

Planning of DC Electric Spring with Particle Swarm Optimization and Elitist Non-dominated Sorting Genetic Algorithm

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Abstract—This paper addresses the planning problem of parallel DC electric springs (DCESS). DCESS, a demand-side management method, realizes automatic matching of power consumption and power generation by adjusting non-critical load (NCL) and internal storage. It can offer higher power quality to critical load (CL), reduce power imbalance and relieve pressure on energy storage systems (RESS). In this paper, a planning method for parallel DCESSs is proposed to maximize stability gain, economic benefits, and penetration of RESs. The planning model is a master optimization with sub-optimization to highlight the priority of objectives. Master optimization is used to improve stability of the network, and sub-optimization aims to improve economic benefit and allowable penetration of RESs. This issue is a multivariable nonlinear mixed integer problem, requiring huge calculations by using common solvers. Therefore, particle Swarm optimization (PSO) and Elitist non-dominated sorting genetic algorithm (NSGA-II) were used to solve this model. Considering uncertainty of RESs, this paper verifies effectiveness of the proposed planning method on IEEE 33-bus system based on deterministic scenarios obtained by scenario analysis.

Index Terms—DC distribution network, DC electric spring, non-dominated sorting genetic algorithm, particle swarm optimization, renewable energy source.

NOMENCLATURE

θ	A set of busbars in the DC distribution network.
θ_{su}	A set of all power supply nodes.
θ_{ESS}	A set of busbars with energy storage systems.
θ_{ES}	A set of busbars with DCESSs.
θ_{RES}	A set of busbars with renewable energy sources.
ξ	A set of transmission lines in the DC distribution network.

n_{sc}	Number of scenarios.
n_T	Number of time nodes.
D_s	Number of days for scenario s .
$U_{i,s,t}$	Bus voltage at time t in the scenario s .
F_U	Upper optimization objective.
C_P	Power purchase cost.
C_{INV}	Investment cost.
$C_{O\&M}$	Operation and maintenance cost.
τ_t	Time-of-use electricity price.
C_{RES}	Penalty cost for discarding power generated by renewable energy sources.
$P_{s,t}^{G_i}$	The purchasing power of the i th power supply node in the scenario s .
δ_{ESS}	Conversion coefficient of the initial investment of ESS.
δ_{ES}	Conversion coefficient of the initial investment of DCESS.
C_{INV}^{ESS}	Investment cost per unit power of ESS.
$C_{INV,P}^{ES}$	Investment cost per unit power of DCESS.
$C_{INV,E}^{ES}$	Investment cost per unit capacity of DCESS.
$P_{i,s,t}^{ESS,c}$	Charging power of the i th energy storage system in the scenario s .
$P_{i,s,t}^{ESS,dc}$	Discharging power of the i th energy storage system in the scenario s .
$P_{i,s,t}^{ES,c}$	Charging power of the i th electric spring in the scenario s .
$P_{i,s,t}^{ES,dc}$	Discharging power of the i th electric spring in the scenario s .
$C_{O\&m}^{ESS}$	Operation and maintenance cost per unit power of ESS.
$C_{O\&m}^{ES}$	Operation and maintenance cost per unit power of DCESS.
C_{CL}	Income from the critical load.
C_{NCL}	Subsidy for the non-critical loads.
α_{CL}	Charging coefficient of the critical loads.
α_{NCL}	Subsidy coefficient for the non-critical loads.
α_{RES}	Penalty coefficient for discarding power generated by renewable energy sources.
$P_{i,s,t}^{CL}$	Power of the critical load.
$P_{i,s,t}^{NCL}$	Power of the non-critical load.
$P_{i,s,t}^{RES}$	Output power of the i th renewable energy source.
$P_{ij,s,t}$	Transmission power of line (i, j) .

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$P_{ij,max}$	Upper limit of the transmission power of line (i, j) .
$P_{j,s,t}$	Injected power of bus j .
$I_{ij,s,t}$	Current of line (i, j) .
$S_{s,t}^{ESS_i}$	The operation state of the i th storage.
$S_{SOC,s,t}^{ESS_i}$	The state of charge of the i th storage.
E_{max}	Storage capacity.
η_c	Charge efficiency.
η_{dc}	Discharge efficiency.
$P_{ESS,max}$	Maximum charging and discharging power of energy storage systems.
ζ	Index of charge-discharge balance error of storages.
$S_{1,s,t}^{ES_i}$	Battery-balancing mode.
$S_{2,s,t}^{ES_i}$	Battery-charging mode.
$S_{3,s,t}^{ES_i}$	Battery-discharging mode.
$S_{SOC,s,t}^{ES_i}$	The state of charge of the internal energy storage of DCES.
E_i	Capacity of the i th DCES.
$P_{ES,max}$	Maximum charging and discharging power of DCES.
σ	Power fluctuation range of the non-critical loads.
f_m^{max}	Population-maximum value of objective function m .
f_m^{min}	Population-minimum value of objective function m .

I. INTRODUCTION

DC distribution network benefits from the rapid development of power electronics technology and has been widely concerned for its role in reducing the power conversion process, improving the reliability of power supply and promoting the consumption of new energy. However, due to intermittence and randomness of renewable energy sources (RESs), high proportion of renewable energy access will damage power supply ability and operation security of DC distribution network [1]–[3]. In addition, emergence of new forms of energy use has further enhanced uncertainty faced by the power system. Previous control methods, e.g., power generation schedules, hierarchical control strategy and application of energy storage systems (ESS) [4]–[6], are all generation-side management approaches, dealing with power imbalance caused by RESs from the perspective of power generation matching power consumption and failing to respond flexibly and quickly to power imbalance of the grid. Therefore, these methods cannot fundamentally solve the issue of power imbalance and new energy consumption. The combination of generation-side management and demand-side management can further reduce the issues above.

Electric spring (ES), a new demand-side management method that can actively store and release energy, offers a new solution to the above issue. The load of the bus where ES is installed is divided into critical load (CL) and non-critical load (NCL), according to their requirements of power quality [7]. CL has weak ability to withstand power fluctuation and voltage change, while NCL allows a large range of power fluctuation.

By adjusting power of the NCL and controlling internal energy storage, this kind of smart equipment can realize dynamic matching between power consumption and power generation, suppress power fluctuation of the grid, and eliminate power imbalance. In [8], the concept of ES is extended to the field of DC application and based on topology of AC electric spring (ACES), the first generation of DC electric spring (DCES) is proposed. In addition to dealing with power imbalance, benefits brought by DCES are manifold. In grid-connection of wind generation, voltage drop often occurs at the junction point. The combination of DCES and low voltage ride through (LVRT) [9] can stabilize voltage, which can be applied to various types of wind generations and simplify control. ESS is a common means to suppress power fluctuation, which is often combined with photovoltaic (PV) generation. However, relying only on ESSs to maintain power balance often leads to high-power charging and discharging, shortening the service life of ESSs and increasing the cost of ESSs [10]–[13]. Combining the ESSs with DCESs can not only optimize the operation of the DC network, but also reduce the operation cost of ESSs. Since the emergence of ES, most research on it has focused on the field of control strategy, and less on its planning. In addition, most research on planning takes ACES as the research object, and there are few studies on DCES planning. In this paper, the latest topology of DCES proposed in [14] is adopted as the research object. As shown in Fig. 1, it consists of a DC/DC three-port converter (TPC) [15] and a bi-directional buck-boost converter (BBC) [16]. Compared with first-generation DCES, this topology avoids using a low-pass filter with large volume, hence power density is higher. Compared with second-generation DCES [17], its structure and control are simpler, resulting in higher reliability. The most significant difference from the previous two generations of DCES is the latest topology realizes parallel connection between the CL and the DCES, which is conducive to its large-scale application in the power system.

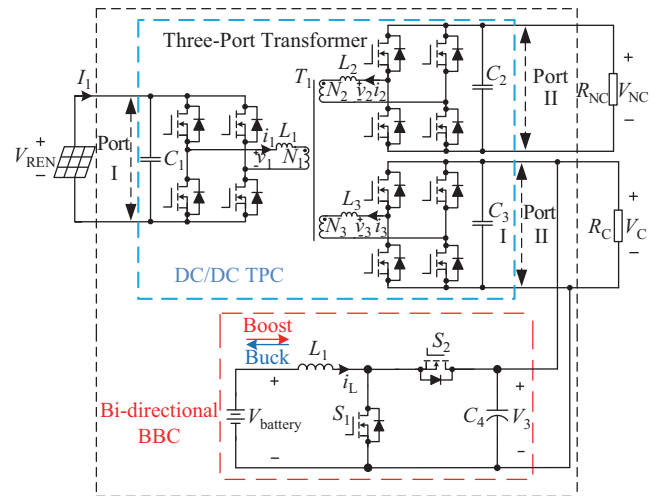


Fig. 1. Topology of DCES studied in this paper.

It should be noted that DCES is not applied as a replacement for ESS, but to help ESS approach randomness caused by RESs and load. Therefore, DCES planning, and ESS plan-

ning are not completely equivalent, and it is necessary to plan DCES systematically to maximize its auxiliary effect. ESS is load fluctuation that is borne by itself. Therefore, sufficient capacity is required to ensure stable operation of the system. Compared with ESS, DCES shifts some load fluctuations to non-critical loads, which is more flexible and can reduce the capacity requirements of ESS, but the economic cost is higher. Influence of PV on ESS is reduced by assisting ESS with DCES, such as adding DCES near the PV side. On the whole, DCES further reduces rate of light and wind abandonment and cost of electricity purchase to improve overall economic efficiency. Location of DCES greatly affects its effect. The planning problem of DCES can refer to distribution network planning and energy storage planning. According to existing literature [18]–[21], to deal with uncertainty faced by the network, planning methods considering uncertainty factors are generally based on multi-scenario technology, chance constraint theory or fuzzy mathematical theory. In summary, the planning method based on multi-scenario technology transforms the uncertainty planning model into its own deterministic equivalence class, and then establishes its equivalent deterministic planning model, to reduce the difficulty of modeling and solving. The planning method based on chance constraint theory allows the planning scheme not to meet electrical constraints to a certain extent, and can control risk of the planning scheme according to actual demand in the planning process. However, calculation time of this method is generally long when system scale increases. The planning method based on fuzzy mathematics theory uses fuzzy numbers to describe uncertain factors in the planning process, but the disadvantage is that the precision of planning results is not high. To deal with uncertainty faced by the network, scenario analysis method is adopted to transform the uncertainty optimization problem into a deterministic optimization problem, which simplifies the solving process of ES planning. Based on historical data, the K-Means clustering method is adopted for scenario extraction to consider the uncertainty of PVs and load. In terms of planning objectives, model structure and methodology, energy storage planning and distribution network planning can also provide references. Model structure can be divided into single-layer planning and multi-layer planning. The objective function of the former is generally simple, and it is difficult to address complex objectives, so this method has certain limitations in practical application. The latter adopts the idea of decomposition and coordination, which can better deal with complex planning objectives. However, the difficulty of solving would increase accordingly. Using a single intelligent algorithm to solve the multi-layer model has certain limitations, and the hybrid algorithm is usually used to approach it. The optimal storage planning proposed in [22] takes cost minimization as the objective, employs the point estimate method to solve probabilistic optimal power flow, and uses a hybrid Tabu search/particle swarm optimization algorithm to solve the problem. In [23], a data-driven uncertainty modeling approach is designed and a distributionally robust optimization model is built to determine optimal ESS planning. The objective here is to minimize the investment cost of ESSs and operating cost. In

the planning of ESSs in isolated microgrids [24], optimal plan decisions and operations are determined to reduce operating cost from ESS applications, load leveling and reserve. The electric spring allocation proposed in [25], considering types of ACES, aims to minimize total cost and voltage violation risk. Natural aggregation algorithm is used to solve this model. In [21], DCES is employed to mitigate distribution power loss of DC microgrids. The objective function consists of two parts: one for reducing voltage deviation and the other for reducing network loss. Intelligent algorithms commonly employed include genetic algorithm (GA) [26], ant colony optimization algorithm (ACO), immune algorithm (IA), tabu search algorithm (TS), particle swarm optimization algorithm (PSO) [27], etc. Among them, GA is a method to find the optimal solution by imitating selection and heredity of nature. This method is extensible and easy to combine with other algorithms [28], but it cannot make use of feedback information from the network in time, so the search speed of GA is slow and the training time is long. Compared with GA, ACO and IA are less dependent on the setting of algorithm parameters and the quality of the initial group. By using their heuristic intelligent search mechanism, they can search for the global optimal solution even if they start from the poor solution population, which has strong adaptability and robustness. TS is improved on the basis of local search, which overcomes the problem of falling into local optimum and has the ability of global search. TS is often combined with other algorithms as a hybrid method. PSO is the most frequently used intelligent algorithm. Compared with other algorithms, PSO is an efficient parallel search algorithm, which is suitable for optimization in dynamic and multi-objective optimization environments, and has fast computational speed. Global search ability can be further improved by appropriate improvement. Here, a bi-level model is adopted to divide DCES planning into a main planning problem and a sub-problem of optimal operation. The main planning problem aims to improve stability of DC distribution network, and the sub-problem of optimal operation is to consider economy and renewable energy consumption. PSO is adopted to solve the main planning problem, and asymmetric learning factors and linearly decreasing inertia weight are introduced to improve global search ability further. The sub-problem is also a multi-objective problem, so NSGA-II, a multi-objective problem-solving method based on evolutionary algorithm, is employed to reduce computational complexity, improve solution accuracy, avoid artificially specifying shared parameters and ensure diversity.

The contribution of this work is as follows.

- 1) In this paper, parallel DCES is planned for the first time, which enriches planning research of DCES and lays a foundation for the wide application of parallel DCES.
- 2) A master optimization including sub-optimization is used to determine the location and capacity of the parallel DCES. Three gains brought by this kind of DCES are considered comprehensively, namely, grid stability gain, economic benefit and increase in the allowed penetration rate of renewable energy.
- 3) Creatively integrating ESS operation into DCES planning, the two are distinct but compatible.

4) A hybrid algorithm composed of PSO and NSGA-II is used to solve the model. The advantages of the two algorithms are integrated, and the global search ability of the algorithm is improved.

This paper is organized as follows. In Section II, the objectives and constraints of this planning method are introduced and the operating modes of the latest DCES are described. In Section III, a bi-level optimization model is built to determine location and capacity of DCESs and PSO and NSGA-II are employed to solve this model. The result obtained from the case study is presented in Section IV, and it is analyzed from three aspects: grid operation, renewable energy consumption and energy storage operation. Finally, this paper is concluded in Section V.

II. PROBLEM FORMULATION

A. Operating Modes of the Parallel DCES

The working process of DCES is a coordination process between NCL and internal energy storage. In general, slight power imbalance can be handled by adjusting the NCL. When requirements of regulation cannot be met, internal energy storage would be charged or discharged to further adjust the power balance and stabilize the power supply of the CL. The NCL and DCES constitute the smart load. By adjusting the smart load, overall load changes with power generation to a certain extent. The DCES proposed in [14] has three operating modes. Battery-balancing Mode Power supply is almost consumed by the CL and NCL and power flowing through the internal storage of DCES is quite low. When the mathematical model of the DCES is established, the power of the CL is equal to its required power, the power of the NCL fluctuates within the allowable range, and the charge and discharge power of the DCES is equal to 0.

2) Battery-charging Mode

Even if the NCL consumes more power than its required value, power supply is still more than load consumption. In this case, the DCES stores energy, the NCL runs in high-power operating mode, and the power of the CL is equal to its required power.

3) Battery-discharging Mode

In this mode, power supply is insufficient. Energy storage inside the DCES discharges to stabilize the power supply of the CL and the NCL works in a state of low power.

B. Optimization Objective

In this paper, installation position and capacity of DCESs are optimized from operation stability of DC distribution network, economic efficiency and consumption of RESs, among which stability is taken as the primary consideration while economy and RESs are considered as secondary factors.

Compared with AC systems, operation of DC distribution network does not need to consider frequency problem and the key to ensuring operation stability is to maintain stability of bus voltages. Therefore, minimization of annual voltage deviation shown as (1) is taken as the upper optimization goal to improve stability gain brought by DCESs.

$$\min F_U = \sum_{s=1}^{n_{sc}} \sum_{t=1}^{n_T} \sum_{i \in \theta} |U_{i,s,t} - U_N| D_s \quad (1)$$

Economic efficiency and penetration of RESs are considered in the lower layer. Power purchase cost, investment cost, operation and maintenance (O&M) cost constitute economic objective and abandonment rate of RESs is also converted into penalty cost. Part of the electric energy purchased from superior substations is converted to power loss and the rest is consumed by load. By minimizing power purchase cost shown as (2), economic benefit can be improved and power loss can be reduced as well.

$$C_P = \sum_{s=1}^{n_{sc}} \sum_{t=1}^{n_T} \sum_{i \in \theta_{su}} \tau_t P_{s,t}^{G_i} D_s \quad (2)$$

The investment cost mainly comes from ESSs and DCESs. Under the condition that the configuration of ESSs is determined, the investment cost of ESSs is related to the operating power. The investment cost of DCESs is affected by the capacity and operating power of DCESs.

$$\begin{aligned} C_{INV} = & \sum_{s=1}^{n_{sc}} \sum_{t=1}^{n_T} \sum_{i \in \theta_{ESS}} \delta_{ESS} C_{INV}^{ESS} (P_{i,s,t}^{ESS,c} + P_{i,s,t}^{ESS,dc}) D_s \\ & + \delta_{ES} \left[\sum_{s=1}^{n_{sc}} \sum_{t=1}^{n_T} \sum_{i \in \theta_{ES}} C_{INV,P}^{ES} (P_{i,s,t}^{ES,c} + P_{i,s,t}^{ES,dc}) D_s \right. \\ & \left. + C_{INV,E}^{ES} E_i \right] \quad (3) \end{aligned}$$

In daily operation, sacrificing power quality of the NCLs requires a subsidy fee. Meanwhile, corresponding guarantee fee is charged for the CLs to reduce the operating cost of DCESs. Total O&M cost is shown as follows.

$$\begin{aligned} C_{O\&M} = & \sum_{s=1}^{n_{sc}} \sum_{t=1}^{n_T} \sum_{i \in \theta_{ESS}} C_{O\&M}^{ESS} (P_{i,s,t}^{ESS,c} + P_{i,s,t}^{ESS,dc}) D_s \\ & + \sum_{s=1}^{n_{sc}} \sum_{t=1}^{n_T} \sum_{i \in \theta_{ES}} C_{O\&M}^{ES} (P_{i,s,t}^{ES,c} + P_{i,s,t}^{ES,dc}) D_s \\ & + C_{NCL} - C_{CL} \quad (4) \end{aligned}$$

$$C_{NCL} = \alpha_{NCL} \sum_{s=1}^{n_{sc}} \sum_{t=1}^{n_T} \sum_{i \in \theta_{ES}} |P_{i,s,t}^{NCL} - P_{E,i,s,t}^{NCL}| D_s \quad (5)$$

$$C_{CL} = \alpha_{CL} \sum_{s=1}^{n_{sc}} \sum_{t=1}^{n_T} \sum_{i \in \theta_{ES}} P_{i,s,t}^{CL} D_s \quad (6)$$

Consumption of RESs can be reflected by the following penalty cost, which is total discarded optical power multiplied by corresponding penalty coefficient.

$$C_{RES} = \alpha_{RES} \sum_{s=1}^{n_{sc}} \sum_{t=1}^{n_T} \sum_{i \in \theta_{RES}} (P_{E,i,s,t}^{RES} - P_{i,s,t}^{RES}) D_s \quad (7)$$

C. Optimization Constraints

Assuming the DC distribution network doesn't output power and electric energy generated by RESs is consumed locally. A feasible solution should satisfy the following constraints: bus voltage constraint, line transmission power constraint, power

purchase constraint, power flow constraint, renewable energy generation constraint, and operation constraints related to the ESSs and DCEs. These constraints are formulated as follows.

$$0.95U_N \leq U_{i,s,t} \leq 1.05U_N \quad \forall i, t, s \quad (8)$$

$$0 \leq P_{ij,s,t} \leq P_{ij,\max} \quad \forall s, t, (i, j) \in \xi \quad (9)$$

$$P_{s,t}^{G_i} \geq 0 \quad \forall s, t, i \in \theta_{su} \quad (10)$$

$$\begin{cases} \sum_{k:j \rightarrow k} P_{jk,s,t} - \sum_{i:i \rightarrow j} (P_{ij,s,t} - r_{ij} I_{ij,s,t}^2) = P_{j,s,t} \\ U_{i,s,t} - U_{j,s,t} = r_{ij} I_{ij,s,t} \\ P_{ij,s,t} = U_{i,s,t} I_{ij,s,t} \end{cases} \quad \begin{matrix} \forall j \in \theta \\ \forall (i, j) \in \xi \\ \forall (i, j) \in \xi \end{matrix} \quad (11)$$

$$0 \leq P_{i,s,t}^{\text{RES}} \leq P_{E,i,s,t}^{\text{RES}} \quad \forall s, t, i \in \theta_{\text{RES}} \quad (12)$$

The following are operation constraints of the ESSs, including constraints of operating state, allowable range of state of charge (SOC) and limit of charge and discharge power. In charging state, the status indicator is equal to 0; otherwise, it is equal to 1.

$$S_{s,t}^{\text{ESS}_i} \in \{0, 1\} \quad \forall s, t, i \in \theta_{\text{ESS}} \quad (13)$$

$$\begin{cases} S_{\text{SOC},\min}^{\text{ESS}_i} \leq S_{\text{SOC},s,t-1}^{\text{ESS}_i} + \frac{\eta_c P_{i,s,t}^{\text{ESS},c}}{E_{\max}} \leq S_{\text{SOC},\max}^{\text{ESS}_i} \\ S_{s,t}^{\text{ESS}_i} = 0 \\ S_{\text{SOC},\min}^{\text{ESS}_i} \leq S_{\text{SOC},s,t-1}^{\text{ESS}_i} - \frac{P_{i,s,t}^{\text{ESS},dc}}{\eta_{dc} E_{\max}} \leq S_{\text{SOC},\max}^{\text{ESS}_i} \\ S_{s,t}^{\text{ESS}_i} = 1 \end{cases} \quad (14)$$

$$\begin{cases} 0 \leq P_{i,s,t}^{\text{ESS},c} \leq P_{\text{ESS},\max} \\ 0 \leq P_{i,s,t}^{\text{ESS},dc} \leq P_{\text{ESS},\max} \end{cases} \quad \forall s, t, i \in \theta_{\text{ESS}} \quad (15)$$

$$\left| \int_1^{n_T} P_{i,s,t}^{\text{ESS},c} dt - \int_1^{n_T} P_{i,s,t}^{\text{ESS},dc} dt \right| \leq \zeta E_{\max} \quad \forall s, i \in \theta_{\text{ESS}} \quad (16)$$

Operation constraints of the DCEs shown as (17)–(21) include operation state constraint, charge-discharge power constraints and regulation capacity constraints. Intelligent load here consists of the DCEs and NCL and its adjustment ability is limited by the capacity and power of the NCL. In addition, the capacity of the NCL to withstand power fluctuation is also limited and should meet a certain range.

$$\begin{cases} S_{1,s,t}^{\text{ES}_i} + S_{2,s,t}^{\text{ES}_i} + S_{3,s,t}^{\text{ES}_i} = 1 \\ S_{1,s,t}^{\text{ES}_i}, S_{2,s,t}^{\text{ES}_i}, S_{3,s,t}^{\text{ES}_i} \in \{0, 1\} \end{cases} \quad \forall t, s, i \in \theta_{\text{ES}} \quad (17)$$

$$\begin{cases} S_{\text{SOC},\min}^{\text{ES}_i} \leq S_{\text{SOC},s,t-1}^{\text{ES}_i} + \frac{\eta_c P_{i,s,t}^{\text{ES},c}}{E_i} \leq S_{\text{SOC},\max}^{\text{ES}_i} & S_{2,s,t}^{\text{ES}_i} = 1 \\ S_{\text{SOC},\min}^{\text{ES}_i} \leq S_{\text{SOC},s,t-1}^{\text{ES}_i} - \frac{P_{i,s,t}^{\text{ES},dc}}{\eta_{dc} E_i} \leq S_{\text{SOC},\max}^{\text{ES}_i} & S_{3,s,t}^{\text{ES}_i} = 1 \end{cases} \quad (18)$$

$$\begin{cases} 0 \leq P_{i,s,t}^{\text{ES},c} \leq P_{\text{ES},\max} \\ 0 \leq P_{i,s,t}^{\text{ES},dc} \leq P_{\text{ES},\max} \end{cases} \quad \forall s, t, i \in \theta_{\text{ES}} \quad (19)$$

$$\left| \int_1^{n_T} P_{i,s,t}^{\text{ES},c} dt - \int_1^{n_T} P_{i,s,t}^{\text{ES},dc} dt \right| \leq \zeta E_i \quad \forall s, i \in \theta_{\text{ES}} \quad (20)$$

$$(1 - \sigma) P_{E,i,s,t}^{\text{NCL}} \leq P_{i,s,t}^{\text{NCL}} \leq (1 + \sigma) P_{E,i,s,t}^{\text{NCL}} \quad \forall s, t, i \in \theta_{\text{ES}} \quad (21)$$

III. METHODOLOGY

A multi-objective, bi-level model shown as Fig. 2 is employed to solve the above problem. Before planning, it is

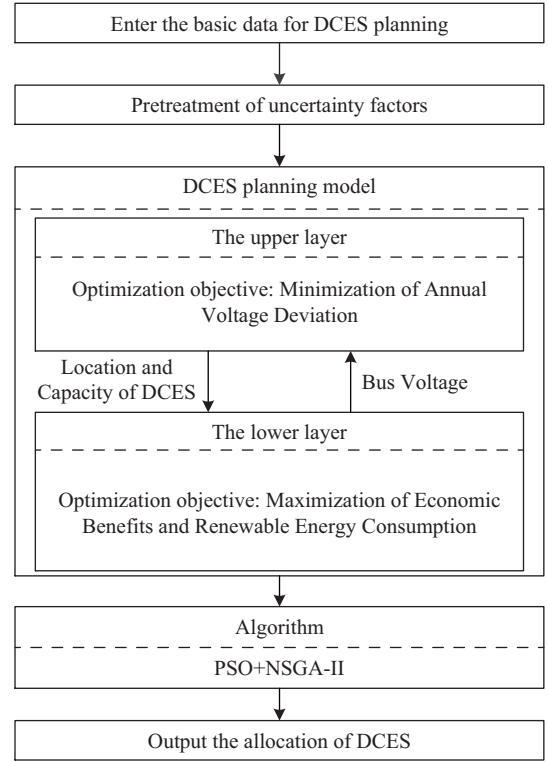


Fig. 2. Planning model of the DCEs.

necessary to preprocess the above uncertainties. In this paper, renewable energy represented by PV, as well as load uncertainty, are considered, and each sample in historical data covers output of RESs and load data within a day. First, historical data should be cleaned, and local outlier factor (LOF) is used to eliminate abnormal data after removing null values. Then, K-means clustering based on Euclidean distance division is employed to analyze and merge the scenarios. K-means clustering is an unsupervised clustering algorithm based on distance partition, which is simple to implement and has strong interpretability. Uncertainty is preprocessed and then enters DCES planning. Upper layer of this model aims to assist ESSs in optimizing the operation of the DC distribution network and reducing voltage fluctuation caused by RESs. PSO, a population-based algorithm, is employed here to solve the issue. Compared with commercial solvers, adopting PSO to deal with such issues is less complex and requires fewer constraint conditions. The particle swarm algorithm begins by creating initial particles and assigning them initial velocities. In the upper layer, each particle represents a candidate configuration of DCEs, and initial velocities are randomly generated vectors with dimensions equal to the number of buses. In other words, the number of dimensions per particle is equivalent to the number of buses, and each dimension denotes the installation capacity of the DCEs on the corresponding bus. The objective function, i.e., annual voltage deviation, at each particle location is evaluated to determine individual and group optimal locations. The velocity of the next iteration is influenced by the current velocity, the optimal position of each particle and the optimal position of the group. The new position of each individual can be

achieved by adding new velocity to the current position. From the function of DCESs, sufficient installation can maximize stability gain, but will increase investment cost and reduce economic benefit. To avoid excessive installation of DCESs and relieve computational burden, each particle is limited when being updated, i.e., setting the installation capacity of the bus with less than average installation capacity to 0. Iterations proceed until the algorithm reaches a stopping criterion. The solution process is shown as Fig. 3. In order to improve the global optimization ability of the algorithm, linearly decreasing weight and asymmetric learning factors are introduced in this paper. Updating of velocity is related to individual learning rate c_1 , group learning rate c_2 and inertia weight ω . Learning rates c_1 and c_2 determine the influence of individual and group optimal solutions on particle optimization trajectories, reflecting the degree of information exchange. The asymmetric learning factor method introduced in this paper employs large c_1 and small c_2 in the early stage of search to make particles diverge into search space as much as possible to enhance the diversity of particles. In the later stage of search, c_1 decreases and c_2 increases to strengthen the convergence ability of particles to the global optimal solution. The updated formula of the learning rates is shown as (22) and (23).

$$c_1 = c_{1i} + k \times (c_{1f} - c_{1i}) / k_{\max} \quad (22)$$

$$c_2 = c_{2i} + k \times (c_{2f} - c_{2i}) / k_{\max} \quad (23)$$

where, c_{1i} and c_{2i} are initial values of c_1 and c_2 . c_{1f} and c_{2f} are final values of c_1 and c_2 . k and $k_{\max}$ are the numbers of

the current iteration and total iteration, respectively.

Weight ω reflects the velocity update is affected by current speed. A larger ω is conducive to jumping out of the local optimal value and facilitating global search, while a smaller ω is conducive to accurate local search and algorithm convergence. Therefore, a large ω can be adopted at the beginning of the search, and it will gradually decrease with the iteration process. ω decreases linearly according to the following formulation.

$$\omega = \omega_{\max} - \frac{k \times (\omega_{\max} - \omega_{\min})}{k_{\max}} \quad (24)$$

$\omega_{\max}$ and $\omega_{\min}$ are maximum and minimum of ω .

In the step of calculating annual voltage deviation, the configuration of DCESs is passed to the lower layer as a known condition. The lower layer of this model takes account of the impact of DCESs on RESs, the cost of electricity purchase, investment, operation and maintenance of the distribution network comprehensively and feeds the voltage of each bus at each moment back to the upper layer to calculate the fitness value. The solution of the lower layer is also a multi-objective optimization problem. Classical approaches to this kind of issue, e.g., weighted-sum approach, mainly focus on consolidating multiple objectives into a single objective. The weighted-sum approach converts several objectives into one by pre-multiplying each objective with a weight. In this case, due to the subjectivity of weights, the optimal solution obtained by this method may not be the optimal solution to the problem. Compared with the weighted-sum approach, the evolutionary multi-objective optimization (EMO) does not have the above issue. NSGA-II, a popular EMO method, is adopted to solve the lower layer. NSGA-II is proposed based on the non-dominated genetic algorithm and introduces non-dominated sorting, elite strategy, and crowded tournament selection operator to reduce computational complexity, improve solution accuracy, avoid artificially specifying shared parameters and ensure diversity [29]. The process of NSGA-II is detailed in Fig. 4.

In NSGA-II, each individual denotes a candidate solution of power of DCESs and has two attributes, i.e., a non-domination rank r_i and a crowding distance d_i . According to these two attributes, a crowded tournament selection operator can be defined as follows. If the non-dominated rank of solution i is better than that of solution j , solution i wins; if they have the same non-dominated rank, the one with large crowding distances wins. Crowding distance d_i reflects the size of normalized search space, which is not occupied by other solutions around solution i and can be calculated according to the following procedure.

1) Record population size as s . For each individual i in the population, assign $d_i = 0$.

2) For each objective function m shown as (2)–(5), and the population is sorted in increased order of function value and index of individual i is recorded as I_i^m .

3) For each objective function m shown as (2)–(5), assign a large distance to boundary solutions and for all other solutions $j = 2$ to $(s - 1)$, assign

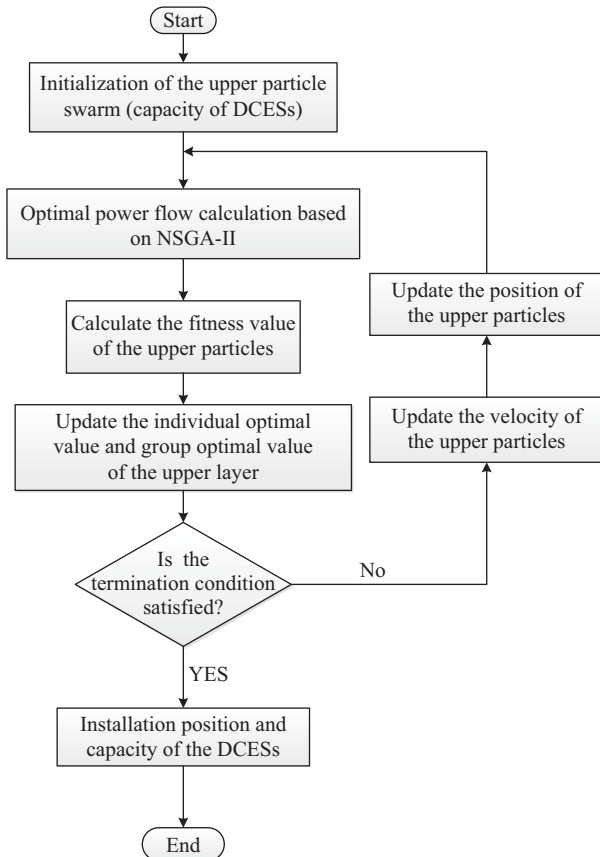


Fig. 3. Solution process of particle swarm optimization.

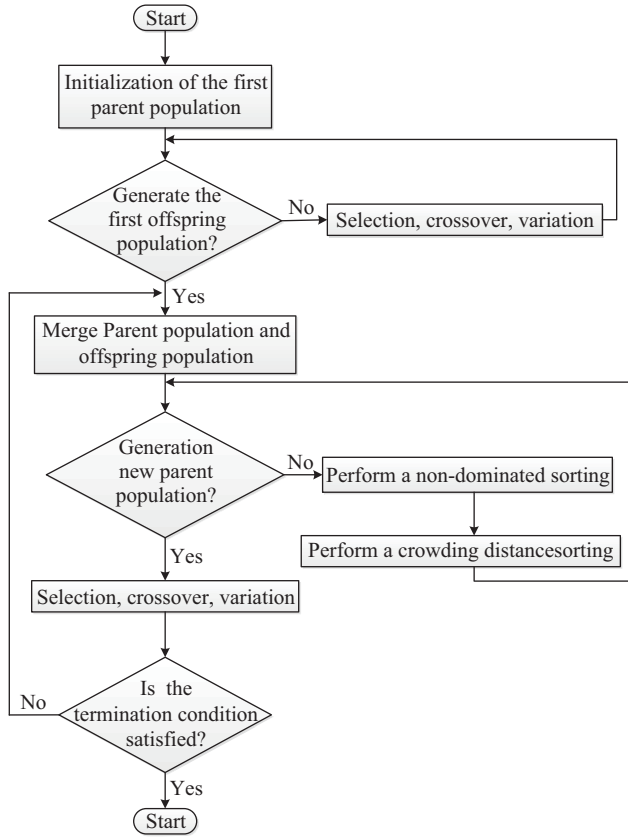


Fig. 4. Process of elitist non-dominated sorting genetic algorithm.

$$d_{I_j^m} = d_{I_j^m} + \frac{f_m^{(I_{j+1}^m)} - f_m^{(I_{j-1}^m)}}{f_m^{\max} - f_m^{\min}} \quad (25)$$

Constraints here can be handled by modifying definition of domination in NSGA-II. Solution i is said to constrain-dominate solution j if any of the following conditions are satisfied:

- 1) Solution i is feasible and solution j is not.
- 2) Both i and j are infeasible, but i has a smaller constraint violation.
- 3) Both i and j are feasible but i dominates j .

IV. CASE STUDY

IEEE 33-bus system is adopted to verify the effectiveness of the planning method. The power reference value of this system is 10MVA and the reference voltage of this system is 12.66 kV. Bus 1 is the power supply node. In this case, PVs and ESSs are taken into account and their installation positions are shown in Fig. 5. ESSs are installed in bus 6, bus 17 and bus 31 with the maximum capacity of 1 MWh and the upper limit of charge and discharge power of 250 kW. System services' the peak demand of 3715 kW and the proportions of NCL and CL are shown in Table I. Considering the uncertainty of RESs, a year is divided into three scenarios, namely spring and autumn (S&A), summer and winter. The number of class cluster members determines the proportion of each scenario.

In this paper, time-of-use electricity price is used to calculate cost related to electricity consumption. The price is 0.11 \$/kWh from 8:00 a.m. to 8:00 p.m., and 0.06 \$/kWh

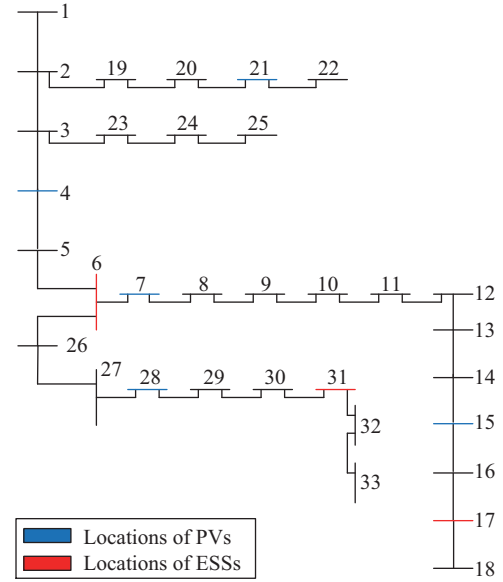


Fig. 5. IEEE 33-bus system under study.

TABLE I
BUS AND LOAD PARAMETERS

Bus	P (kW)	Critical load ratio (%)	Non-critical load ratio (%)	Bus	P (kW)	Critical load ratio (%)	Non-critical load ratio (%)
1	0	55	45	18	90	87	13
2	100	55	45	19	90	48	52
3	90	60	40	20	90	66	34
4	120	35	65	21	90	78	22
5	60	26	74	22	90	42	58
6	60	39	61	23	90	22	0.78
7	200	50	50	24	420	55	45
8	200	43	57	25	420	30	70
9	60	29	71	26	60	41	59
10	60	47	53	27	60	29	71
11	45	65	35	28	60	20	80
12	60	28	72	29	120	34	66
13	60	31	69	30	200	67	33
14	120	57	43	31	150	59	41
15	60	74	26	32	210	42	58
16	60	18	82	33	60	30	70
17	60	34	66				

in other time periods. The PSO runs with a population size of 200 for 400 generations, while the NSGA-II runs with a population size of 100 for 200 generations. Other parameters of this system are shown in Table II.

The convergence process of the main optimization is shown in Fig. 6, and configuration results are shown in Table III. In Fig. 7, the power of the ESS in bus 6 before and after the installation of DCESS is compared. After DCESS are employed, the frequency of high-power charging and discharging is significantly reduced and the dependence of the system on energy storage is reduced. On the premise of improving system stability, in order to improve the economy, the inherent storage device in the system is not only used to regulate bus voltage, but also to store electricity when the price is low and provide electricity during peak load. Installation of DCESS in close proximity to the ESS, e.g., bus 26, can distribute its responsibility and thus adjust the voltage at a relatively low cost.

TABLE II
OTHER PARAMETERS

Parameter	Value
Charge and discharge efficiency (%)	95
Service life of ESS	15
Service life of DCEs	20
Investment cost per unit power of ESS (\$/kW)	0.29
O&M cost per unit power of ESS (\$/kW)	0.057
Investment cost per unit power of DCEs (\$/kW)	0.2
Investment cost per unit capacity of DCEs (\$/kWh)	54.75
O&M cost per unit power of DCEs (\$/kW)	0.038
Power fluctuation range of NCL (%)	20
Unit power subsidy for NCL (\$/kW)	0.04
Unit power charge for CL (\$/kW)	0.1
The penalty coefficient for RESs	0.7
Discount rate	0.05
Upper limit of line transmission (MW)	1
Index of charge-discharge balance error of storages	0.05
the initial values of c_1	2
the initial values of c_2	0.5
the final values of c_1	0.5
the final values of c_2	2
the maximum of ω	0.9
the minimum of ω	0.4

TABLE III
CONFIGURATION RESULT

Installation positions of DCEs	Capacity (kWh)
Bus 12	386.9
Bus 19	433.38
Bus 25	325.56
Bus 26	336

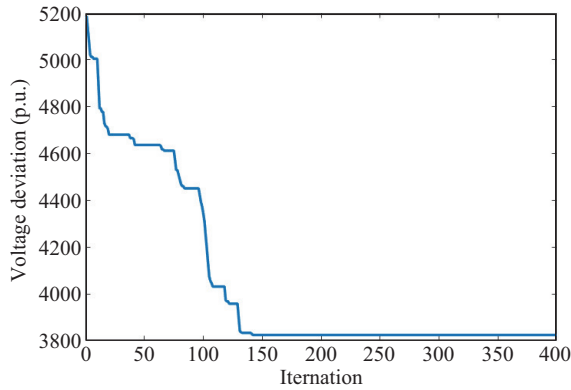


Fig. 6. Convergence curve of IEEE 33-bus system.

To confirm better global search ability and effects of the proposed model, this paper uses PSO algorithm and GA algorithm respectively, to realize the planning of DC distribution network. In the two methods, weights are used to combine the two objectives into one objective function for optimization. Figs. 8 (a) and (b) show network loss before and after optimization of the two optimization algorithms, reflecting change in comprehensive economic cost. After calculation, the DCEs are placed in bus (2, 18, 27, 31) and (5, 17, 26, 30), respectively.

In Table IV, the solution result is compared with those of PSO and genetic algorithm, which are common Intelligent algorithms. According to the results, the optimization effect of using PSO and GA alone is similar. After the introduction of the two-level model and NSGA-II on the basis of PSO,

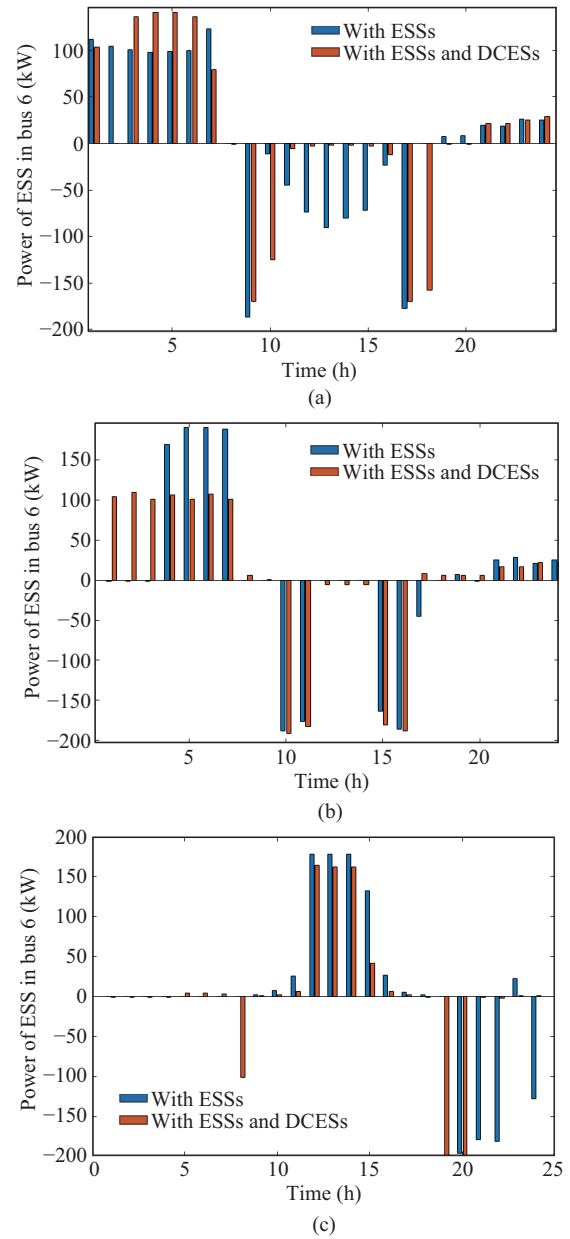


Fig. 7. Power of the ESS in bus 6. (a) In S&A. (b) In summer. (c) In winter.

TABLE IV
COMPARISON OF DIFFERENT ALGORITHM

Performance index	PSO	GA	PSO and NSGA-II
Annual voltage deviation (p.u.)	4055.63	4132.12	3824.54
Annual power purchase cost (\$)	708940.5	715620.7	687435.7
Annual investment cost (\$)	45212.5	43774.2	41268.38
Annual O&M cost (\$)	167526.3	168521.3	159463.5
Annual penalty cost for discarding light (\$)	5824.33	6225.17	4665.94
Annual total cost (\$)	927503.63	934141.36	892833.53

all economic indexes are reduced because the subjectivity of artificial enactment weight is avoided.

There are two main reasons for the reduction in electricity cost. On one hand, effective use of renewable energy reduces

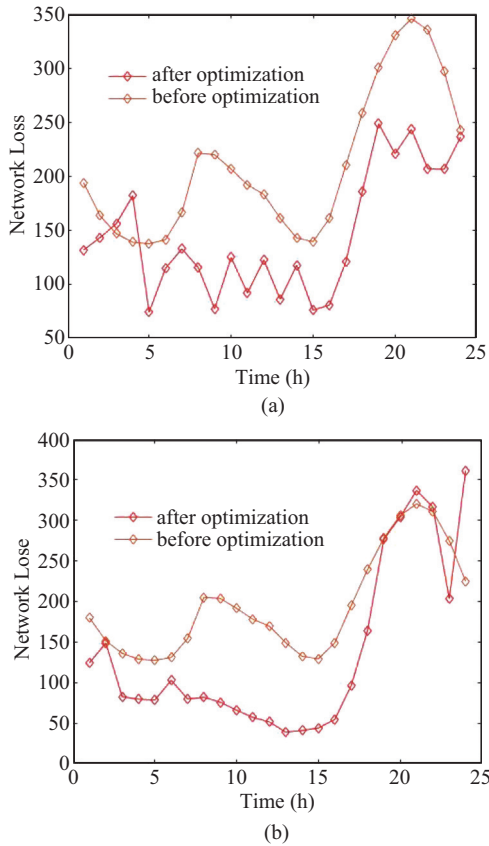


Fig. 8. Network losses. (a) Network loss of PSO. (b) Network loss of GA.

external power supply; on the other hand, coordinated operation of DCEs, RESs and ESSs relieves transmission pressure of lines and reduces power loss of the system. Penalty cost for abandoning power generated by RESs is reduced to 34.1% after the configuration, and the capacity of the distribution network to absorb renewable energy is further improved. The DCEs can stabilize the voltage of the bus, which is close to RESs, and assist the operation of ESSs when installed in the position close to energy storage.

V. CONCLUSION

Parallel DCEs fits the connection mode of the grid, and it is suitable for large-scale applications. However, there are few studies on its planning. In this paper, a planning method is proposed to maximize stability gain, economic benefits, and positive impact on RESs by combining parallel DCEs with existing energy storage devices in the DC distribution network. The contributions of this work can be summarized as follows. First, according to the working characteristics of parallel DCEs, planning for it is proposed, considering all positive influences brought by DCEs. This model highlights the optimization of system stability and on this premise, reduces total cost and promotes absorption of RESs. Second, ESSs, the most common means of suppressing power fluctuation, are added to the planning, which is more applicable to practical application scenarios. Finally, in multi-objective planning of the sub-optimization, a popular EMO method is adopted to deal with this multi-objective issue, which can

reduce computational complexity, improve solution accuracy and avoid artificially specifying shared parameters. Results of the case study show that the proposed planning method for DCEs has good convergence, and reduces voltage deviation caused by RESs and the total cost of system as well. For the bus close to the RES, DCEs play a role of stabilizing voltage and supporting voltage. For ESSs in DC distribution network, DCEs reduce dependence on ESSs and the frequency of high-power charging and discharging. The planning proposed in this paper fills the vacancy of application of parallel DCEs. In follow-up research, how to expand the types of CL and NCL, and how to improve the robustness of the planning model are worth studying.

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