Multi-Objective Planning of Distributed Photovoltaic Power Generation Based on Multi-Attribute Decision Making Theory

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ABSTRACT Photovoltaic (PV) power generation has been heavily connected into distribution network recently. However, the intermittent and uncertainty of PV generation system will significantly affect the security operation of distribution network. Therefore, the planning of PV system shows urgency in the extensive planning of distribution network. Herein, a multi-objective PV planning model is proposed in this paper, active power losses, voltage deviation, voltage harmonic distortion and static voltage steady index are considered and discussed in the operation of distribution network. In order to dispose the complex coupling of these different objectives, multi-attribution decision making theory method combined with the game theory is proposed for coordinating the different objectives. The comprehensive weight model of the different objectives is used to present the combined effect of PV system toward distribution network. Furthermore, an improved PSO algorithm is developed for the solution of the multi-objective problem. Simulation results and the application in practical system show that the proposed PV generation system planning model and solution method are effective.

INDEX TERMS Photovoltaic (PV) power generation, multi-objective planning model, particle swarm optimization, multiple attribution decision making theory.

I. INTRODUCTION
With the increasingly sever energy crisis and environmental problems during the last decades, renewable distributed generation (DG) such as wind turbines generation system and photovoltaic (PV) generation system are encouraged globally to mitigate energy and environmental problems supported with financial incentives [1]–[3]. Furthermore, the photovoltaic generation systems have expanded significantly due to the continuous dropping price of photovoltaic panels recently. However, the installation of PVs, which has the intermittent and uncertainty characteristics, may bring security concerns in the distribution network operation condition who has not ready to accept so many amount of PVs. Hence, it calls for a placement and sizes planning guidance for the PVs in distribution network [4]–[6].

There are many works about the planning of PV focused on the effects in the distribution network such as voltage profile, active power losses and power quality as economic problems. The idea planning of PV integration is to determine the placement and capacity with a comprehensive optimal system performance index. The PV system is considered as power electronics inverter based static generator and PV systems have been studied for improving system voltage stability. In [7], a probability-weighted robust optimization method is proposed for the allocation of wind turbines and PVs, which maximizes the total profit over a long term planning horizon. A multiple objectives DGs planning optimization model is proposed to minimize active and reactive power loss and voltage deviation simultaneously in [8]. Stochastic optimization techniques have been used in DG planning problem in [9], and a large number of scenarios have to be generated in these stochastic optimization methods. To improve the uncertainty modeling efficiency, authors in [10] proposed a probabilistic optimization approach for the load uncertainty.
In [11], a multi-disciplinary approach to jointly plan for PEV charging stations and PV power plants is proposed, and a two-stage stochastic programming model for the sites and sizes of them is calculated.

In [12], a data-driven method for the detection and estimation of residential PV system installations based on consumption behaviors is proposed, and the existence of the unauthorized PV installation is further verified. Compared with the stochastic optimization, system voltage stability margin as the DG planning optimization objective is studied in [13]. Herein, plug-in electric vehicle penetration level and allocation of different types of DG are optimized simultaneously to achieve multiple objectives in [14]. The probabilistic optimization approach has been applied to the planning problems. Authors in [15] proposed a methodology for sizing of DGs from a micro-grid context, and the resulting problem is addressed using the prospects of particle swarm optimization and genetic algorithm methods.

A dynamic expansion planning of distribution networks with DGs is proposed in [16], [17], and a relatively new meta-heuristic algorithm is employed to solve the resulting problem. However, the uncertainty and operational variability are not accounted for in this work. Since DG includes intermittent energy sources, the planning model should adequately take into consideration the uncertainty and variability, including the absence of electricity demand. Authors in [18] proposed a method for the economic and network-driven DG placement planning problem considering reliability level and the power loss of the electrical distribution network. Furthermore, the customers’ load type is modeled and load-model-based power flow is applied instead of conventional power flow.

In [19], a multistage expansion planning problem is invested considering distributed generations and distribution network. In [20], the DG units are considered in the expanded on distribution investment deferral. Authors in [21], [22] presented a scenario-based robust distributed generation investment planning model considering the uncertainties of DGs and load demand. In [23], a multi-objective optimization model considering fluctuation of output power, utilization of electrical equipment and losses of renewable energy is established for the planning of PV capacity for the wind farm expansion, which is a two-stage method to smooth the fluctuation of output active power and improve system operation economy.

The PVs installation planning problem is a multi-objective optimal and decision problem, and there are many experienced solutions in the literatures. Non-dominated sorting genetic algorithm II (NSGA-II) has successfully been used for solving many scenarios with multi-objective problems [24], [25]. Authors in [26] proposed a multi-objective evolutionary algorithm based on decomposition to optimize the sizes and locations of DGs and SCs in large scale distribution networks. Authors in [27] proposed a LS-based method analytical technique to determine the location and sizes of DGs. In [28], a constriction-factor PSO method is used for the planning of DG location and sizes, various factors such as profit, incentives on capital, replacement, startup et al, have been taken into account in the model to provide choices for distribution utilities to section. A novel incentive-based distribution system expansion planning model is proposed in [29].

Authors in [30] proposed a new constrained multi-objective Particle Swarm Optimization (PSO) to calculate the placement of DGs based on power loss reduction and voltage stability improvement. A planning model that accounts for the full distribution of generator outages and solar resource variability for the study the effect of time resolution and solar PV penetration is discussed in [31]. Authors in [32] presented fuzzy analytical hierarchical process based on fuzzy set theory, which is used to modify weights averaging combination to address the transformers’ health condition. In [33], a VHO algorithm based on decision selection is proposed to address the family hybrid VLC-Femto system, it can compensate for the weakness of classical AHP and improve efficiency of the communication system.

The contributions of the paper can be summered as follow: 1) A multi-objectives PV planning model combine with the active power loss, voltage deviation, voltage harmonics distortion, and static voltage stability index is proposed, and the model comprehensive considered the different aspects power network operation. 2) Multi-attribute decision making theory method combined with the game theory is proposed for coordinating the different objectives. The comprehensive weight model of the different objectives is used to present the combined effect of PV system toward distribution network. 3) Improved PSO algorithm is used to address the optimization of the comprehensive model. 4) The effective of the proposed model and method is verified by the simulation and practical power system application in Hainan province.

The rest of the paper is organized as follows: In Section II, the objective of the PV planning problem is proposed and discussed. The multi-decision theory and PSO algorithm for the solution of the proposed model are presented in Section III. Section IV, numerical studies are concerned to verify the efficiency of the proposed method. The conclusion is present in Section V.

II. MULTI-OBJECTIVE MODELING OF PV PLANNING

PV placement in distribution network locally supplies part of active demand of customers. Thus, the power flow of distribution network will redistribute. As a result, the power loss of will decrease due to the reduction of the line current in the feeder. However, PV generation system integrates into power system through PWM based power electronics inverter, which will bring harmonics current in direct proportion with its capacity of PV generation system. Harmonics current will worsen the power quality which is disadvantage to the electrical equipment. Voltage stability is the key point in the operation of distribution network, and the active power injection of PV will change the power flow which will improve the voltage stability index of power system and improve the security of the system. The injection of active
power will increase the voltage magnitude which will bring the security problem. In this paper, multi-objective will be considered in the model including active power loss, static voltage stability, harmonics index and voltage deviation. The weights of these factors will be calculated by multi decision theory.

A. OBJECTIVE FUNCTION

1) Active power loss of distribution network

PV generation system will supply active power to the local customers, which will reduce the line current and active power loss of distribution network. The calculation of active power loss is based on the power flow distribution, and it can be written as:

\[
P_{\text{Loss}} = \sum_{k=1}^{m} G_k [V_i^2 + V_j^2 - 2V_i V_j \cos(\theta_i - \theta_j)]
\]

where \( m \) is the number of branches in the distribution network, \( G_k \) is the conductance of the branch \( k \), \( V_i \) and \( V_j \) are the voltage amplitudes of the buses \( i \) and \( j \) which is the ends of branch \( k \), \( \theta_i \) and \( \theta_j \) are the voltage phases of buses \( i \) and \( j \) respectively.

2) Voltage deviation

Voltage deviation is defined as the difference between actual voltage and the rated voltage, which can be written as:

\[
\Delta U_i = \frac{U_i - U_N}{U_N} \times 100\%
\]

From equation (2), it can be seen that the voltage deviation is a percentage number based on the rated voltage of the system. \( U \) is the actual voltage and \( U_N \) is the rated voltage of the system. The system voltage deviation (VD) is presented by the mean of the voltage deviation of each node.

\[
VD = \frac{1}{n-1} \sum_{i=1}^{n-1} |\Delta U_i |
\]

where \( \Delta U_i \) is the voltage deviation of the \( i \)-th bus, the total number of nodes is \( n \) in the distribution network.

3) Voltage harmonic distortion

With the connection of PV generation system, harmonic current from the PWM inverter will be injected into distribution network which will increase the harmonic component of node voltage. Herein, voltage harmonic distortion is defined as follow:

\[
THD_k = \frac{\sqrt{\sum_{i=2}^{n} U_{ki}^2}}{U_{k1}} \times 100\%
\]

where, \( U_{ki} \) is the \( i \)-th harmonic voltage of bus \( k \), \( U_{k1} \) is the fundamental voltage of bus \( k \). Furthermore, the total voltage harmonic distortion rate of the distribution network is defined as the sum of the all node voltage distortion rates. It can be presented as:

\[
THD = \sum_{k=1}^{n} THD_k
\]

\( THD_k \) is the voltage harmonic distortion rate of the node \( k \), \( n \) is the total number of nodes in the distribution network.

4) Static voltage stability index (VSI)

Static voltage stability index means that the possibility of voltage instability with the increasing of load or distribution generations system connected. Based on the power flow, the ultimate power transfer capacity of the line presents the boundary point of system voltage instability. The static voltage stability index of line \( i \) can be expressed as

\[
L_i = 4[(XP_j - RQ_j)^2 + (XQ_j + RP_j)^2V_i^2]/V_i^4
\]

where, \( R \) and \( X \) are line resistor and reactance respectively, \( P_j \) and \( Q_j \) are active and reactive power at the end of line in bus \( j \), \( V_i \) is voltage of the bus \( i \) at the head of line. For a complex distribution network, the static voltage stability index of line is different due to the transfer power of line is different. Here, static voltage stability index in distribution network is presented by the maximum value of \( L \), which is written as:

\[
VSI = \max[L_1, L_2, L_3, \ldots, L_n]
\]

The basic requirements for the operation of a distribution network are to ensure reliable continuous power supply, good power quality and economical operation. However, the active power injected from PV generation system will change the power flow distribution which will change the distribution network operational index. So a multi-objective model of PV planning can be written as the comprehensive objective of the former factors and can be written as:

\[
F = \min[\lambda_1 P_{\text{loss}} + \lambda_2 VD + \lambda_3 THD + \lambda_4 VSI]
\]

where, \( P_{\text{loss}} \) is active power loss of distribution network which presents the economy index of PV generation system planning scheme, \( VD \) is the voltage deviation after the PV connected, \( THD \) represents reliability index of the PV planning scheme suing harmonic, \( VSI \) represents the static voltage stability index in the distribution network. \( \lambda_i \) is the weight of different operation index.

B. CONSTRAINTS

The planning of PV generation system should satisfy the security operation profile of distribution network. Therefore, power flow and voltage balance are the basic index of the stable operation of distribution network. Furthermore, power reverse and PV capacity also should be considered as the operation constraints in the modeling of the planning problem. Here, the constraints of the problem can be written as follows;

1) Power flow balance constraint:

\[
\begin{align*}
P_{PV_i} - P_{L_i} &= \sum_{j \in \Omega_N} P_{ij} \quad \forall i \\
Q_{PV_i} - Q_{L_i} &= \sum_{j \in \Omega_N} Q_{ij} \quad \forall i \\
P_{ij} &= U_{ij}(G_{ij} \cos \theta_{ij} + B_{ij} \sin \theta_{ij}) \\
Q_{ij} &= U_{ij}(G_{ij} \sin \theta_{ij} + B_{ij} \cos \theta_{ij})
\end{align*}
\]
where, \( P_{PV_i} \) and \( Q_{PV_i} \) are the active power and reactive power from the PV system at bus \( i \), \( P_{ij} \) and \( Q_{ij} \) are the active power and reactive power consumed by the load at the bus \( i \), \( P_{ij} \) and \( Q_{ij} \) are the active power and reactive power flowing between bus \( i \) and bus \( j \), \( U_i \) is the voltage of bus \( i \), \( \theta_{ij} \) is the voltage phase angle difference between bus \( i \) and bus \( j \), \( G_{ij} \) and \( B_{ij} \) are conductance and susceptance of the branch.

2) Voltage deviation constraint

\[
U_{i,\min} \leq U_i \leq U_{i,\max}
\]

(10)

where \( U_{i,\min} \) and \( U_{i,\max} \) are the lower and upper limits of bus voltage amplitude, which can be set in \([0.93\ 1.07]\) in distribution network.

3) Power reverse constraint

The rising penetration of PV generation system will increase the output active power of the generation. However, the surplus power will be delivered into main grid with the same load. It is not allowed to reverse the surplus power into main grid in the power system operation. So the active power through the main transformer \( P_T \) can be written as:

\[
P_T \geq 0
\]

(11)

4) Total PV capacity constraint

It means that the total distributed PV capacity is limited by its own installed capacity, and \( P_{DG_{\max}} \) is maximum allowable total PV power capacity.

\[
\sum P_{DG} \leq P_{DG_{\max}}
\]

(12)

III. MULTI-ATTRIBUTE DECISION MAKING THEORY

A. ENTROPY-WEIGHT METHOD

Multi-attribute decision making method which refers to the selecting the finite alternatives with comprehensive evaluation index has been widely used to solve the decision making problems. The purpose of the multi-attribute decision making method is selecting or ranking the candidate based on the given objective. In the process of multi-attribute decision making method, information and entropy are used to present ordering and disordering state of system respectively. Generally, the smaller the information entropy is, the greater degree of the index changes. As a result, the weight of the objective is greater.

Supporting that there are many existing status of the system, and the probability of each status is \( p_i \), so the entropy of the system can be presented as:

\[
e = - \sum_{i=1}^m p_i \ln p_i
\]

(13)

The entropy will be maximum when the probability of each status is the same, and the maximum entropy is \( e_{\max} = \ln m \). The process of the multi-attribute decision making method can be present as follow:

1) Constructing multiple objective matrix

For a multi-objective system with \( m \) objectives \( M_1, M_2, \ldots, M_n \), and the attribute of each objective is \( n N_1, N_2, \ldots, N_n \), the relationship between objective and attribute and can be written a \( m \times n \) matrix as follow:

\[
X_{m \times n} = \begin{bmatrix}
x_{i1} & x_{i2} & \cdots & x_{in} \\
x_{11} & x_{12} & \cdots & x_{1n} \\
x_{21} & x_{22} & \cdots & x_{2n} \\
\vdots & \vdots & \ddots & \vdots \\
x_{m1} & x_{m2} & \cdots & x_{mn}
\end{bmatrix}
\]

(14)

where, \( x_{ij} \) is the original decision attribute value, which is a quantitative value or qualitative fuzzy value.

2) Normalization

In order to calculation the relationship matrix, normalization based on (15) is used here,

\[
x_{ij}' = \begin{cases}
x_{ij} - \min(x_{ij}) \\
\max(x_{ij}) - \min(x_{ij}) \\
\max(x_{ij}) - x_{ij} \\
\max(x_{ij}) - \min(x_{ij})
\end{cases}
\]

(15)

where, \( \min(x_{ij}) \) is the minimum value of \( x_{ij} \), \( \max(x_{ij}) \) is the maximum value of \( x_{ij} \). However, if \( x_{ij} \) is positive value, the first equation is used, and if \( x_{ij} \) is negative value, the second equation is used.

3) Index weighting matrix calculation

Calculating the proportion of \( x_{ij}' \) in the j-th index based on equation (16), and as a result, the new decision matrix can be written as equation (17):

\[
x_{ij}'' = \frac{x_{ij}'}{\sum_{i=1}^m x_{ij}'}
\]

(16)

\[
X_{m \times n}'' = \begin{bmatrix}
x_{11}'' & x_{12}'' & \cdots & x_{1n}'' \\
x_{21}'' & x_{22}'' & \cdots & x_{2n}'' \\
\vdots & \vdots & \ddots & \vdots \\
x_{m1}'' & x_{m2}'' & \cdots & x_{mn}''
\end{bmatrix}
\]

(17)

4) Entropy index calculation:

The information entropy of the j-th objective can be calculated based on equation (18) and (19):

\[
e_j = \frac{1}{\ln m} \sum_{i=1}^m x_{ij}'' \ln x_{ij}''
\]

(18)

\[
W_j = \frac{1 - e_j}{\sum_{j=1}^m (1 - e_j)} = \frac{1 - e_j}{n - \sum_{j=1}^m e_j}
\]

(19)

where, \( e_j \) and \( W_j \) are the information entropy and weight of each objective respectively.

If the \( j \)-th attribute of each objective is the same, the entropy of the \( j \)-th is equal to 1, and it’s entropy weight is zero. Entropy weight is used to calculate the discrimination of evaluation objective for each attribute. Entropy weight method is used to evaluate the attribution weight of the problem, and remove the attributes which is not good in the evaluation system based on its characteristics.
B. COMBINATION WEIGHTING METHOD WITH GAME THEORY

The PV distribution system planning model contains four individual objectives which are power loss of distribution, voltage deviation, static voltage stability index and voltage distortion. However, the individual objective only considers single operation characteristic of distribution network and lacking the comprehensive evaluation index. In order to give a comprehensive evaluation index, the weight of these objectives should be determined. In this paper, a novel method combined the subjective weight of the expert system with the objective weight based on entropy method is proposed to determine the weights of the individual objective, which can improve the rationality and comprehensiveness of the evaluation system.

Supposing that the weights of the multi objectives are obtained from L objectives, and the weight vector can be written as:

\[ \omega_k = (\omega_{k1}, \omega_{k2}, \ldots, \omega_{kn}) \quad k = (1, 2, \ldots, L) \]  \hspace{1cm} (20)

The comprehensive weight is a linear combination of these L weight vectors which is:

\[ \omega = \sum_{k=1}^{L} \alpha_k \omega_k^T \quad (\alpha_k > 0) \]  \hspace{1cm} (21)

The optimization of \( \omega \) is achieved by controlling the size of \( \alpha_k \). Minimum the distance between \( \omega \) and each \( \omega_k \):

\[ \min \left| \sum_{k=1}^{L} \alpha_k \omega_k^T - \omega_k \right|, \quad k = (1, 2, \ldots, L) \]  \hspace{1cm} (22)

According to the differential properties of the matrix, the optimal condition is:

\[ \begin{bmatrix} \omega_1 \cdot \omega_1^T & \omega_1 \cdot \omega_2^T & \cdots & \omega_1 \cdot \omega_l^T \\ \omega_2 \cdot \omega_1^T & \omega_2 \cdot \omega_2^T & \cdots & \omega_2 \cdot \omega_l^T \\ \vdots & \vdots & \cdots & \vdots \\ \omega_l \cdot \omega_1^T & \omega_l \cdot \omega_2^T & \cdots & \omega_l \cdot \omega_l^T \end{bmatrix} \begin{bmatrix} \alpha_1 \\ \alpha_2 \\ \vdots \\ \alpha_l \end{bmatrix} = \begin{bmatrix} \omega_1 \cdot \omega_1^T \\ \omega_2 \cdot \omega_2^T \\ \vdots \\ \omega_l \cdot \omega_l^T \end{bmatrix} \]  \hspace{1cm} (23)

There is a \( (\alpha_1, \alpha_2, \ldots, \alpha_l) \) which is normalized to get the comprehensive weight vector \( \omega^* \).

\[ \alpha_k^* = \frac{\alpha_k}{\sum_{k=1}^{L} \alpha_k} \]  \hspace{1cm} (24)

\[ \omega^* = \sum_{k=1}^{L} \alpha_k^* \cdot \omega_k^T \]  \hspace{1cm} (25)

IV. IMPROVED PARTICLE SWARM ALGORITHM BASED PV PLACEMENT PLANNING

A. STANDARD PARTICLE SWARM ALGORITHM

Particle swarm algorithm is a swarm intelligence algorithm based on the preying behavior of bird. Through sharing their position and velocity information with companions, bird block will approach the position of prey gradually and capture the prey finally. Mimicking bird predation, particle swarm algorithm is designed for the optimization of problem, fitness function and solution space are used to present the food and foraging area respectively. The evaluation of the particle swarm can be written as equation (26):

\[ v_i^{k+1} = \omega \cdot v_i^k + c_1 \cdot rand_1 \cdot (pbest_i^k - x_i^k) + c_2 \cdot rand_2 \cdot (gbest^k - x_i^k) \]  \hspace{1cm} (26)

\[ x_i^{k+1} = x_i^k + \omega \cdot v_i^k \]  \hspace{1cm} (27)

where, \( v_i^k \) and \( x_i^k \) are the speed and position of the i-th particle in the k-th iteration, \( pbest_i^k \) represents the individual historically optimal solution of the i-th particle, \( gbest^k \) represents the global optimal solution of all particle, \( \omega \) is inertia weight to maintain coefficient of speed at the previous moment. \( c_1 \) and \( c_2 \) are the acceleration factors, which represent the trend of the particle approaching the individual extreme point and the global extreme point respectively. \( rand_1 \) and \( rand_2 \) are acceleration weight coefficients randomly generated in the interval \([0,1]\).

In order to improve the convergence speed and accuracy of the algorithm, the update formula of the inertia weight \( \omega \) is set as follow:

\[ \omega = \omega_{\text{max}} - \frac{\omega_{\text{max}} - \omega_{\text{min}}}{k_{\text{max}}} \cdot k \]  \hspace{1cm} (28)

\( \omega_{\text{max}} \) and \( \omega_{\text{min}} \) are the maximum and minimum values of inertia weight, \( k_{\text{max}} \) is the maximum number of iterations, and \( k \) is the current number of iterations.

B. IMPROVED PARTICLE SWARM ALGORITHM

There are some shortages during the process of the algorithm. For example, it is easy to trap in a local optimum and slower convergence in the later stages of solution. For the optimal configuration problem of PV system in distribution network, the paper draws an improved particle swarm algorithm to solve the problem.

Global optimal and individual optimal are easy to trap in local optimal due to the random of standard particle swarm algorithm during the evolution of the algorithm. Here, the individual optimal and global optimal will be selected if there is stagnation.

A N-dimension 0-1 vector \( Vec_{pbest_i} \) is generated, and alter the i-th dimension position of \( x_i \) by the i-th dimension position of \( pbest_i \), if \( Vec_{pbest_i}^{[j]} = 1 \). However, if \( Vec_{pbest_i}^{[j]} = 0 \), the i-th dimension position of \( x_i \) won’t be changed. Calculated the new fitness of the new \( x_i \) and, as a result, the \( pbest_i \) is updated by the better one.

Cross mutation operation improves the convergence speed of the population, but it may destroy the diversity of the population. So when the variance of the population is lower than
the set threshold, initialize the population by the following strategy:

\[ X^j_k = b^j_{\text{min}} + r(b^j_{\text{max}} - b^j_{\text{min}}) \]

(29)

where, \( b^j_{\text{min}} \), \( b^j_{\text{max}} \) are the lower and upper bounds of the j-th position when the population is reinitialized, and they are obtained according to equation (30):

\[
\begin{align*}
    b^j_{\text{min}} &= \min(X^j_{\text{min}}, gbest_k^j - \lambda(gbest_k^j - X^j_{\text{min}})) \\
    b^j_{\text{max}} &= \max(X^j_{\text{max}}, gbest_k^j - \lambda(gbest_k^j - X^j_{\text{max}}))
\end{align*}
\]

(30)

where \( \lambda = 1 - \frac{k}{k_{\text{max}}} \), which approaches from 1 to 0 as the number of iterations increases. \( X^j_{\text{min}}, X^j_{\text{max}} \) are the lower and upper bounds of the j-th dimension of the particles, respectively.

C. ALGORITHM PROCESS FOR PV PLANNING

The flow chart of the PV planning method is show in FIGURE 1, and the process can be presented as follow:

1) Input the parameters of distribution network including the number of buses, line impedance, load power, etc.

2) Power flow calculation. According to the placement of the PV system in the distribution network, calculation power flow and harmonic power flow based on the decoupling method. The constraints should be considered in the power flow calculation using penalty function.

3) Initializing particle swarm algorithm parameters which are population size, maximum number of iterations, initial position and speed.

4) Objective calculation. Based on the position and speed of the swarm, each single objective is calculated and use entropy-weight method and game theory to determine the weight of each objective in the comprehensive objective. The process of entropy weight method and game theory is in section III.

5) Algorithm evaluation. Based on the improved PSO algorithm, update the position, speed, \( pbest_i, gbest \) of the current generation particles.

6) Stopping conditions checked. The maximum number of iterations and the convergence accuracy error are chosen as the stop condition of the algorithm. If it is satisfied, the iteration is terminated and the optimal solution is output; if not, go to step 4.

V. EXPERIMENTAL ANALYSIS

A. SIMULATION SYSTEM

IEEE 33 distribution network is used for the simulation system to verify the proposed PV placement planning which is shown in FIGURE 2. The detailed parameter of the simulation system is shown in the Appendix. The rated voltage is 12.66kV and the rated power of the system is 10MVA. The total active power and reactive power of the system are 3.175MW and 2.3MVar respectively. The parameters of the particle swarm algorithm in the example are set as follows: the number of initialized particles is 50, the dimension is equal to the number of PV system, the maximum number of iterations is 100, the acceleration factors \( c_1 \) and \( c_2 \) are both 2, and the inertia weights \( \omega_{\text{max}} \) and \( \omega_{\text{min}} \) are 0.8 and 0.4, respectively. The penalty factors for voltage deviation, power feed-back and total PV capacity are all taken as \( 10^5 \), the maximum total installed capacity of PV system is 3MW, and the power factor keeps 1.

B. PLANNING OF PV SYSTEM IN DISTRIBUTION NETWORK

20 scenarios of PV systems installed capacity are generated randomly and the bound of the capacity is range 0 and 3MW. Under these operational conditions, the different objectives about active power loss, voltage deviation, static voltage stability and harmonic voltage distortion are calculated. 20 scenarios of PV systems and the objectives are shown in TABLE 1. Normalizing each objective and the information entropy is calculated based on equation (18), objective weights of each index are calculated based on equation (19), the result is shown in TABLE 2.

From TABLE 2, the objective weights of each index are determined by the entropy weight that is \( \omega_{\text{2}}, \text{which is}(0.1812, 0.3313, 0.1958, 0.2918) \). Combined with the subjective weight based on expert decision tree learning method, the comprehensive weight of the four indexes can be calculated and the result is shown in TABLE 3. Then the expression of the distribution network operation comprehensive objective can be written as:

\[
\text{Objective} = 0.3173^{*}PL + 0.2945^{*}VD + 0.1324^{*}VSI + 0.2559^{*}THD \tag{31}
\]
Six scenarios are selected to verify the effectiveness of the planning model proposed in this paper. The PV system is installed in single bus, and each scenario just considers one objective. The six scenarios are presented as follow: 1): No PV power is installed; 2): Considering the Power loss; 3): Considering voltage deviation VD; 4): Considering voltage stability index VSI of the system; 5): Considering total voltage distortion rate THD; 6): Considering the comprehensive index F of the distribution network. The result is shown in TABLE 4.

It can be seen that there is no harmonic power flow in scenario 1 since there is no PV installed in the system, however, the voltage deviation constraints are not met, and the VD index is the maximum one. The system power loss of scenario 2 is the minimum, but the static voltage stability index is the maximum one, even exceeding the VSI where no PV installed. It is advantage to the economical operation of the distribution network, but it reduces the stability of the system. The voltage deviation of scenario 3 is the minimum, but the system power loss is the maximum. The static voltage stability of scenario 4 is the best, but the voltage distortion rate and power loss is large. The voltage distortion rate of scenario 5 is the lowest, but the voltage deviation is obviously higher than others. The static voltage stability index of scenario 6 is very close to the results in scenario 5, although the improvement effect of voltage distortion is not as good as scenario 4, but it is much better than schemes 2, 3, and 5. Furthermore, scenario 6 effectively reduces the voltage deviation and power loss. In summary, scenario 6 has the best overall improvement of the distribution network indexes.

Considering the situation of multi-bus installed, the optimal configuration of the comprehensive index is obtained, and the results are shown in the TABLE 5. It can be seen from TABLE 5 that the multi-objective of the distribution network operation decreases as the number of connected photovoltaic power sources increases. Therefore, the photovoltaic power supply should be distributed as much as possible to optimize the operation status of the distribution network.

C. PRACTICAL APPLICATION
The actual distribution network of a certain place of Hainan province is selected as the optimal configuration for photovoltaic installed. The structure of the grid is mostly radial and simplify model of the distribution network is shown in FIGURE 3.
Bus 57 is the balanced bus, and the remaining buses as PQ nodes. The total active power of load is 65.127MW, the maximum total installed PV capacity is set to not exceed 80MW, and the single photovoltaic power supply is not to exceed 20MW. The improved particle swarm algorithm is used to solve the photovoltaic power access strategy.

Based on the entropy weight method, the objective weights of the power loss, voltage deviation, static voltage stability, and voltage distortion indexes of the Power Grid are first obtained (0.2239, 0.4045, 0.1974, 0.1742), and the subjective weights are still taken (0.3769, 0.2784, 0.1046, 0.2402), the comprehensive weight calculated by game theory combination is (0.3072, 0.3359, 0.1469, 0.2101). The calculation results are shown in TABLE 6. It verifies that decentralized install PV system is helpful to optimize the operation status of the distribution network.

**VI. CONCLUSION**

PV distributed generation system is an important renewable generation system in power system. The capacity and placement planning is important for the security operation of distribution network with the large scale connected of PV system. A multi-objective PV system planning model based on active power loss, static voltage stability, voltage deviation, and voltage distortion is proposed in this paper. Furthermore, game theory combined with information entropy weight to determine the weight of each objective in the multi-objective model. An improved particle swarm algorithm combining cross mutation is proposed and used in the optimal configuration of PV system planning. Finally, the verification calculation is performed in IEEE 33 power system and an actual distribution network, the result shows that the proposed multi-objective model is efficient and the installed of the PV system can improve the reliability of the distribution network operation.

**APPENDIX**

See table 7.

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