure diagram of multi-objective decision-making.

IV. DESIGN AND RESULT ANALYSIS OF GRID PLANNING FOR 18-BUS TRANSMISSION NETWORK

A. Raw Data of 18-Node System

The eight-bus system is one of the common examples in power grid planning. With this system, the final planning results can assess the benefits and drawbacks of the algorithms, and the results were contrasted to those of other algorithms [37]. There are ten nodes and nine lines in the 18-node system, and the system will increase to 18 nodes and 27 lines at a certain level in the future. Detailed parameters of this system are shown in Tables I and II.

From the above data, we can see that 18 new lines need to be built, and the number of lines that can be built is 22. Choose 18 lines from 22 lines. Different choices of these lines constitute different planning schemes. According to the objective function, choose the best planning scheme to complete the planning.

When the distribution system with DG is optimized using the binary-coded quantum PSO technique, let one particle in the particle swarm be 1100110010011001100000001010, which indicates that the number of lines to be built is five, the number of lines to be rebuilt is four, and the number of load nodes is five, then the first five binary codes indicate the code of newly built lines and lines 1, 2, and 5. The last four binary codes indicate that the line codes need to be upgraded, and lines 1 and 4 are selected. The last five codes indicate the type of DG connected to the load node, 0 indicates wind power, and 1 indicates photovoltaic. Finally, the binary code indicates the number of DG connected to the load node and converts it to decimal. Then the number of DG connected to the load node represented by the above particles is 3, 0, 0, and 1. This completes the binary coding of distribution network planning particles with DG, and the coding of other particles is the same. It was discovered that introducing various limitations improves the performance of hierarchical PSO (HPSO). The suggested PSO method's results are compared and confirmed with the outcomes of other approaches that have recently been used. The comparison analysis shows that the suggested technique outperforms the old method in terms of running costs and emissions [38].

TABLE I. 18 NODE SYSTEM DATA

Node Number	Power Generation (10 000 KW)	Load (10 000 KW)	Node Number	Power Generation (10 000 KW)	Load (10 000 KW)
1	0	55	10	750	94
2	360	84	11	540	700
3	0	154	12	0	190
4	0	38	13	0	110
5	760	639	14	600	32
6	0	199	15	0	200
7	0	213	16	495	132
8	0	88	17	0	400

TABLE II. LINE DATA OF 18-NODE SYSTEM

Branch Number	Two-End Node	Line Reactance (PU)	Line Capacity (10 000 KW)	Original Number of Lines	Number of Expandable Lines	Length (KM)
1	1–2	0.0176	230	1	1	70
2	1–11	0.0102	230	0	2	40
3	2–3	0.0348	230	1	0	138
4	3–4	0.0404	230	1	0	155
5	4–7	0.0325	230	1	0	129
6	4–16	0.0501	230	0	1	200
7	5–6	0.0501	230	0	1	106
8	5–11	0.0267	230	1	3	60
9	5–12	0.0513	230	0	0	40
10	6–7	0.0121	230	0	2	50
11	6–5	0.0126	230	1	1	40
12	6–13	0.0126	230	0	3	50
13	6–14	0.0554	230	0	1	50
14	7–8	0.0141	230	0	2	220
15	7–9	0.0318	230	1	1	60
16	7–13	0.0126	230	0	0	126

B. Optimization Results and Analysis

The suggested technique is used in this study to plan the transmission network for an 18-bus system, with the multi-objective optimization goal of minimizing construction and maintenance costs while minimizing power shortfall. To obtain the final planning outcome, run the debugged program in MATLAB. The mathematical formulation of power grid planning is created in accordance with multi-objective power grid planning by choosing appropriate objectives. It is now possible to use the quantum element swarm optimization (QPSO) technique to resolve discrete issues. The Pareto border as determined by binary-coded quantum PSO (BQPSO) is shown in Fig. 5.

The eight-bus network is used to evaluate the technique in this study, with the objective of multi-objective optimization, such as minimizing the construction cost and the loss of the distribution network, to plan the expansion of the distribution network and the fixed capacity, and addressing planning of DG. To compare the final optimization results, this study also uses a binary-coded quantum PSO algorithm to plan the distribution network without DG and runs the debugged program in MATLAB.

Figure 6 shows the Pareto frontier of multi-objective optimization planning of distribution networks with and without DG.

The graphic shows that, regardless of that scenario, there is no solution distribution in the areas of low line loss and low expenditure, because there are no solutions that meet the conditions in these areas. For the number and distribution of solutions in both cases, the planning scheme with DG is better than that without DG. The increase in DG will increase the complexity of the algorithm, which means that there will be more alternatives, and so there will be better quantity and distribution. At the same construction cost, the line loss of the planning scheme with DG is much less than that without DG, which is the reason for introducing DG and is consistent with reality. Therefore, the BQPSO algorithm can find Pareto's optimal solution. In a case study, Zhang et al. designed an integrated distributed energy system with combined heat and power (CHP), PV, and

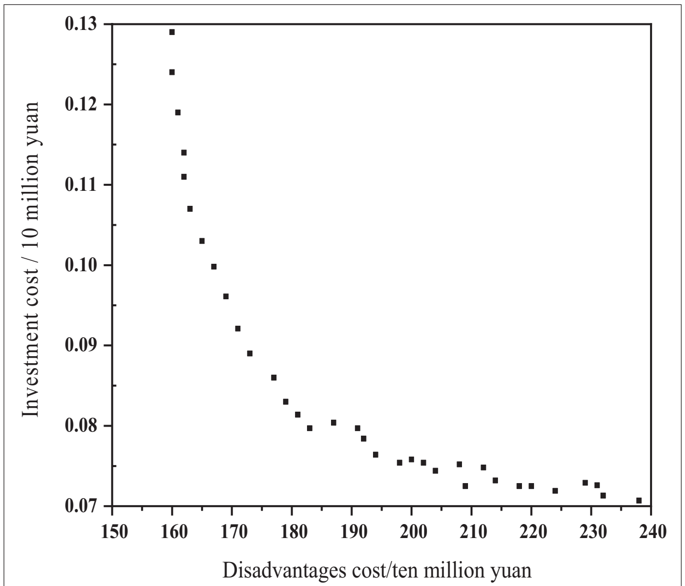

Fig. 5. Pareto frontier obtained by BQPSO algorithm.

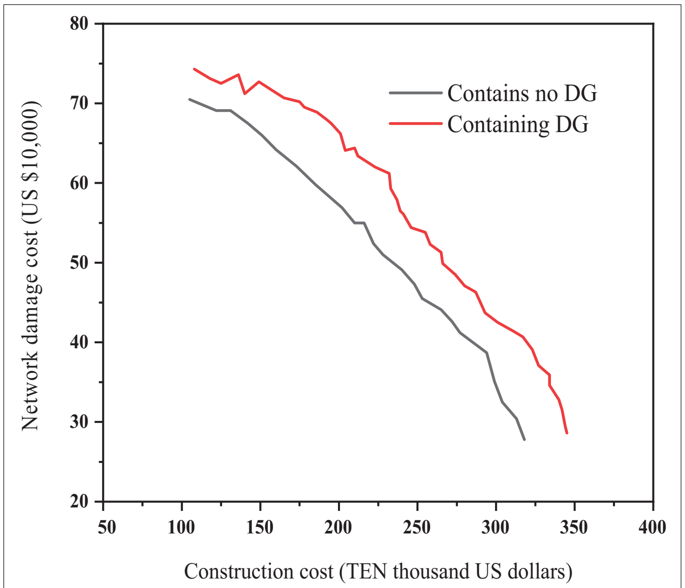

Fig. 6. Pareto frontier obtained by BQPSO algorithm.

electric and/or thermal energy storage for a hospital and large hotel buildings. The findings demonstrate that the recommended optimal solution may be utilized to find the best distribution of energy system design that strikes a balance between the economic and environmental outcomes of diverse structures. Electricity peak shaving of 800 kW and 600 kW might be obtained during the summer and transition seasons, respectively [39].

The distributed generation is optimized according to the results in Table III, and the objective function value under this planning scheme is calculated and compared with the optimization result of the improved genetic algorithm. The table shows that different algorithms produced varied results for each particular investment component. The table shows that different algorithms produced varied results for each particular investment component. But, in the final optimization result, the results obtained by the BQPSO algorithm are better. This proves that the BQPSO algorithm can solve optimization problems and has better optimization ability.

According to the data in the table, it is found that although there is no DG cost in the planning scheme without DG, the line loss increases, which makes the final planning cost still higher, while the planning scheme with DG has a lower planning cost. DG has advantages in cost, especially in reliability. With the qualitative improvements, we should consider introducing DG into distribution network planning.

TABLE III. COMPARISON OF DISTRIBUTION NETWORK EXPANSION PLANNING RESULTS WITH DIFFERENT ALGORITHMS

Expense	With DG or Not	With DG
Investment in line ($10 000)	188.6	115.2
DG expenses ($10 000)	0	43.87
Line loss ($10 000)	68.4	62.31
Comprehensive ($10 000)	257	221.38

V. DISCUSSION

In this study, according to the multi-objective power grid planning, the mathematical model of power grid planning is established by selecting suitable objectives so that it can be applied to solving discrete problems. First of all, taking 18-bus transmission network system expansion planning and 8-bus distribution network expansion planning with distributed generation as examples, the effectiveness and efficiency of the algorithm for solving multi-objective programming are verified. Then, for the multi-objective Pareto optimal solution set, the crowded distance sorting method is used to construct it. Finally, MATLAB software is used to simulate the example and the corresponding planning results are obtained. From the model verification results, it can be observed that the quantum PSO algorithm applied in this research can complete the task of power grid planning well under the premise of ensuring the calculation speed in the multi-objective design of a smart grid.

VI. CONCLUSION

Lightning protection of the power system and substation is very important for the whole power supply system. It is the primary measure to ensure that the power system operates normally, and it can greatly reduce the damage of lightning to weak current equipment in substations. In the actual engineering operation process, different measures and methods should be taken according to different situations to reduce the impact of lightning on weak current equipment in substations and ensure the safe operation of the power system. According to the basic characteristics of quantum PSO, combined with the characteristics of power system planning, the economic and reliability of smart grid planning are taken as the optimization goal, and the planning of transmission grid is studied. For the smart distribution network with DG, the improved quantum swarm algorithm is also used to optimize the DG capacity and location and the distribution network expansion planning. The final optimization results are compared with those obtained by other intelligent algorithms by programming language, which verifies the effectiveness and practicability of the algorithm used in this study in smart grid planning. Power grid planning is the key content for the planning of a power system, and it is also the guarantee for the security, stability, and economy of the power system. In smart grid optimization, multi-objective will become more and more common. For multi-objective selection, formulating corresponding standards may be more conducive to the unification of future smart grid planning.

Peer-review: Externally peer-reviewed.

Author Contributions: Concept – F.L., B.J., J.B., S.N.S.; Design – F.L., B.J., Z.Y., S.N.S.; Supervision – F.L., B.J.; Materials – H.X., J.W., J.B.; Data Collection and/or Processing – F.L., B.J., Z.Y., H.X.; Analysis and/or Interpretation – J.W., J.B., S.N.S.; Literature Review – F.L., B.J., J.B., S.N.S.; Writing – F.L., B.J., Z.Y.; Critical Review – F.L., B.J., Z.Y., H.X., J.W., J.B., S.N.S.

Declaration of Interests: The authors have no conflicts of interest to declare.

Funding: The authors declared that this study has received no financial support.

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