Planning Strategies for Distributed PV-Storage Using a Distribution Network Based on Load Time Sequence Characteristics Partitioning

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Abstract: At present, due to the fact that large-scale distributed photovoltaics can access distribution networks and that there is a mismatch between load demand and photovoltaic output time, it is difficult for traditional distributed photovoltaic planning to meet the partition-based control of high permeability photovoltaic grid-connected operations. As a solution to this problem, this paper proposes a planning method for photovoltaic storage partitions. First of all, a partitioning method for electrical distance modularity based on voltage/active power and voltage/reactive power is presented, along with a modified AP-TD-K-medoids trilevel clustering algorithm that was designed to cluster and partition the distribution network. In addition, according to the partitioning results, a bilevel co-ordination planning model for distributed photovoltaic storage was developed. The upper level aimed to minimize the annual comprehensive cost for which the decision variables are the photovoltaic capacity, energy storage capacity, and power of each partition. The lower level aimed to minimize system network losses, and the decision variables for this are the photovoltaic installation capacity and energy storage installation location of the intrapartition node. Finally, we adopted the particle swarm algorithm with bilevel iterative adaptive weight to solve the planning model, and the simulation was carried out on the distribution system of the IEEE33 nodes. The results show the rationality of the model and the effectiveness of the solution method.

Keywords: distribution network partition; trilevel clustering; distributed photovoltaic; energy storage system; siting and sizing

1. Introduction

In recent years, the supply and demand of coal, oil, and natural gas resources and global carbon emissions have continued to rise, leading to the increasingly prominent problem of the depletion of nonrenewable energy and environmental pollution [1–3]. Distributed photovoltaic generation (DPG) has developed rapidly due to its advantages of convenient installation, environmental friendliness, and a high utilization rate [4]. Regarding large-scale access of DPG to the distribution network, problems have emerged [5]. Photovoltaic power generation is intermittent, volatile, and sequential, which affects the safe and economical operation of the power grid [6,7]. For example, the bidirectional power flow of the system and the voltage limitation of the access point cannot account for local consumption, resulting in increased network losses to the system. The efficient charging and discharging of power of the energy storage system (ESS) and the fast adjustment characteristics of load fluctuations can effectively alleviate the problem of the time mismatch between DPG output and load demand and form a space-time complement to DPG [8,9]. Therefore, the concept of large-scale grid connection planning based on DPG grid connections supported by ESS regulation came into being.
At present, a large number of scholars have conducted research on the location selection and capacity determination of DG and ESSs. The work presented in [10] used the related characteristics of wind and load and established a DG site selection and capacity planning model with the minimum annual comprehensive cost. However, it ignored the problem of voltage stability reduction. Reference [11] established the ESS site selection and capacity planning model with the lowest annual comprehensive cost to solve the overvoltage problem caused by the mismatch between the maximum output of DG and the maximum load sequence but ignored the overall planning of DG and ESSs. Balu et al. [12] established a minimum annual cost planning model for DG investment, operation, and management. They used the MCS-embedded MPDEA algorithm to solve the planning model but did not consider the timing characteristics of the load, DG, and the planning of the ESS. Higher et al. [13] suggested a hybrid chaos binary PSO algorithm based on Pareto set theory for the optimal siting and sizing of DGs in the distribution network, considering the yearly minimization of power loss, costs, and rate of voltage. But they have not considered the impact of the load and the collaborative planning of an ESS. In [14], a genetic algorithm was utilized to obtain the optimal placement and size of ESSs in the distribution network with simultaneous power loss, net present value minimization, and voltage profile enhancement. But the impact of the timing load on the ESS has not been considered.

The above references have studied the site selection and capacity adjustment of DGs and ESSs connected to the distribution network from multiple perspectives, which can effectively alleviate the instability of the distribution network after multiple DGs are connected to the grid. When small-capacity DPG is connected to the distribution network on a large scale in a decentralized manner, the load characteristics of the installed DPG nodes are transformed into power characteristics, and the power supply mode of the distribution network changes from the main network to the main network and DPG compatibility [15]. The multienergy supply mode will pose problems for the centralized control of DPG [16] and make it difficult to meet the control time requirements, causing the power fluctuations in DPG to affect the reliable operation of the distribution grid [17]. Therefore, when planning high-penetration DPG and ESSs, partitional [18] and hierarchical programming [19] strategies are employed to solve the problem of time-sequencing centralized control and complicated planning.

At present, the partition control of distribution networks consists mainly of active power control and reactive voltage control, the majority of which occurs from the latter [20]. Reference [18] partitions the distribution network through reactive power and uses a particle swarm optimization algorithm to optimize the reactive power of DPG in the partition to stabilize the voltage level. Jay et al. [21] have suggested an isoperimetric clustering algorithm based on relative electrical distance measurements for partitioning the power system into voltage-apparent power couplings and dividing the distribution network into partitions. In [22], an electrical coupling strength matrix was used to establish a weight network model and to divide the distribution network based on the fast Newman algorithm. However, there is little research on integrating distribution network partition controls into a source–storage siting and sizing model.

For the above problems, this paper conducts in-depth research on large-scale DPG and ESS grid-connected planning through the idea of grid-partition-node hierarchical planning. Previously, based on reference [23], a partitioning method of the electrical distance modularity of voltage/active power and voltage/reactive power was proposed. According to the timing characteristics of the load, the voltage/active power and voltage/reactive electrical distances are calculated separately, and a new AP-TD-K-medoids trilevel clustering method based on modularization was used for partitioning. Simultaneously, the hierarchical coordination method was adopted to optimize the problem of planning and running the system in two different time dimensions to establish interpartitioning and intrapartitioning planning strategies. The upper level takes the partition as its node and plans the DPG and ESS capacity and power of each partition based on the minimum comprehensive annual cost. The lower level takes each node of the intrapartition as a unit and purposes the
minimum network loss of the system to program the location of the DG and ESS access nodes in the cluster. The planning model is solved by the particle swarm optimization algorithm with bilevel iterative adaptive weights, and the proposed case was evaluated by indicators such as selfbalance degree, energy penetration rate, capacity penetration rate, and power penetration. Concurrently, the effectiveness and rationality of the proposed bilevel programming model of voltage/active power and voltage/reactive power electrical distance modular partitioning for load timing characteristics was verified by simulating the power distribution system of the IEEE33 nodes.

2. Partitioning Method and Formulations

2.1. Partition of Active Distribution Network

Sensitivity of Active and Reactive Power for Conventional Voltages

In the traditional static active distribution network system with \( N \) nodes, the network loss and voltage drop of the system are related to the impedance and load between the nodes [24], as shown in Figure 1.

![Figure 1. Equivalent diagram of distribution network.](image)

Nodal voltage loss without considering the transverse component of the voltage:

\[
\Delta u_i = U_{i-1} - U_i = \frac{\sum P_{Li} \times R_i + \sum Q_{Li} \times X_i}{U_0}
\]  

(1)

System network loss:

\[
f_i = \frac{(\sum P_{Li})^2 + (\sum Q_{Li})^2}{U_i^2}
\]  

(2)

where \( U_i \) is the node voltage, \( U_0 \) is the reference voltage, \( \sum P_{Li} \) and \( \sum Q_{Li} \) are the active power and reactive power at the lower end of the node input, respectively, \( R_i \) is the equivalent resistance, and \( X_i \) is equivalent reactance.

The line with long line, multinode, and heavy load is selected as the main line. Assuming that the voltage of the power node injected into the beginning of the power grid is \( U_0 \), the next node, \( U_1 \), is the first node, and the influence of system network loss is ignored; the voltage drop between nodes is

\[
\begin{align*}
\Delta u_i &= U_{i-1} - U_i \\
\Delta u_{i-1} &= U_{i-2} - U_{i-1} \\
&\vdots \\
\Delta u_1 &= U_0 - U_1
\end{align*}
\]  

(3)
Added to the above formulas gives

$$U_i = U_0 - (\Delta u_1 + \cdots + \Delta u_n)$$  \hspace{1cm} (4)

After expanding Formula (4) and substituting the variables, we obtain

$$U_i = f(P_{Li}, \cdots, P_{Li}, Q_{Li}, \cdots, Q_{Li})$$  \hspace{1cm} (5)

The above formula shows that $U_i$ changes with $P_{Li}$ and $Q_{Li}$. It is

$$\begin{cases}
\Delta P_{Li} = \Delta P^1_{Li} - \Delta P^0_{Li} \\
\Delta Q_{Li} = \Delta Q^1_{Li} - \Delta Q^0_{Li} \\
\Delta U_i = \Delta U^1_i - \Delta U^0_i
\end{cases}$$  \hspace{1cm} (6)

Formula (5) is expanded with Taylor series, ignoring the higher-order terms of power of $P_{Li}$ and $Q_{Li}$. The matrix equation is

$$\begin{bmatrix}
\Delta U_1 \\
\Delta U_2 \\
\vdots \\
\Delta U_n
\end{bmatrix} =
\begin{bmatrix}
\frac{\partial U_1}{\partial P_{Li}} & \frac{\partial U_1}{\partial P_{Lj}} & \cdots & \frac{\partial U_1}{\partial Q_{Li}} \\
\frac{\partial U_2}{\partial P_{Li}} & \frac{\partial U_2}{\partial P_{Lj}} & \cdots & \frac{\partial U_2}{\partial Q_{Li}} \\
\vdots & \vdots & \ddots & \vdots \\
\frac{\partial U_n}{\partial P_{Li}} & \frac{\partial U_n}{\partial P_{Lj}} & \cdots & \frac{\partial U_n}{\partial Q_{Li}}
\end{bmatrix}
\begin{bmatrix}
\Delta P_{Li} \\
\Delta P_{Lj} \\
\vdots \\
\Delta P_{Ln}
\end{bmatrix} +
\begin{bmatrix}
\frac{\partial U_1}{\partial Q_{Li}} & \frac{\partial U_1}{\partial Q_{Lj}} & \cdots & \frac{\partial U_1}{\partial Q_{Li}} \\
\frac{\partial U_2}{\partial Q_{Li}} & \frac{\partial U_2}{\partial Q_{Lj}} & \cdots & \frac{\partial U_2}{\partial Q_{Li}} \\
\vdots & \vdots & \ddots & \vdots \\
\frac{\partial U_n}{\partial Q_{Li}} & \frac{\partial U_n}{\partial Q_{Lj}} & \cdots & \frac{\partial U_n}{\partial Q_{Li}}
\end{bmatrix}
\begin{bmatrix}
\Delta Q_{Li} \\
\Delta Q_{Lj} \\
\vdots \\
\Delta Q_{Ln}
\end{bmatrix}$$  \hspace{1cm} (7)

Node static voltage sensitivity from Formula (7) can be written as follows:

$$[\Delta U] = [S^P_{ij}] [\Delta P] + [S^Q_{ij}] [\Delta Q]$$  \hspace{1cm} (8)

where $S^P_{ij}$ and $S^Q_{ij}$ are the voltage sensitivities of active power and reactive power. $\Delta P = [\Delta P_1, \Delta P_2, \cdots, \Delta P_n]^T$ and $\Delta Q = [\Delta Q_1, \Delta Q_2, \cdots, \Delta Q_n]^T$.

After calculating the change in injected power at each node in the voltage sensitivity matrix $S$, the change in node voltage can be calculated using Formula (8):

$$\begin{cases}
\frac{\partial U_i}{\partial P_{Li}} = -\frac{\min(i,j)}{U_0} \sum_{j=1}^{\min(i,j)} X_j \\
\frac{\partial U_i}{\partial Q_{Li}} = -\frac{\sum_{j=1}^{\min(i,j)} R_j}{U_0}
\end{cases}$$  \hspace{1cm} (9)

In the distribution network, due to the randomness of load demand and the intermittency of high-penetration DG grid connection, large voltage fluctuations will be caused, resulting in inconsistent node voltage regulation requirements [25]. Based on the temporal properties of the load, when the distribution network is partitioned using Formula (8), the partition result obtained is a single-period section, and its quality depends on the given operating state. As a result, static voltage sensitivity is no longer applicable. To obtain a more reasonable partition scheme for the distribution network, this paper proposes using time-series comprehensive voltage sensitivity to calculate the different states of the distribution network in each period.

2.2. Active and Reactive Sensitivity of Sequential Voltage

Subsequently, redefining the active and reactive sensitivity of the voltage is as follows:

$$\begin{cases}
{\text{sen}}^P_{ij,t} = \sum_{t=1}^{T} S^P_{ij,t} \\
{\text{sen}}^Q_{ij,t} = \sum_{t=1}^{T} S^Q_{ij,t}
\end{cases}$$  \hspace{1cm} (10)
where $S^p_{ij,t}$ and $S^Q_{ij,t}$ are elements in the active and reactive voltage sensitivity matrix of node $i$ to node $j$ at time $t$, and $sen^p_{ij,t}$ and $sen^Q_{ij,t}$ are the active and reactive voltage sensitivity matrix of node $i$ to node $j$ at time $t$.

Hence, since the active and reactive sensitivity coefficients of the voltage are not proportional, considering its comprehensive sensitivity, the sensitivity matrix is weighted and summed:

$$c_{ij} = \gamma \cdot sen^p_{ij,t} + (1 - \gamma) \cdot sen^Q_{ij,t}$$  \hspace{1cm} (11)

where $\gamma$ is the weight ($\gamma \in [0, 1]$), the value is $\gamma = \frac{\Delta U^P_i}{\Delta U^{P,t}_i}$, $\Delta U^P_i$ is the voltage change caused by the active power of node $i$ at time $t$, and $\Delta U^{P,t}_i$ is the change of the total voltage caused by the active power of node $i$ at the moment of $t$.

To normalize the sensitivity matrix and expand the differences between the coordinates:

$$Z_{ij} = -\log\left|\frac{c_{ij}}{\max c_{ij}}\right|$$  \hspace{1cm} (12)

As a result, the electrical distance $D$ is defined by computing the Euclidean distance between the nodes in the sensitivity matrix:

$$d_{ij} = \sqrt{\sum_{v=1}^{n-1} |Z_{iv} - Z_{jv}|^2}$$  \hspace{1cm} (13)

where $d_{ij}$ is the electrical distance between node $i$ and node $j$, the electrical distance matrix $D$ is a $n - 1$ factorial square matrix, and the diagonal elements are 0.

According to the formula above, a smaller voltage sensitivity will result in a smaller electrical distance between two-node and a stronger coupling internode. A higher voltage sensitivity corresponds to a greater electrical distance between two-node and a weaker coupling internode.

2.3. Distribution Network Partition of the AP-TD-K-Medoids Algorithm

K-medoids clustering is more sensitive to noise than K-means clustering, but the selection of initial values for both is not objective [26]. Although the AP algorithm [27] does not require the specification of the initial cluster center, the multiple similar points it generates make the number of clusters larger than it actually is [28]. Since the distance between the AP clustering candidate points is smaller than the distance between the class points, TD can remove more points of the same type of AP to obtain the typical optimal cluster center point [29, 30]. To partition the distribution network, the paper proposes the method using improved K-medoids tri-level clustering. To begin with, kap($kap > k$) candidate cluster center points are obtained from the electrical distance matrix by the AP algorithm. Additionally, the TD algorithm is applied to select $k$ initial cluster centers from the $kap$ candidate cluster center point. Last but not least, the optimized cluster center is used as the initial cluster center of K-medoids for the final partition clustering. Specific steps are as follows:

**Step 1.** Input sample data $X = (x_1, \cdots, x_n)^T$, define the number of clusters $k$, select AP similar reference type to get $\theta \in [0, 1]$.

**Step 2.** Calculate the similarity matrix:

$$s(i, j) = -d^2(x_i, x_j) = -\|x_i - x_j\|^2$$  \hspace{1cm} (14)

**Step 3.** Calculate the responsibility value between the sample points:

$$r(i, j) = s(i, j) - \max\{a(i, j') + s(i, j')\}, j \neq j'$$  \hspace{1cm} (15)
Step 4. Calculate the availability value between the sample points:

\[
a(i, j) = \begin{cases} 
\min \{0, r(j, i)\} + \sum_{i' \neq i, j} \max(0, r(i', j)), & i = j \\
\sum_{i' \neq j} \max(0, r(i', j)), & i \neq j 
\end{cases}
\]  

(16)

Step 5. Update \( r_{ij} \) and \( a_{ij} \):

\[
\begin{align*}
  r_{i+1}(i, j) &= \lambda \cdot r_{i}(i, j) + (1 - \lambda) \cdot r_{i+1}(i, j) \\
  a_{i+1}(i, j) &= \lambda \cdot a_{i}(i, j) + (1 - \lambda) \cdot a_{i+1}(i, j) 
\end{align*}
\]  

\( \lambda \in [0, 1) \)  

(17)

Step 6. Cluster center \( V_{kap} = \{V_1, \ldots, V_n\} \) is obtained. In Formula (18), the distance \( dis(i, j) (1 \leq i \leq n, 1 \leq j \leq n) \) between each pair of sample points is calculated to form the distance matrix \( D \), and the distance sum of the data is calculated using Formulas (19) and (20).

\[
dis(x_i, x_j) = \sqrt{(x_1 - y_1)^2 + \cdots + (x_m - y_m)^2} 
\]  

(18)

\[
\text{sum}(x_i) = \sum_{j=1}^{N} \text{dis}(x_i, x_j) 
\]  

(19)

\[
\text{avg}[U] = \frac{\sum_{j=1}^{N} \text{sum}(x_j)}{N} 
\]  

(20)

Step 7. The isolated points whose distance sum is greater than the mean value of the sample distance sum are excluded from the sample set.

Step 8. Update the sample set \( V_{kap} \) and the distance matrix \( D \) of the sample. Then, construct the minimum spanning tree, cut off the \( k - 1 \) largest branches in descending order of weights, and obtain \( k \) clusters.

Step 9. The obtained cluster centers are used as the initial cluster centers of the K-medoids algorithm for clustering. If the partition modularity evaluation index or the number of iterations \( m > M \) reaches a maximum value, the output of the partition result corresponds to the maximum modularity value. If not, return to step 4 and recalculate.

2.4. Evaluation Index of Partition Modularity

It is also significant to note that although the initial center is selected based on AP clustering without specifying the number of cluster centers, the reference degree of similarity needs to be determined beforehand. As the number of class centers is determined by the reference degree, a reasonable reference degree, the most reasonable decoupling case should be selected as the optimal case. Therefore, a modularity index for partitions was proposed in the reference [31]:

\[
B(A, \Phi) = \frac{1}{2m} \sum_{i \in N} \sum_{j \in N} \left[ A_{ij} - \frac{k_i k_j}{2m} \right] \delta(i, j) 
\]  

(21)

where \( A_{ij} \) is the edge weight connecting nodes \( i \) and \( j \) and \( A_{ij} = 1 - \frac{d_{ij}}{\max_{ij} d_{ij}} \) is the partition case. \( \Phi = \delta(i, j) = 1 \), nodes \( i \) and \( j \) are in the same partition. \( k_i \) is the sum of all edge weights connected to node \( i \), \( k_i = \sum_{j \in N} A_{ij} \). \( m \) is the weight of all nodes, \( m = \frac{1}{2} \sum_{i \in N} \sum_{j \in N} A_{ij} \). \( \frac{k_i k_j}{2m} \) is the expected of edge weights of nodes \( i \) and \( j \) when the system is randomly linked.

From Formula (21), it appears that when the modularity evaluation index is greater, the nodes at both ends of the branch with greater weights need to be divided into the same partition, indicating that the nodes are closely connected. Conversely, the nodes at
both ends of the branch whose weight is less than expected were divided into different partitions, indicating that the connection of the internodes is weaker. After partitioning, the electrical distance of the intranodes of the intrapartition is close, whereas the distance of the interpartitions is sparse. On the one hand, it enhances the complementary degree of active power timing of the intrapartition as well as the level of autonomy. On the other hand, it improves the reactive power balance and voltage control capabilities of the intrapartition and reduces the transfer of reactive power of the interpartition. According to reference [31], when $B \to 1$, a better partition quality can be achieved. The partition flow is shown in Figure 2.

Figure 2. Distribution network partitioning process.
3. Planning Method and Modelling

As shown in Figure 3, with the distribution network partition as the research object, a bilevel programming model is established after the distribution network has been partitioned. The upper level considers each partition as a unit, and DPG capacity, ESS capacity, and power as decision variables as the initial conditions for optimizing the lower-level particles. The lower level considers each node in a partition as a unit, and DPG capacity and ESS position as decision variables to transmit the optimal network loss of the distribution network to the upper level.

**Figure 3. Photovoltaic energy storage bilevel programming model.**
3.1. Upper-Level Planning Model

The upper level takes partition as the research object—“Network-Partition”. Based on the time-series change of interpartition load, a planning model with the objective of achieving minimum annual comprehensive cost is established to solve the DPG capacity, ESS capacity, and power of each partition.

3.1.1. Objective Function

Minimum annual cost of integrated

\[ \min C = C_{\text{invest}} + C_O + C_{\text{buy}} - C_s \]  

where \(C_{\text{invest}}, C_O, C_{\text{buy}}, C_s\) are the investment and construction costs, operation and maintenance costs, power purchase costs, and government subsidies.

1. Annual cost of investment construction

\[
C_{\text{invest}} = \sum_{g=1}^{N_G} \left[ \frac{r(1 + r)^T_{\text{DPG}}}{(1 + r)^T_{\text{DPG}} - 1} c_{\text{DPG}}^{\text{g}} P_{\text{DPG}}^{\text{g}} + \frac{r(1 + r)^T_{\text{ESS}}}{(1 + r)^T_{\text{ESS}} - 1} \left( c_{\text{ESS}}^{\text{g}} E_{\text{ESS}}^{\text{g}} + c_{\text{ESS}}^{\text{p}} P_{\text{ESS}}^{\text{g}} \right) \right]
\]

where \(N_G\) is the number of partitions. \(r\) is the discount rate, which is 0.06, \(T\) is the planning period, 20 years for DPG and 10 years for ESS, \(c_{\text{DPG}}^{\text{g}}, c_{\text{ESS}}^{\text{g}}, c_{\text{ESS}}^{\text{p}}\) are the per-unit capacity of DPG, investment construction cost of ESS, and the unit power investment cost of ESS, respectively, and \(P_{\text{DPG}}^{\text{g}}, E_{\text{ESS}}^{\text{g}}, P_{\text{ESS}}^{\text{g}}\) are the rated capacity of DPG, the rated capacity, and the power of the ESS in the intrapartition \(g\), respectively.

2. Annual cost of operation maintenance

\[
C_O = \sum_{t=1}^{T} \sum_{g=1}^{N_G} \left[ p_{\text{DPG}}^{\text{g},l} c_{\text{m}}^{\text{DPG}} + P \left( |p_{\text{ESS}}^{\text{g},t} - p_{\text{ESS}}^{\text{g},t}| \right) c_{\text{ESS}}^{\text{g}} + c_{\text{ab}}^{\text{DPG}} \left( p_{\text{ESS}}^{\text{g},t} - p_{\text{ESS}}^{\text{g},t} \right) \right]
\]

where \(p_{\text{DPG}}^{\text{g},t}\) is the power generation of partition \(g\) at time \(t\) of DG, \(p_{\text{ESS}}^{\text{g},t}\) are the charging and discharging power of ESS of partition \(g\) at time \(t\), and \(c_{\text{m}}^{\text{DPG}}, c_{\text{ESS}}, c_{\text{ab}}^{\text{DPG}}\) are DPG, ESS unit maintenance cost, and DPG curtailment cost, respectively.

3. Annual power purchasing cost

\[
C_{\text{buy}} = \sum_{t=1}^{T} \sum_{l=1}^{N_L} c_{\text{price}}^{l} P_{l,t}^{p}
\]

where \(N_L\) is the number of link branches in the main network and \(P_{l,t}^{p}\) is the power connected to branch \(l\) through the main network at time \(t\).

4. Annual government subsidy

\[
C_s = \sum_{t=1}^{T} \sum_{g=1}^{N_G} P_{\text{g}}^{\text{DPG}}(t) \cdot \eta_i \cdot c_{b}(t)
\]

where \(c_{b}\) is the government subsidy fee for DPG unit power generation, and \(\eta_i\) is DG power generation efficiency.
3.1.2. Constraints

1. DPG capacity and power output constraints of partition

\[
\begin{align*}
\{ & \quad 0 \leq P_{g}^{DPG} \leq \sum_{i=1}^{N_{g}} P_{g, i}^{DPG, max}, \forall g \in \{1, \ldots, N_{G}\} \\
0 & \leq P_{g, t}^{DPG} \leq P_{g}^{DPG} \}
\end{align*}
\]  

(27)

where \(N_{G}\) is the number of partitions, \(N_{g}\) is the number of nodes in partition \(g\), \(P_{g}^{DPG}\) is the installed capacity of DPG in partition \(g\), \(P_{g, i}^{DPG, max}\) is the maximum capacity of the DPG installed on node \(i\) in partition \(g\), and \(P_{g, t}^{DPG}\) is the active power of DPG in partition \(g\) at time \(t\).

2. Power balance

\[
\sum_{g=1}^{N_{G}} (P_{g, t}^{DPG} + P_{g, t}^{ESS}) + \sum_{l=1}^{N_{L}} P_{l, t}^{p} = \sum_{g=1}^{N_{G}} \sum_{i=1}^{N_{g}} P_{i, t}^{load} + \sum_{l=1}^{N_{SL}} P_{l, t}^{Loss}
\]

(28)

where \(N_{L}\) is the number of link branches in the main network, \(N_{SL}\) is the number of distribution network branches, \(P_{i, t}^{load}\) is the load active power of the node \(i\) in partition \(g\) at time \(t\), and \(P_{l, t}^{Loss}\) is the network loss of branch \(l\) transmitted from the lower level to the upper level at time \(t\).

3. Constraints on the reverse transmission power of the main network link branch

\[
P_{l, t}^{p} \leq -P_{l, t}^{p, max}, \forall l \in \{1, \ldots, N_{L}\}, \forall t
\]

(29)

where \(P_{l, t}^{p, max}\) is the maximum reverse transmission power that is allowed by the main network link branch \(l\) to pass.

4. Interpartition interaction branch power

\[
\left| P_{l, t}^{IP} \right| \leq P_{l, t}^{IP, max}, \forall l \in \{1, \ldots, N_{CI}\}, \forall t
\]

(30)

where \(N_{CI}\) is the number of interpartition interaction branches, and \(P_{l, t}^{IP, max}\) is the maximum power allowed by interpartition interaction branch \(l\).

5. Power constraints of ESS

\[
\left| P_{g, t}^{ESS} \right| \leq P_{max, g}^{ESS}, \forall g \in \{1, \ldots, N_{G}\}
\]

(31)

where \(P_{max, g}^{ESS}\) is the maximum output power of ESS in partition \(g\).

6. Charge and discharge efficiency constraints

\[
\eta_{t} = \begin{cases} 
\eta_{dr, Eff, g, t} = 1 \\
-\frac{1}{\eta_{tr, Eff, g, t}} = -1 
\end{cases}, \forall g \in \{1, \ldots, N_{G}\}
\]

(32)

where \(\eta_{dr}\) is discharge efficiency, and \(\eta_{tr}\) is charging efficiency.

7. State-of-Charge (SOC) constraint of the ESS

\[
\begin{align*}
S_{min} & \leq S_{g, t} \leq S_{max} \\
S_{g, t} & = S_{0} + \left( \sum_{l=1}^{T} \frac{u_{E, l, Eff, g, l}}{\eta_{l}} \right), \forall g \in \{1, \ldots, N_{G}\}
\end{align*}
\]

(33)
where $S_{g,t}$ is the state of charge in partition $g$ at time $t$, $S_{\text{max}}$ and $S_{\text{min}}$ are the upper and lower limits of the state of charge, and $S_0$ is the initial state of charge.

3.2. Lower-Level Planning Model

The capacity of DPG and ESS in each partition is determined by the planning of the superior, but the network loss of the power distribution system is affected by the installed capacity of the DPG of the node and the installation location of the ESS. Therefore, the lower level takes each node in the partition as a research object—“Partition-Node”. It is a goal to establish the minimum network loss and to optimize the DPV capacity of the nodes in the partition, as well as the location of ESS.

3.2.1. Objective Function

Minimum annual active power loss

$$\min P_{CL} = \sum_{t=1}^{T} \sum_{l=1}^{N_{SL}} P_{loss}^{k,l,t}$$ (34)

where $P_{CL}$ is the loss of power network.

3.2.2. Constraints

1. Power flow constraints

$$P_{i,t} = U_{i,t} \sum_{j=1}^{N} U_{j,t} (G_{ij} \cos \theta_{ij,t} + B_{ij} \sin \theta_{ij,t})$$

$$Q_{i,t} = U_{i,t} \sum_{j=1}^{N} U_{j,t} (G_{ij} \cos \theta_{ij,t} - B_{ij} \sin \theta_{ij,t})$$ (35)

where $N$ is the number of system nodes, $U_{i,t}$ and $U_{j,t}$ are the voltage amplitudes of nodes $i$ and $j$ at time $t$, $G_{ij}$ and $B_{ij}$ represent the admittance of the $ij$ branch, and $\theta_{ij,t}$ is the power angle of node $ij$ at time $t$.

2. DPG installation capacity constraints of each node of the intrapartition

$$P_{g}^{DPG} = \sum_{i=1}^{N_{g}} p_{g,i}^{DPG}, \forall g \in \{1, \ldots, N_G\}$$ (36)

where $p_{g,i}^{DPG}$ is the access DPG capacity of node $i$ in partition $g$.

3. DPG node installation capacity constraints

$$0 \leq P_{g,i}^{DPG} \leq P_{g,i,\text{max}}, \forall i \in \{1, \ldots, N_{g}\}$$ (37)

where $p_{g,i,\text{max}}$ is the maximum of the installed DPG capacity of node $i$ in partition $g$.

4. Voltage constraints in the partition

$$U_{g,i,t}^{\text{min}} \leq U_{g,i,t} \leq U_{g,i,t}^{\text{max}}$$ (38)

where $U_{g,i}$ is the voltage value of node $i$ at time $t$ in partition $g$, and $U_{g,i}^{\text{min}}$ and $U_{g,i}^{\text{max}}$ are the upper and lower limits of node $i$ voltage in partition $g$.

5. Line transmission power constraints of the intrapartition

$$P_{g,i}^{\text{min}} \leq P_{g,i,t} \leq P_{g,i}^{\text{max}}$$ (39)
where $P_{g,l,t}$ is the transmission power of branch $l$ at time $t$ in partition $g$, $l$ is the number of branches in the partition, $l \in N_{SL,g}$, and $N_{SL,g}$ is the number of branches in the group in partition $g$.

3.3. Planning and Operation Evaluation Indicators

3.3.1. Self-Balancing Degree

The degree of self-balancing $S_{A,g}$ is the ratio of the difference between the total partitional load and the purchased electricity to the total load during the planning period. When the degree of selfbalance is higher, the self-control ability of intrapartition is stronger, and the connection of interpartitions is weaker [32].

$$S_{A,g} = \frac{\sum_{t=1}^{T} \left( \sum_{i=1}^{N_g} p_{load,i,t} - \sum_{i=1}^{N_g} p_{p,l,t} \right)}{\sum_{t=1}^{T} \sum_{i=1}^{N_g} p_{load,i,t}}, g \in 1, 2, 3, \ldots, N_{G}$$  

(40)

3.3.2. Energy Penetration

Energy penetration measures the ratio between the DPG output and the total load power consumption within the partition during the planning period. The higher the ratio, the greater the photovoltaic penetration and absorption in the partition [33].

$$S_{EP,g} = \frac{\sum_{t=1}^{T} \sum_{i=1}^{N_g} p_{DPG,i,t}}{\sum_{t=1}^{T} \sum_{i=1}^{N_g} p_{load,i,t}}, g \in 1, 2, 3, \ldots, N_{G}$$  

(41)

3.3.3. Capacity Penetration

Capacity penetration $S_{CP,g}$ is the ratio of the moment of maximum photovoltaic output to the moment of maximum power consumption within the planning period. The higher the ratio, the larger the remaining output of DPG, the greater the demand for ESS, and the closer the connection of interpartitions [33].

$$S_{CP,g} = \frac{\max_{t \in \{1, \ldots, T\}} \left( \sum_{i=1}^{N_g} p_{DPG,i,t} \right)}{\max_{t \in \{1, \ldots, T\}} \left( \sum_{i=1}^{N_g} p_{load,i,t} \right)}, g \in 1, 2, 3, \ldots, N_{G}$$  

(42)

3.3.4. Power Penetration

Power penetration $S_{PP,g}$ is the maximum value of the ratio of the total DPG output to the total load within the partition at the same time during the planning period. The higher the ratio, the greater the demand for ESS, the smaller the ratio, and the lower the absorption capacity [33].

$$S_{PP,g} = \begin{cases} \max_{t \in \{1, \ldots, T\}} \left( \frac{\sum_{i=1}^{N_g} p_{DPG,i,t}}{\sum_{i=1}^{N_g} p_{load,i,t}} \right), & p_{load,i,t} \neq 0 \\ 0, & p_{load,i,t} = 0 \end{cases}$$  

(43)
3.4. Bilevel Model Solution Method

The programming model algorithms for solving DPG and ESS include traditional algorithms and intelligent algorithms. Among the traditional algorithms, linear programming and nonlinear programming are representative. When using the linear programming method to solve the planning model, it is essential to linearize the power flow in the distribution network. In the solution process, it is necessary to run through multiple power flow calculations to make the final expected plan deviate from the actual planning result [34]. Nonlinear programming is used to address nonlinear optimization problems with discrete and continuous variables. Taking the optimal power flow planning method as an example, it can deal with the uncertainty of DG output and the load demand in the distribution network sequence model, which belongs to the nonlinear and nonconvex optimization problem, but its technical parameters need to be configured reasonably otherwise it will be difficult to converge [35]. However, intelligent algorithms have attracted attention because of their advantages, such as few adjustment parameters, few iterations, fast convergence, parallel computing, and easy implementation. When solving a programming model with multiple decision variables, the improper selection of optimization parameters will also lead to a local optimal solution. To solve the above problems, this paper adopts the PSO algorithm with the adaptive weight proposed in [36]. According to the distance between each particle and the global optimal particle position, the inertia weight of the particle is determined to update the velocity parameter of PSO adaptively. With this algorithm, the search ability is improved, and the globally optimal solution is found more efficiently. The calculation process is shown in Figure 4, and the specific steps are as follows:

**Step 1.** Parameter setting. Input distribution network structure load parameters, constraint conditions, upper and lower level population size upperpop and lowerpop, particle inner cycle iteration times upperk and lowerk, maximum iteration times upperiter and loweriter, etc. Initialize the power flow to obtain the initial branch power flow and node voltage parameters.

**Step 2.** Initialize the upper-level particle population. With partition as a unit, initialize the position (DPV capacity, ESS capacity, and power of each partition) and velocity of the particle population. Particles that meet the constraints are put into the objective function to obtain global optimum value, global optimum fitness, local optimum value, and local optimum fitness. Set the current number of iterations to upperiter = 0, and the number of loop iterations in the upper-level particle population to be upperk = 1.

**Step 3.** Update the upper-level particles. Using the difference between the particle and the global optimum particle, optimize the value of the inertia weight, and update the velocity and position of the particle.

**Step 4.** Optimize the lower-level particles as follows:

1. The particles updated by the upper level are used as conditions of the lower level for initializing the particle population of each partition to calculate the position (DPV capacity of each node, ESS position) and velocity of each partition particle in parallel. In order to determine the fitness value of the system network loss objective function, global optimum value, global optimum fitness, local optimum value, and local optimum fitness, particles that meet the constraint conditions are connected to the distribution network for power flow calculation. Set the current iteration number loweriter = 0, and the inner cycle number of the lower-level population particles lowerk = 1;

2. Update the lower-level particles. In the same manner as step 3, update the DPG capacity of each node of the intrapartition. The access position of ESS is optimized through a binary particle swarm algorithm formula;

3. Update the fitness of the lower-level particles. The particles that meet the constraint conditions are connected to the distribution network for power flow calculation to update the DPV output power and ESS charge and discharge data. Connect it to the objective function to get the fitness value of the lower-level particle;

4. If the fitness value of the updated particle is less than the current global optimum fitness value or local optimum fitness value, the global optimum value, global optimum
fitness, local optimum value, and local optimum fitness of the lower-level particle swarm should be updated, otherwise unchanged. When the condition lowerk < lowerpop is satisfied, return to 2, otherwise, take the current optimal value and optimal fitness of the group as the optimization results and proceed to 5;

5. Determine the maximum number of iterations. If the condition loweriter < maxloweriter is satisfied, return to step 2; otherwise, take the current global optimum value and global optimum fitness of the group as the optimization result, and proceed to step 5.

Figure 4. Bilevel nested PSO algorithm for distribution network.
Step 1. Depending on the optimal power achieved by the upper particles in the lower level, the global optimum value, the global optimum fitness, the local optimum value, and the local optimum fitness of the upper-level particles are updated. The method is the same as 4. If upper_k < upperpop, return to step 3; otherwise, take the current global optimum value and the global optimum fitness of the group as the optimization result, and proceed to step 6.

Step 2. Verify the convergence condition. If the condition upperiter < max upperiter is satisfied, move on to step 3. Otherwise, output the optimization result of bilevel location selection and capacity determination.

4. Case Study

In Figure 5, node 0 is the slack bus and can be regarded as the power source point, whereas the remaining nodes are the load points. In the primary system, there are 33 nodes and 32 branches; the rated voltage is 12.66 kV and the total load is 3715 kW + j2300 kvar. The system parameters can be found in reference [10]. The node voltage range is 0.95–1.05. The DG type is DPG for which the power factor is 0.85, the annual investment coefficient is 0.06, the rated capacity of a single node is 50kW, and the maximum installed active capacity of the node is 200 kW. The maximum capacity of the ESS is 1MW, the state of charge of the battery is 10~90%, and the ESS charge and discharge efficiency is 0.9. In the system, the installation costs of DPG and ESS are 12,000 CNY/kW and 1270 CNY/kW, the unit active power installation cost of ESS is 1650 CNY/kW, the operation maintenance cost is 0.08 CNY/kWh, and the government subsidy for DPG is 0.25 CNY/kWh; the tiered electricity prices for electricity sales and purchases are shown in Table 1. The solar irradiance has an intensity of 700 W/m². Photovoltaic output and load data are shown in Figure 6. The particle swarm simulation parameters are set to upperiter = 200, loweriter = 100, upperpop = upperk = 50, lowerpop = lowerk = 30 and c₁ = c₂ = 1.5.

![IEEE 33-bus distribution network](image1)

**Figure 5.** IEEE 33-bus distribution network.

**Table 1.** Time of use power price.

<table>
<thead>
<tr>
<th>Period /h</th>
<th>Electricity Price for Sale (RMB/kw h)</th>
<th>Power Purchase Price (RMB/kw h)</th>
</tr>
</thead>
<tbody>
<tr>
<td>00:00-08:00</td>
<td>0.17</td>
<td>0.13</td>
</tr>
<tr>
<td>08:00-11:00</td>
<td>0.49</td>
<td>0.38</td>
</tr>
<tr>
<td>11:00-16:00</td>
<td>0.83</td>
<td>0.65</td>
</tr>
<tr>
<td>16:00-19:00</td>
<td>0.49</td>
<td>0.38</td>
</tr>
<tr>
<td>19:00-22:00</td>
<td>0.83</td>
<td>0.65</td>
</tr>
<tr>
<td>22:00-24:00</td>
<td>0.49</td>
<td>0.38</td>
</tr>
</tbody>
</table>

![Typical PV output and load demand curve](image2)

**Figure 6.** Typical PV output and load demand curve.
5. Results and Discussion

5.1. DPG and ESS Siting and Sizing Selection Cases

In order to highlight the advantages of the proposed bilevel partitioning case, three different cases are selected for comparison with the case proposed in this paper:

Case 1: a single-level nonpartitioned DPG and ESS site selection strategy is adopted. That is, the DPG and ESS use each node in the distribution network as a unit for joint planning and site selection. According to the variance of network loss sensitivity, the installation nodes of DPG and ESS are selected as 1, 2, 7, 8, 9, 10, 11, 12, 26, 27, 28, 29, 30, 31, 32, and 33.

Case 2: a bilevel nonpartitioned DPG and ESS siting and sizing strategy is adopted. The upper level plans the DPG capacity, ESS capacity, and power of each partition, and the lower level optimizes the upper-level capacity according to the network loss in the partition. The number of ESS installations is seven.

Case 3: a bilevel partition planning strategy that only considers DPG is adopted. The upper level plans the DPG capacity and location of each partition, and the lower level optimizes the capacity of the upper level according to the network loss of the intrapartition.

Case 4: a bilevel partitioned DPG and ESS siting and sizing strategy is adopted. The upper level plans the DPG capacity, ESS capacity, and the power of each partition, and the lower level programs the DPG sizing and ESS siting with the node of the intrapartition as the unit and transmits the network loss to the upper level.

5.2. Upper-Level Planning Results

AP-TD-K-medoids was used to perform trilevel clustering on the electrical distance of the distribution network to obtain the optimal number of partitions. In Figure 7, when the number of partitions is 7, the modularity evaluation index is the highest, and then it shows a downward trend. Figure 8 shows the final distribution network partition results. It can be seen that the interpartitions are connected to each other, and the nodes of each intrapartition are also linked. There are no isolated points or unconnected points aggregated into partitions in the partition clustering results.

![Figure 7. Partitional modularity index.](image)

![Figure 8. IEEE 33-bus distribution network partition results.](image)
Figure 9 shows the planning results of DPG and ESS sizing in each case. Table 2 demonstrates the economic indicators of each program planning. It can be seen from Table 2 that when the distribution network is not planned, only the main network supplies power to the load, which makes the power purchase cost higher. For the four cases after planning, the cost of power purchase has been greatly reduced due to the intervention of DPG and the ESS. Therefore, planning the distribution network is necessary.

![Graph of DPG capacity and ESS capacity](image)

(a) Capacity of each partition of DPG

(b) Capacity of each partition of the ESS

Figure 9. The upper level plans the capacity of each partition of the DPG and ESS.

Table 2. Capacity and cost of the upper-level DPG and ESS.

<table>
<thead>
<tr>
<th>Case</th>
<th>Not Planned</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
</tr>
</thead>
<tbody>
<tr>
<td>DG capacity/kW</td>
<td>-</td>
<td>360.0</td>
<td>740.180</td>
<td>784.619</td>
<td>837.195</td>
</tr>
<tr>
<td>ESS capacity/kW</td>
<td>-</td>
<td>67.085</td>
<td>593.502</td>
<td>0.0</td>
<td>464.946</td>
</tr>
<tr>
<td>Investment cost/million</td>
<td>-</td>
<td>0.612</td>
<td>1.430</td>
<td>1.360</td>
<td>1.519</td>
</tr>
<tr>
<td>Maintenance costs/million</td>
<td>-</td>
<td>0.154</td>
<td>0.334</td>
<td>0.347</td>
<td>0.364</td>
</tr>
<tr>
<td>Power purchase/million</td>
<td>9.051</td>
<td>8.149</td>
<td>6.616</td>
<td>6.249</td>
<td>5.882</td>
</tr>
<tr>
<td>Government subsidies/million</td>
<td>-</td>
<td>0.169</td>
<td>0.368</td>
<td>0.389</td>
<td>0.401</td>
</tr>
<tr>
<td>Total cost/million</td>
<td>9.051</td>
<td>8.746</td>
<td>8.013</td>
<td>7.563</td>
<td>7.364</td>
</tr>
</tbody>
</table>
When comparing Case 1 and Case 4, according to the capacity planning of DPG in Figure 9a, the capacity configuration of DPG in the two cases is quite different. The DPG in Case 4 is 2.33 times the installed capacity of Case 1. In Case 1, the installation nodes of DPG are mainly concentrated in Partitions 1, 4, and 7. The capacity of the DPG in Case 4 is uniformly distributed in seven partitions. It can be seen from the ESS planning capacity in Figure 9b that there is a big difference in the capacity configuration of the ESS in the two cases. The ESS in Case 4 is 6.93 times the capacity of Case 1. In Case 1, the ESS installation nodes are mainly concentrated in Partitions 1, 4, and 7. In Case 4, the capacity of the ESS is evenly installed in seven partitions. It can be seen from Table 2 that due to the high cost of DPG and the ESS, the installation and operation maintenance costs of Case 4 are higher than those of Case 1 by 147.95% and 136.01%. However, the DPG penetration in Case 4 is relatively high, so the power purchase rate of the main network is reduced by 27.82%, and the government subsidy is increased by 136.30%. From the analysis of the overall planning results, distribution network planning with bilevel partitioning improves the intervention capacity of DPG, makes the capacity of DPG in each partition more evenly distributed, and reduces the total investment cost by 15.80%.

When comparing Case 2 and Case 4, it can be seen that there are differences in the capacity configuration of DPG between the two cases in Figure 9a. The DPG in Case 4 is 1.13 times the installed capacity of Case 2. In Case 2, the installation nodes of DPG are mainly concentrated in Partitions 2 and 3. In Case 4, the installed capacity of DPG is more uniformly distributed in each partition. The ESS capacity planning in Figure 9b shows that the capacity configuration of the ESS in the two cases is quite different. The ESS in Case 4 is 0.78 times the installed capacity of Case 1. The installed capacity of ESS in Case 1 is mainly concentrated in Partitions 2, 5, 6, and 7. In Case 4, the capacity of the ESS is uniformly distributed in seven partitions. In Table 2, due to the higher cost of DPG and the ESS, the investment and operation maintenance costs of Case 4 have increased by 6.24% and 8.94% compared to Case 2. However, the DPG penetration rate in Case 4 is relatively high, so the power purchase rate of the main network is reduced by 11.10%, and the government subsidy is increased by 8.90%. From the analysis of the overall planning results, distribution network planning with bilevel partitioning improves the installed capacity of DPG and the uniform distribution of the capacity in each partition, reduces the capacity allocation of the ESS in each partition, and decreases the total investment cost by 8.09%.

When comparing Case 3 and Case 4, according to the capacity planning of DPG in Figure 9a, the difference in capacity configuration for DPG between the two cases is slightly smaller. The DPG in Case 4 is 1.07 times the installed capacity of Case 1. The installed locations of DPG in Case 3 and Case 4 are relatively uniformly distributed in each partition. It can be seen from the ESS planning capacity in Figure 9b that the capacity configuration of the ESS in the two cases is quite different. In Case 3, the ESS is not installed. In Case 4, the capacity of the ESS is evenly installed in seven partitions. It can be seen from Table 2 that due to the higher cost of DPG and the ESS, the investment and operation maintenance costs of Case 4 have increased by 11.68% and 4.84% compared to Case 3. However, the DPG penetration rate in Case 4 is relatively high, so the power purchase rate of the main network is reduced by 5.81%, and the government subsidy is increased by 3.07%. From the analysis of the overall planning results, distribution network planning with bilevel partitioning improves the intervention capacity of DPG, makes the capacity of DPG in each partition more uniformly distributed, and reduces the total investment cost by 2.63%.

5.3. Lower-Level Planning Results

It can be seen from Figure 10a,b that, in Cases 1–3, due to the intermittent characteristic of DPG and the absence of the ESS or insufficient installed capacity, the network loss in the distribution network increases. Therefore, the ESS plays an essential role in the planning of DPG. When compared with Case 3, the daily loss in each partition of Case 4 is reduced by 13.36, 5.43, 18.11, 41.84, 12.94, 5.57, and 5.82%. The daily loss of the interpartitional
branches is reduced by 12.77, 15.31, 27.7, 8.33, and 5.03%. Figure 10c,d show that the output of DPG from 7:00–18:00 and the ESS from 18:00–20:00 can meet the load demand to reduce the branch power flow, so the proportion of system network loss and power loss in Case 2 and Case 4 is relatively small during 7:00–20:00, especially at 10:00 when Case 4 has the lowest system network loss and power loss with a decrease of 14.22% and 14.06% compared to Case 3.

Figure 10. System loss Power loss proportion.

Based on Figure 11, the minimum node voltage in Cases 1–4 is 1.5, 1.9, 1.3, and 3.2% higher than in preplanning, which is 0.951. Since the planning of Case 3 does not consider the ESS, the voltage value is slightly increased. It can be seen from the range of voltage changes that Cases 1–4 have increased by 52, 44, 56, and 20% compared to before planning. The configuration of DPG and the ESS in the distribution network not only reduces the voltage amplitude variation but also effectively suppresses load fluctuations, which makes Case 4 work best.
Based on Figure 11, the minimum node voltage in Cases 1–4 is 1.5, 1.9, 1.3, and 3.2% higher than in preplanning, which is 0.951. Since the planning of Case 3 does not consider the ESS, the voltage value is slightly increased. It can be seen from the range of voltage changes that Cases 1–4 have increased by 52, 44, 56, and 20% compared to before planning. The configuration of DPG and the ESS in the distribution network not only reduces the voltage amplitude variation but also effectively suppresses load fluctuations, which makes Case 4 work best.

Figure 11. The voltage amplitude of different cases.

5.4. Evaluation Indicators for Planning and Operation

According to the partition selfbalancing index in Figure 12a, the value of Case 4 is higher, and the distribution is more uniform in each partition compared with the other cases. In addition, the average selfbalance degree of Cases 1–4 is 0.118, 0.181, 0.282, and 0.313, and is the highest in Case 4. The above shows that, in Case 4, the power transfer of interpartitions is weak, the coupling degree between the nodes of the intrapartition is strong, and partition autonomy is high. It can be seen from Figure 12b that the penetration of Partitions 1, 4, and 7 in Case 1 is higher, the penetration of Partition 1 in Case 3 is higher, and the penetration of other partitions is lower. The reason for this is that, in Case 1 and Case 3, the installed capacity of the ESS is insufficient or not installed. In Case 2, although the ESS devices are installed in each partition to even the penetration rate, the local DPG peak output did not match the peak load time, and the planned DPG capacity was low, resulting in low energy penetration. In Case 4, the ESS devices are planned in the units of the partitions, which not only alleviates the timing characteristics of the load demand but also improves the planning and configuration capacity of the DPG. The energy
permeabilities of Cases 1–4 analyzed by the mean are 0.135, 0.195, 0.271, and 0.338. It shows that Case 4 has the strongest absorption capacity for DPG, and the energy penetration of each partition is the best. In Figure 12c,d, the critical value of capacity and power penetration is 1. In Cases 1–3, the capacity penetration of each partition is greater than the critical value, indicating that the DPG output of each case is greater than the power required by the load in the partition, and the remaining power flows to other partitions, which increases network loss and leads to an increase in power penetration. However, in Case 4, the capacity and power penetration of each partition are both less than 1. Therefore, according to the overall planning evaluation indicators, Case 4 is the most reasonable one.

6. Conclusions

By calculating the electrical distance of the load sequence characteristics in the distribution network, an AP-TD-K-medoids trilevel clustering algorithm was used to cluster and divide the electrical distance and the bilevel planning strategy of a large-scale DPG and ESS grid connection between interpartitions and intrapartitions. It can be seen from the planning of the bilevel partition of the distribution network that upper-level planning makes the planned capacity of DPG and the ESS in each partition distributed as evenly as

![Figure 12](image-url)

**Figure 12.** Evaluation indicators for each program.
is possible; the lower level minimizes the cost of investment planning under the premise of ensuring minimum network loss. In order to fully illustrate the effectiveness of the bilevel zoning of the distribution network, the self-balancing degree, capacity penetration, energy penetration, and power penetration were used to evaluate different distribution network planning cases. The results show that in the distribution network planned by partitioning, the coupling between the nodes in the partition was strengthened, and the connection between the partitions was significantly weakened; that is, the above experiment is reasonable. Therefore, the use of bilevel distribution network planning not only reduces the time mismatch between DPG output power and load demand but also decreases the power supply pressure of the main network, diminishes system network loss, enhances voltage quality, and improves economic benefits. In addition, the bilevel planning of distribution network partitions can enhance its autonomy. At this stage, successful results have been obtained for the grid-connected planning of high-permeability DPG and ESS in the IEEE-33 node power distribution system. In large power grids, due to the complexity of the power supply methods and a large number of distributed sources, the partition and planning model can be established and optimized in the future after considering many uncertain factors.

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**References**

8. Gao, Y.; Xue, F.; Yang, W.; Yang, Q.; Sun, Y.; Sun, Y.; Liang, H.; Li, P. Optimal operation modes of photovoltaic-battery energy storage system based power plants considering typical scenarios. *Prot. Control Mod. Power Syst.* **2017**, 2, 36. [CrossRef]

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