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Tri-level allocation method of distributed energy storage system based on sharing strategy in active distribution networks

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Abstract. More and more distributed energy storage (DES) are integrating into active distribution networks (ADNs), which has a positive effect on both distribution companies (DISCOs) and consumers. In order to achieve peak-load shifting and reduce the electricity purchasing costs, from the perspective of an independent energy storage operator, a tri-level allocation model of DES in an ADN is built based on a sharing strategy. The tri-level model is a multi-objective optimization problem: the upper-stage model optimizes the siting and sizing of DES with the objective of minimizing the annual costs of investment; the middle-stage model realizes an optimal distribution of energy storage capacity to the DISCO and consumers with the objective including the operating costs of the DISCO and consumers, and peak-valley differences; in the lower-stage model, the optimal operation scheme of DES can be acquired with the objective of minimizing the operating costs of the DISCO and consumers. A method combining adaptive genetic algorithm (GA) and second-order cone programming (SOCP) is adopted to solve the model. Simulation results on the IEEE 33 bus system show that the tri-level allocation method can effectively reduce the RES investment costs, reduce the peak-valley differences, and improve the revenues of both the DISCO and consumers.

1. Introduction

With the development of renewable energy and the construction of smart grids, amounts of distributed energy resources (DERs) are connected in active distribution networks (ADNs). Distributed energy storage (DES) provides greater flexibility for ADNs because it can store energy when there is excess power supply and release energy during periods of high demand[1]. DES can not only solve the problems of unstable power consumption and high electricity purchasing cost for consumers, but also reduce the peak load demand, and mitigate the negative impact on ADNs caused by the random output of renewable energy generations (REGs) [2].

At present, scholars have studied the optimal allocation of DES in different ways. Considering the uncertainty of renewable energy output, a bi-level optimization model is proposed in [4] to determine the siting and sizing of DES, and then the charging and discharging scheme of DES is obtained. A comprehensive optimization method of capacity allocation of DES is proposed in [5]: the upper model optimizes the capacity of DES; the lower model determines the location of the DES with the goal of



adjusting load peak cutting and valley filling. Taking demand side response into consideration, reference [6] proposes a coordinate optimization method to determine the siting and sizing of DES, and maximize the economic profit of the distribution company. References [7] and [8] consider the independent energy storage manager, and propose an optimal allocation method of DES. Reference [9] consider the costs and benefits of ADNs, and establish a multi-objective bi-level model to determine the siting and sizing of DES.

The DES allocation methods of the above literature mainly optimize the siting and sizing of DES, and their optimization objectives only consider the interests of DISCOs or consumers. However, as aforementioned, DES has a positive beneficial effect on both the DISCO and consumers, and the interests of both the DISCO and consumers should be taken into account in the DES planning model. How to allocate the capacity of DES to maximize the benefits of the DISCO and consumers is a challenge.

Based on the above analysis, from the perspective of an independent energy storage operator, this paper considers a sharing strategy and proposes a tri-level allocation model of the distributed energy storage system. The tri-level model is a multi-objective optimization problem. A method combining adaptive genetic algorithm (GA) and second-order cone programming (SOCP) is adopted to solve the model. An IEEE 33 node system is used to verify the validity of the proposed method.

2. Tri-level allocation model of distributed energy storage system based on sharing strategy

The framework of the tri-level allocation model of DES based on sharing strategy is shown as Fig.1.

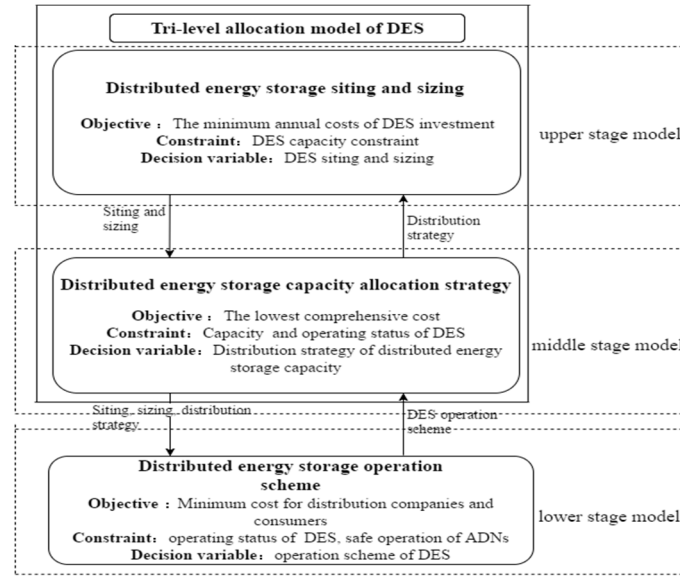


Figure 1. The framework of the tri-level allocation model of DES based on sharing strategy

2.1. The Upper-stage Model

In the upper model, the minimum annual costs of investment are taken as the objective function to determine the siting and sizing of DES. The annual cost includes DES investment cost, operation cost and maintenance cost. The investment cost includes fixed cost, variable cost with power, and environmental cost caused by DES installation. The objective function is expressed as follows:

$$F(X_i) = \min_{X, Y_t} [C_{inv}(X_i) + \sum_{i=1}^N 365 \cdot x_i \cdot C_{ope}(X, Y_t)] \quad (1)$$

Where X is the set of optimization variables of the upper model, that is, the siting and sizing of DES. Y_t is the set of the middle optimization variables, which is returned by the middle model; $C_{inv}(X_i)$ is the investment cost in the objective function of the upper model, and $C_{ope}(X, Y_t)$ is the daily cost of the

DES. N is the total number of nodes, x_i is the variable 0-1. If there is a DES installed at node i , then $x_i = 1$, otherwise $x_i = 0$. The cost of investment can be expressed as:

$$C_{inv}(X_i) = \sum_{i=1}^N [\pi_{ess}(C_{1,i} \cdot x_i + C_{2,i} \cdot E_i + C_{3,i} \bar{P}_i) + C_{en} + C_{om,i} \bar{P}_i] \quad (2)$$

Where π_{ess} is a capital recovery factor, which can convert the current investment cost into the same annual payment during the planning period. $C_{1,i}$ is the fixed cost of installing DES at node i , $C_{2,i}$ is the unit capacity cost of DES installation, $C_{3,i}$ is the unit output power cost of DES, E_i is the capacity of DES at node i , $\bar{P}_i$ is the output power of DES at node i , C_{en} is the environmental cost. $C_{om,i}$ is the operation and maintenance cost required to output unit power. The environment cost can be expressed as:

$$C_{en} = 365 \sum_{i=1}^N \sum_{t=1}^{24} \phi \sigma_{ESS} \Delta t \bar{P}_i \quad (3)$$

Where σ_{ESS} is the environmental impact caused by the unit output of the DES, and ϕ is the environmental control cost caused by the unit impact. The daily cost of normal operation of the DES can be expressed as:

$$C_{ope}(X, Y_t) = C_{0,t} P_{0,t} \Delta t - T_w \quad (4)$$

Where T_w is the daily energy cost when no DES is installed, $C_{0,t}$ is the unit power cost in time t , and $P_{0,t}$ is the continuous input power on the reference node in time t . In the process of planning the siting and sizing of DES, the main constraints are the maximum allowable DES permeability of ADN, the maximum number of DES access, the maximum capacity of DES. Constraints are expressed as:

$$\left\{ \begin{array}{l} num_{min} \leq \sum_{i=1}^N x_i \leq num_{max} \\ x_i ESS_{min} \leq E_i \leq x_i ESS_{max} \\ 0 \leq \bar{P}_i \leq x_i P_{max} \\ \sum_{i=1}^N \bar{P}_i \leq \rho P_{Load} \end{array} \right. \quad \begin{array}{l} (5) \\ (6) \\ (7) \\ (8) \end{array}$$

Where num_{min} and num_{max} are the minimum and maximum number of DES access, ESS_{min} and ESS_{max} are the minimum and maximum allowable capacity of DES, P_{max} is the maximum output power of the DES, P_{Load} is the total active load of the system, and ρ is the maximum permissible DES permeability of the ADN.

2.2. The Middle-stage Model

In the middle stage model, DES is allocated to power distribution companies and consumers to maximize the benefits of both parts. The objective function can be expressed as:

$$\min(w_1 \Delta L + w_2 C_d + w_3 C_c) \quad (9)$$

$$\Delta L = L_{high} - L_{low} \quad (10)$$

Where w_1 , w_2 , and w_3 are the weights of various targets; ΔL is the peak and valley difference of the system; C_d , C_c are the power purchase costs of the power distribution company and the consumers.

Suppose that at time t , the total amount of energy storage in the charging state of the distribution company side at the node n is $P_{t,n}^{ch,d}$, the total energy storage in the discharging state is $P_{t,n}^{disch,d}$, the total energy storage in the charging state on the consumer side is $P_{t,n}^{ch,c}$, and the total energy stored in the

discharging state is $P_{t,n}^{disch,c}$. Then the C_d 、 C_c in the objective function are expressed as follows:

$$C_d = \sum_{n=1}^N \sum_{t=1}^T A_t^d (P_t^{ori} + P_{t,n}^{ch,d} + P_{t,n}^{ch,c} - P_{t,n}^{disch,d} - P_{t,n}^{disch,c}) \Delta t \quad (11)$$

$$C_c = \sum_{n=1}^N \sum_{t=1}^T A_t^c (P_t^{ori} + P_{t,n}^{ch,d} + P_{t,n}^{ch,c} - P_{t,n}^{disch,d} - P_{t,n}^{disch,c}) \Delta t \quad (12)$$

Where T is the system operation cycle, A_t^d and A_t^c are the unit electricity prices purchased by distribution companies and consumers, and P_t^{ori} is the original load in the system.

In the process of determining the allocation strategy of DES, the main constraints are the total energy amount of DES and the peak constraint of the system.

$$\sum_{n=1}^N (ESS_n^c + ESS_n^d) \leq ESS_{total} \quad (13)$$

$$\sum_{n=1}^N P_t^{ori} + P_{t,n}^{ch,d} + P_{t,n}^{ch,c} - P_{t,n}^{disch,d} - P_{t,n}^{disch,c} \leq P_{max}^{peak} \quad (14)$$

Where ESS_n^c and ESS_n^d are the capacity of DES shared by the consumer and the distribution company, ESS_{total} is the total energy and P_{max}^{peak} is the maximum peak power allowed by the system.

2.3. The Lower-stage Model

The lower-stage model determines the operation scheme of the DES with the goal of minimizing the operating cost of the DISCO and consumers. The objective function can be expressed as:

$$\min \sum_{i=1}^N \pi_t^{cus} (P_{t,n}^{ch,c} - P_{t,n}^{disch,c}) \Delta t + \alpha (p_{peak} - p_{velly}) + \pi_t^{dis} (P_{t,n}^{ch,d} - P_{t,n}^{disch,d}) \Delta t \quad (15)$$

Where π_t^{cus} is the electricity purchase price of the consumers at time t ; π_t^{dis} is the electricity purchase price of the distribution company at time t ; α is the penalty coefficient, indicating the extra cost caused by the peak-valley difference of the system.

The main constraints are DES operation state constraints and power grid operation security constraints. The DES operation state constraints are expressed as follows:

$$SOC_{lower} \leq SOC_{ini} + \sum_{i=1}^N [(P_{t,n}^{ch,c} + P_{t,n}^{ch,d}) \Delta t \eta_{ch} - (P_{t,n}^{dis,c} + P_{t,n}^{dis,d}) \Delta t / \eta_{dis}] \leq SOC_{upper} \quad (16)$$

$$\sum_{t=0}^T (P_{t,n}^{ch,c} + P_{t,n}^{ch,d}) \Delta t \eta_{ch} = \sum_{t=0}^T \frac{(P_{t,n}^{dis,c} + P_{t,n}^{dis,d}) \Delta t}{\eta_{dis}} \quad (17)$$

$$0 \leq P_{t,n}^{ch,c}, P_{t,n}^{ch,d}, P_{t,n}^{dis,c}, P_{t,n}^{dis,d} \leq k ESS_{total} \quad (18)$$

Where SOC_{upper} and SOC_{lower} are the upper and lower limits of the DES, SOC_{ini} is the initial state of DES, η_{ch} and η_{dis} are the charging and discharge efficiency of the DES, and k is a fixed coefficient, which is proportional to the allocated energy storage capacity.

Power grid operation security constraints mainly include power balance constraints, node voltage constraints, branch current constraints and power flow reverse constraints. It can be expressed as follows:

$$\sum_{k:(1,k) \in \Omega_b} P_{1k,t} = P_{0,t} - P_{1,t}^L \quad (19)$$

$$\sum_{k:(j,k) \in \Omega_b} P_{jk,t} = \sum_{i:(i,j) \in \Omega_b} (P_{ij,t} - r_{ij} l_{ij,t}) - P_{j,t}^L - (P_{j,t}^{ch} - P_{j,t}^{dis}) \quad (20)$$

$$\sum_{k:(j,k) \in \Omega_b} Q_{jk,t} = \sum_{i:(i,j) \in \Omega_b} (Q_{ij,t} - x_{ij} l_{ij,t}) - Q_{j,t}^L \quad (21)$$

$$v_{j,t} = v_{i,t} - 2(r_{ij} P_{ij,t} + x_{ij} Q_{ij,t}) + l_{ij,t}(r_{ij}^2 + x_{ij}^2) \quad (22)$$

Where Ω_b is the sequential set from node j to node k , $P_{i,t}^L$ and $Q_{i,t}^L$ are the total active and reactive loads of node i in time t , r_{ij} and x_{ij} are the resistance and reactance values between node i and j , $l_{ij,t}$ is the square of the current of the branch i to j in time t . $v_{i,t}$ is the square of the voltage at node i in time t . For the above voltage, current, active and reactive power, the following conditions shall be met:

$$\left\| \begin{array}{c} 2P_{ij,t} \\ 2Q_{ij,t} \\ l_{ij,t} - v_{i,t} \end{array} \right\|_2 \leq l_{ij,t} + v_{i,t} \quad (23)$$

$$V_{i,min}^2 \leq v_{i,w,t} \leq V_{i,max}^2 \quad (24)$$

$$0 \leq l_{ij,w,t} \leq I_{ij,max}^2 \quad (25)$$

Where $V_{i,min}$ and $V_{i,max}$ are the minimum and maximum voltage at node i , $I_{ij,max}$ is the maximum current from node i to j .

3. Solution method

The above tri-level allocation model of distributed energy storage system includes not only integer variables, but also continuous variables, so it belongs to the multi-period mixed integer optimization problem, and there is a quadratic term in the constraints, so it is a nonlinear second-order convex programming problem. The integer variables of the planning problem are decoupled from the continuous variables of the planning problem, and the mixed method of GA and SOCP is used to solve the model.

3.1. Genetic Algorithm for Solving Bi-level Programming Problem

Genetic algorithm is a method to search the optimal solution by simulating the process of natural evolution. The basic ideas and processes of genetic algorithm for solving the problem are shown in Fig.2.

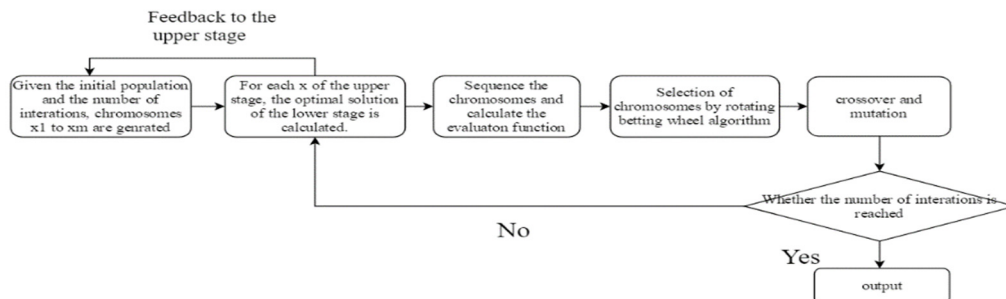


Figure 2. Solving process of genetic algorithm

3.2. Model Transformation of SOCP

In the process of solving the problem, the quadratic programming can be transformed into a second-order cone programming. A second order convex programming can be expressed as:

$$X^T A X + q^T x + c \leq 0 \quad (26)$$

It can be transformed into the following second-order cone problem [10]:

$$\left\| A^{1/2} x + \frac{1}{2} A^{-1/2} q \right\|^2 \leq -\frac{1}{4} q^T A^{-1} q - c \quad (27)$$

The second-order cone programming can be solved by the original interior point dual method, which can be found in [11].

4. Case study

In this paper, an IEEE 33 node system is used to verify the proposed model and algorithm, as shown in Fig.3. The candidate installation node of DES is 9, 12, 14, 20, 26, 30, and the maximum allowable installation capacity of each node is 1000 kW.

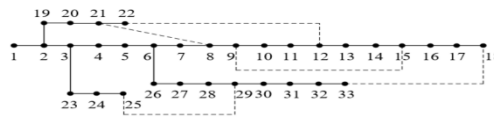


Figure 3. Figure of IEEE33 node

The relevant parameters of DES are shown in table 1.

Table 1. Table of Distributed energy storage parameter

Parameter	Value
Discount rate	0.08
Economic useful life / year	20
Unit rated capacity / kW	100
Investment cost / (yuan / kW)	13000
Operation and maintenance cost / (yuan / kWh)	0.032

In order to facilitate the comparison and verification, this paper sets up three different cases: (1) The siting, sizing and operation scheme of DES are optimized independently. (2) The siting, sizing and operation scheme of DES are optimized in a bi-level model. (3) Considering the sharing strategy, the tri-level allocation method proposed in this paper is carried out for optimization.

The results of different cases are shown in table 2 and table 3:

Table 2. Table of cases

Case	Location and capacity (kW)	Distribution strategy (DISCO / consumers)
Case 1	9(100), 12(0), 14(400), 20(200), 26(300), 30(400)	
Case 2	9 (200), 12 (0), 14 (400), 20 (400), 26 (300), 30 (200)	
Case 3	9 (600),	0.4: 0.6
	12 (300),	0.6: 0.4
	14 (500),	0.6: 0.4
	20 (100),	0.7: 0.3
	26 (700),	0.5: 0.5
	30 (200)	0.3: 0.7

Table 3. Results of different cases

Case	Investment cost (ten thousand yuan)	Income from operation (ten thousand yuan)	Revenue per-unit capacity (10,000 yuan/ kW)	Network loss(ten thousand yuan)	Operating cost (ten thousand yuan)
Case 1	200.56	355.25	0.11	63.95	1322.45
Case 2	201.56	372.68	0.12	49.12	1251.62
Case 3	365.72	698.45	0.14	39.12	1175.12

The results show that, in case 2, the network loss and DES operating costs have been reduced by 23% and 5.4% compared with case 1. In case 3, the investment income per unit capacity is increased to 1400 yuan / kW, the network loss is reduced to 391.2 thousand yuan, and the DES operating cost is reduced to 11.75 million yuan. Thus it can be seen that the reasonable investment and operation of DES can promote the benefits of both parts. The tri-level planning method can effectively reduce the investment cost and network operation cost, and improve the operation benefit.

In addition, due to the change of the siting and sizing of DES, the power flow of the system also changes. It is assumed that under the initial condition of the IEEE 33 node system, each node is fully loaded and the voltage values are all reference values. Using the forward-backward power flow calculation method, the voltage status of each node after being connected to the DES according to different cases is shown in Fig.4. The active and reactive power of each node is shown in Fig.5.

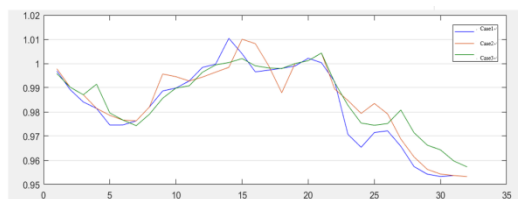


Figure 4. System node voltage

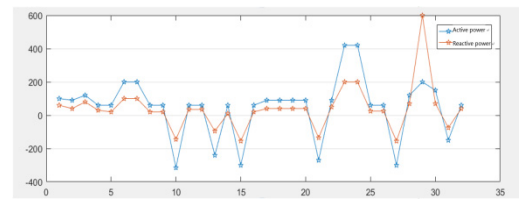


Figure 5. System active and reactive power

It can be seen from figure 4 that with 0.96 and 1.1 as the voltage limits, there are voltage exceeding the limit when connecting to DES according to case 1 and 2. While in case 3, the new method reduces the voltage value where the voltage is too high, improves the low voltage of the terminal node, and stabilizes the voltage fluctuation of the system. As can be seen from figure 5, after the installation of DES, some nodes change from power receiver to power output, which can supply power during the peak period and store energy when there is excess power, so as to reduce the peak-valley difference of the system.

5. Conclusion

In this paper, in order to maximize the benefits of both the DISCO and consumers, a tri-level allocation model of distributed energy storage system is established based on sharing strategy. The conclusions are as follows:

- Distributed energy storage can provide higher flexibility for ADNs, because it can store energy when there is excess power supply and release energy to alleviate network congestion during the period of high demand.
- By optimizing the siting and sizing of DES, it can effectively reduce investment costs and increase operating income. By optimizing the operation strategy of DES, the cost of DISCO and consumers can be effectively reduced.
- The sharing strategy in DES planning model realizes a reasonable distribution of energy storage capacity to the DISCO and consumers, which can effectively reduce voltage fluctuations and peak-valley differences, and improve the revenues of both the DISCO and consumers.

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