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# Cooperative Planning of Active Distribution System With Renewable Energy Sources and Energy Storage Systems

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**ABSTRACT** In this paper, a multi-objective, multi-level model is proposed for active distribution system expansion planning with high-penetration renewable energy sources (RESs) and energy storage systems (ESSs). To optimize the planning of RESs, ESSs, and distribution networks cooperatively, a three-level optimization method is adopted based on the leader–follower strategy of hierarchic optimizations. In this model, the upper level and the middle-level serve to model the planning problems from different perspectives of multi-stakeholders; the lower level serves to model the operation aspect of ESSs. The multi-level model enables us to integrate operation optimization into a planning model and achieve the collaborative optimization of them in different time-scales. The multi-scenario tools and K-means clustering are adopted to deal with the uncertainties and capture the time-variable nature of RESs and load demand. In order to balance the multiple objectives of costs reduction, reliability improvement, and RES penetration promotion, a modified Pareto-based particle swarm optimization is employed to solve the proposed optimization problem. Finally, results obtained by case studies are presented and discussed, where the availability and the effectiveness of the proposed planning model are verified.

**INDEX TERMS** Active distribution system, multi-level optimization, Pareto optimization, distribution network planning, renewable energy source.

## ABBREVIATIONS

| | |
|---|---|
| ADS | Active distribution system |
| RES | Renewable energy source |
| ESS | Energy storage system |
| WG | Wind generation |
| PV | Photovoltaic generation |
| DG | Distributed generation |
| SOC | State of charge |
| TOU | Time of use |
| NPV | Net profit value |
| O&M | Operation and maintenance |
| DGO | Distributed generation operator |
| DSO | Distribution system operator |
| EENS | Expected energy not supplied |
| PSO | Particle swarm optimization |

## INDEXS

| | |
|---|---|
| $a, b, c$ | Index for feeder |
| $i, j$ | Index for bus |
| $m$ | Index for WG |
| $n$ | Index for PV |
| $k$ | Index for ESS |
| $t$ | Index for time |
| $sc$ | Index for scenario |
| $sy$ | Index for statistic year |
| $g, h$ | Index for cluster center |

## SETS

| | |
|---|---|
| $\Omega_{\rm WG}, \Omega_{\rm PV}, \Omega_{\rm ESS}$ | Sets of WG/ PV/ ESS |
| $\Omega_{\rm RF}, \Omega_{\rm AF}, \Omega_{\rm EF}$ | Sets of replacement feeders/ addition feeders/ existing feeders |
| $\Omega_{\rm DE}$ | Sets of distribution equipment |
| $\Omega_{\rm bus}$ | Sets of load buses |

## VARIABLES

| | |
|---|---|
| $CO_{sc}^{\rm net}$ | Operation cost of network in scenario $sc$ |
| $CC_{\rm d}^{\rm feeder}$ | Diurnal capital cost of feeders |


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| | |
|---|---|
| $CM_{\mathrm{d}}^{\mathrm{feeder}}$ | Diurnal O&M cost of feeders |
| $\eta_{sc}$ | Occurrence probability of scenario $sc$ |
| $x_a^{\mathrm{RF}}, x_a^{\mathrm{EF}}, x_a^{\mathrm{AF}}$ | Variables associated with replacement feeder $a$/ addition feeder $b$/ existing feeder $c$ |
| $CC_a^{\mathrm{RF}}, CM_a^{\mathrm{RF}}$ | Diurnal capital cost/ O&M costs of replacement feeder $a$ |
| $CC_b^{\mathrm{AF}}, CM_b^{\mathrm{AF}}$ | Diurnal capital cost/ O&M costs of addition feeder $b$ |
| $CM_c^{\mathrm{EF}}$ | Diurnal O&M costs of existing feeder $c$ |
| $EP^{\mathrm{PV}}, EP^{\mathrm{WG}}$ | Contract prices of PV/ WG |
| $EP_t$ | TOU electricity prices of at time $t$ |
| $P_{n,sc,t}^{\mathrm{PV}}, Q_{n,sc,t}^{\mathrm{PV}}$ | Active/ reactive power output of PV $n$ at time $t$, in scenario $sc$ |
| $P_{m,sc,t}^{\mathrm{WG}}, Q_{m,sc,t}^{\mathrm{WG}}$ | Active/ reactive power output of WG $m$ at time $t$, in scenario $sc$ |
| $P_{i,sc,t}^{\mathrm{load}}, Q_{i,sc,t}^{\mathrm{load}}$ | Active/ reactive load demand of bus $i$ at time $t$, in scenario $sc$ |
| $P_{sc,t}^{\mathrm{loss}}, Q_{sc,t}^{\mathrm{loss}}$ | Active/ reactive network losses at time $t$, in scenario $sc$ |
| $P_{k,sc,t}^{\mathrm{ESS}}, Q_{k,sc,t}^{\mathrm{ESS}}$ | Active/ reactive power consumption/ output of ESS $k$ at time $t$, in scenario $sc$ |
| $I_{a,sc,t}, I_{b,sc,t}, I_{c,sc,t}$ | Electric current for feeder $a$/ $b$/ $c$ at time $t$, in scenario $sc$ |
| $R_a, R_b, R_c$ | Resistance value for feeder $a$/ $b$/ $c$ |
| $\delta_{\Omega_{\mathrm{DE}}}$ | Capital recovery factor of distribution equipment |
| $\delta_{\Omega_{\mathrm{F}}}$ | Capital recovery factor of feeder |
| $\delta_{\Omega_{\mathrm{PV}}}, \delta_{\Omega_{\mathrm{WG}}}, \delta_{\Omega_{\mathrm{ESS}}}$ | Capital recovery factor of PV/ WG/ ESS |
| $r$ | Rate of interest |
| $T_{\Omega_{\mathrm{DE}}}$ | Lifetime of distribution equipment |
| $N_{sc}, N_{sy}$ | Number of scenario/ statistic year |
| $I_{sc}^{\mathrm{EENS}}$ | Average value of EENS for scenario $sc$ |
| $I_{sy,sc}^{\mathrm{EENS}}$ | EENS in scenario $sc$, in statistic year $sy$ |
| $P_{k,sc,t}^{\mathrm{ava}}$ | Reserve capability of ESS $k$ at time $t$, in scenario $sc$ |
| $P_k^{\mathrm{ESS,R}}, S_k^{\mathrm{ESS,R}}$ | Power rating/ energy capacity of ESS $k$ |
| $Soc_{k,sc,t}$ | SOC of ESS $k$ at time $t$, in scenario $sc$ |
| $Soc^{\max}, Soc^{\min}$ | Permissible range of SOC |
| $E_{k,sc,t}^{\mathrm{ESS}}$ | Energy stored in the battery bank of ESS $k$ at time $t$, in scenario $sc$ |
| $\eta_{\mathrm{C}}, \eta_{\mathrm{D}}$ | ESS charging/ discharging efficiency |
| $RESP_{sc}$ | RES penetration in scenario $sc$ |
| $W_{sc}^{\mathrm{RES}}$ | Energy supplied by RESs in scenario $sc$ |
| $W_{sc}^{\mathrm{LD}}$ | Energy of load demand in scenario $sc$ |
| $\pi_{sc}^{\mathrm{DGO}}$ | Diurnal NPV of DGO in scenario $sc$ |
| $\pi_{n,sc}^{\mathrm{PV}}, \pi_{m,sc}^{\mathrm{WG}}, \pi_{k,sc}^{\mathrm{ESS}}$ | Diurnal NPV of PV $n$/ WG $m$/ ESS $k$ in scenario $sc$ |
| $B_{n,sc}^{\mathrm{PV}}, B_{m,sc}^{\mathrm{WG}}, B_{k,sc}^{\mathrm{ESS}}$ | Diurnal benefits of PV $n$/ WG $m$/ ESS $k$ in scenario $sc$ |
| $C_{n,\mathrm{d}}^{\mathrm{PV}}, C_{m,\mathrm{d}}^{\mathrm{WG}}$ | Diurnal total costs of PV $n$/ WG $m$ |
| $C_{k,sc}^{\mathrm{ESS}}$ | Diurnal total costs of ESS $k$ in scenario $sc$ |
| $cc^{\mathrm{PV}}, cc^{\mathrm{WG}}$ | Unit capital cost of PV/ WG (\$/kW) |
| $cc^{\mathrm{PCS}}, cc^{\mathrm{B\&R}}$ | Unit capital cost of ESS related to power conversion system/ storage banks and reservoirs |
| $cm^{\mathrm{PV}}, cm^{\mathrm{WG}}$ | Unit O&M cost of PV/ WG |
| $cm^{\mathrm{FOM}}, cm^{\mathrm{VOM}}$ | Unit fixed/ variable O&M cost of ESS |
| $P_n^{\mathrm{PV,R}}, P_m^{\mathrm{WG,R}}$ | Power rating of PV $n$/ WG $m$ |
| $\lambda_{\mathrm{I}}$ | Maximum of total capacity penetration of RESs |
| $S^{\mathrm{sub}}$ | Power rating of HV/ MV substation |
| $P_{sc,t}^{\mathrm{sub}}, Q_{sc,t}^{\mathrm{sub}}$ | Active/ reactive power output of HV / MV substation at time $t$, in scenario $sc$ |
| $P_{i,sc,t}, Q_{i,sc,t}$ | Active/ reactive power of bus $i$ at time $t$, in scenario $sc$ |
| $U_{i,sc,t}, \theta_{ij,sc,t}$ | Voltage magnitude of bus $i$/ voltage angle difference between bus $i$ and bus $j$ at time $t$, in scenario $sc$ |
| $G_{ij}, B_{ij}$ | Transfer conductance/ susceptance between bus $i$ and bus $j$ |
| $U_i^{\max}, U_i^{\min}$ | Permissible range of voltage magnitude for bus $i$ |
| $I_a^{\max}, I_b^{\max}, I_c^{\max}$ | Maximum of current for feeder $a$/ $b$/ $c$ |
| $I_{\mathrm{DB}}$ | Cluster validity index |
| $N_{\mathrm{C}}$ | Number of cluster center for K-means |
| $N_g$ | Number of vector in cluster center $g$ |
| $d_{gh}$ | Distance between cluster center $g$ and cluster center $h$ |
| $S_g, S_h$ | Dispersions of cluster center $g$/ cluster center $h$ |
| $c_g, c_h$ | Cluster center $g$/ cluster center $h$ |

## I. INTRODUCTION

For the purpose of secure energy supply and handling the problem of climate change, renewable energy sources (RESs), mainly wind generations (WGs) and photovoltaic generations (PVs), have been widely deployed in distribution networks. The integration of RESs brings great benefits to distribution networks, while posing a number of new challenges to the operation and planning [1]–[3]. Therefore, active distribution system (ADS) is introduced and perceived to be flexible enough to accommodate these variable RESs and alleviate these challenges [4], [5].

In traditional distribution network planning, the deterministic strategy "fit and forget" is always implemented to deal with distributed generations (DGs) based on the worst-case scenarios, which leads to economic inefficiency, and ignores the uncertainties and variability brought by high penetration variable RESs. It is no longer valid for ADSs to accommodate these widespread RESs, and therefore it is necessary to develop appropriate models and methodologies for ADS planning.

Optimal planning of ADS has been previously studied and some attention-grabbing planning models have been proposed. Abapour *et al.* [6] and Kaaabi *et al.* [7] introduce planning models of DGs under the active managements. In [6], a long-term dynamic planning model is proposed to determine sizes, locations, and investment time of DGs. Active power regulation of DGs and reactive power compensators management are taken into consideration in the planning model. Kaaabi *et al.* [7] analyze the influences of various multi-DG configurations and propose a planning model to determinate the capacities and locations for multiple WGs based on the multi-configuration, multi-period optimal power flow. But the allocation of DGs and the planning of networks are considered as two separate tasks, so the cooperative planning between them is ignored in these papers.

In [8]–[10], the cooperative planning between DGs and networks are studied. El-Khattam *et al.* [8] and Borges and Martins [9] propose cooperative methods for distribution network planning considering DGs, substations, and feeders. The high-level uncertainties related to load demand, RESs, and electricity prices are taken into account. In [10], a multi-objective algorithm is proposed to determine the plan schemes of network topology and new generation units, where to minimize both the monetary cost and the fault cost of the network for the "most likely" peak-load scenario serves as the optimization objective. However, these models are proposed without active management schemes, which can offer many potential benefits to ADS planning and operation.

Due to the vital roles of energy storage systems (ESSs), such as network upgrade deferral, accommodation of RESs, power quality and reliability improvement [11], Sedghi *et al.* [12] propose an optimal model to determine the locations, capacities, and power ratings of ESSs in ADS. The proposed planning model takes several roles of ESS into account based on the short-term optimal power flow. Saboori *et al.* [13] propose a network expansion planning model incorporating ESSs, and analyze the positive effects of ESSs on bus voltage and line loading. In [14] and [15], DGs and ESSs are included and considered as possible solutions for multi-stage ADS expansion planning.

Regarding the above literature review, it can be observed that many ADS planning models have been proposed. However, the problem of ADS planning has not been tackled yet. Firstly, although the significance of ESSs has attracted researchers' attention, most of researches focus on operation issues rather than planning issues. Even if the operation of ESS is integrated in some works, straightforward models without optimization are adopted to represent the operation scheduling, where the optimal operation of ESSs is not taken into account adequately.

In addition, most of aforementioned literature assume that DGs and ESSs are owned by distribution system operators (DSOs). It is no longer appropriate in the modern electricity market of ADS. With the liberalization of electricity market, distributed generation operators (DGOs) have emerged and become important participants of electricity market, which is a typical scenario in Ontario, Canada and Sacramento Municipal Utility District in California, U.S.A.. But except [16]–[18], most of works fail to give serious consideration for this issue and ignore different planning targets of multi-stakeholders.

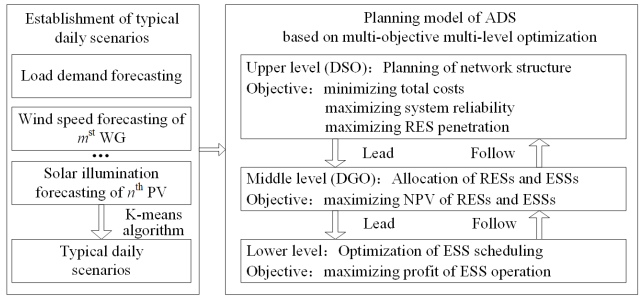


**FIGURE 1. Framework of optimal planning model.**

Meanwhile, the aforementioned planning models tend to use the economic criteria to evaluate planning schemes alone. Although some works have taken the factors of reliability and environment into account, these factors are always converted to the economic criteria, such as the outage cost and emission tax. Thus, these multiple objectives are aggregated to a single objective by means of weight coefficient methods. These approaches with a priori articulation of preferences have the drawback of subjectivity since it is in some cases too much dependent on the personal point of view.

In this regard, a novel ADS planning model is proposed to achieve cooperative planning between RESs, ESSs, and networks based on multi-objective, multi-level optimization methodology. Meanwhile, the emphasis is also given on the collaborative optimization between planning issues in long-time scale and operation issues in short-time scale. The primary contributions are described as follows:

(1) The proposed planning model enables us to take operation optimization of ESS into account adequately, while we make decisions at the stage of planning. It achieves cooperative optimization between planning and operation in different time scales.

(2) The proposed planning model achieves cooperative planning between RESs, ESSs, and networks from different perspectives of multi-stakeholders, and has the ability to provide win-win solutions to deal with different planning goals of them.

(3) The proposed planning model can provide a set of Pareto alternative planning schemes from different perspectives including economy, reliability, and utilization of RESs.

Apart from this introduction, the remainder of this paper is structured as follows. The framework of the proposed planning model is introduced in Section II. Then, we describe planning problem and formulate the planning model in Section III. Section IV presents methods to establish typical daily scenarios and the solving process. In Section V, simulation results are discussed and analyzed. Finally, Section VI concludes this paper with several remarks.

## II. FRAMEWORK OF PLANNING MODEL

The multi-objective, multi-level model is shown in Fig. 1.

To ease the computational burden, and capture hourly variability and uncertainties related to RESs and load demand, time-series profiles of annual power consumption/ generation are grouped into several typical scenarios by K-mean clustering algorithm, shown as the left part of Fig.1. These typical daily scenarios preserve chronological sequences of wind speed, solar illumination, and load demand, which allows representing eventual chronological aspects related to ESS operation.

The right side provides the multi-level model, where the upper level and middle level are adopted to optimize the planning problem of networks, and the allocation problem of RESs and ESSs, respectively. The lower level serves to optimize operation scheduling of ESSs for each typical scenario, which is fed back to the upper level and the middle level to calculate the operation costs of ADS and net profit value (NPV) of DGO at hourly time-steps for each daily scenario.

Each level of the model has its own objectives and decision spaces affected by variables controlled at other levels, which is suitable to model the relationship between DGO and DSO. Meanwhile, the execution of decisions is sequential from the higher level to the lower one, which is consistent with the logic sequence between planning and operation.

To optimize planning and operation in different time scales cooperatively and take the uncertainties into account, the expected values of the total costs, the reliability index, and the penetration of RESs for these multiple typical scenarios serve as the optimization objectives.

## III. PROBLEM FORMULATION

### A. OPTIMIZATION OBJECTIVE

#### 1) OBJECTIVE FUNCTION OF UPPER LEVEL

The upper level serves as the planning of networks from the perspective of DSO. Different from the traditional planning approach, ADS planning needs the best alternatives with a multi-objective approach [5]. In this paper, three objectives are adopted, including economy, reliability, and penetration of RESs.

##### a: ECONOMIC OBJECTIVE

The investment costs, operation and maintenance (O&M) costs constitute the economic objective function shown as Eq.(1)-(7).

$$F_1^{\mathrm{U}} = \mathrm{Min}\left(CC_{\mathrm{d}}^{\mathrm{feeder}} + CM_{\mathrm{d}}^{\mathrm{feeder}} + \sum_{sc=1}^{N_{sc}} \eta_{sc} CO_{sc}^{\mathrm{net}}\right) \tag{1}$$

$$CC_{\mathrm{d}}^{\mathrm{line}} = \frac{\delta_{\mathrm{F}}}{365}\left(\sum_{a\in\Omega_{\mathrm{RF}}} x_a^{\mathrm{RF}} CC_a^{\mathrm{RF}} + \sum_{b\in\Omega_{\mathrm{AF}}} x_b^{\mathrm{AF}} CC_b^{\mathrm{AF}}\right) \tag{2}$$

$$CM_{\mathrm{d}}^{\mathrm{feeder}} = \frac{1}{365}\left(\sum_{a\in\Omega_{\mathrm{RF}}} x_a^{\mathrm{RF}} CM_a^{\mathrm{RF}} + \sum_{b\in\Omega_{\mathrm{AF}}} x_b^{\mathrm{AF}} CM_b^{\mathrm{AF}} + \sum_{c\in\Omega_{\mathrm{EF}}} x_c^{\mathrm{EF}} CM_c^{\mathrm{EF}}\right) \tag{3}$$

$$CO_{sc}^{\mathrm{net}} = \sum_{t=1}^{24}\left(\left(EP_t P_{sc,t}^{\mathrm{sub}}\Delta t\right) + \sum_{n\in\Omega_{\mathrm{PV}}}\left(EP^{\mathrm{PV}} P_{n,sc,t}^{\mathrm{PV}}\Delta t\right) + \sum_{m\in\Omega_{\mathrm{WG}}}\left(EP^{\mathrm{WG}} P_{m,sc,t}^{\mathrm{WG}}\Delta t\right)\right) \tag{4}$$

$$P_{sc,t}^{\mathrm{sub}} = \sum_{i\in\Omega_{\mathrm{bus}}} P_{i,sc,t}^{\mathrm{load}} + \sum_{k\in\Omega_{\mathrm{ESS}}} P_{k,sc,t}^{\mathrm{ESS}} + P_{sc,t}^{\mathrm{loss}} - \sum_{m\in\Omega_{\mathrm{WG}}} P_{m,sc,t}^{\mathrm{WG}} - \sum_{n\in\Omega_{\mathrm{PV}}} P_{n,sc,t}^{\mathrm{PV}} \tag{5}$$

$$P_{sc,t}^{\mathrm{loss}} = \sum_{a\in\Omega_{\mathrm{RL}}} I_{a,sc,t}^2 R_a x_a^{\mathrm{RF}} + \sum_{b\in\Omega_{\mathrm{AL}}} I_{b,sc,t}^2 R_b x_b^{\mathrm{AF}} + \sum_{c\in\Omega_{\mathrm{EL}}} I_{c,sc,t}^2 R_c x_c^{\mathrm{EF}} \tag{6}$$

$$\delta_{\Omega_{\mathrm{DE}}} = \left(r(1+r)^{T_{\Omega_{\mathrm{DE}}}}\right)/\left((1+r)^{T_{\Omega_{\mathrm{DE}}}} - 1\right) \tag{7}$$

##### b: RELIABILITY OBJECTIVE

The annual expected energy not supplied (EENS) serves as the index to evaluate the reliability of ADS. EENS is calculated by sequential Monte Carlo Simulation, which has the merit of high precision of system chronological representation [19]. So, to minimize EENS serves as the second objective, shown as Eq.(8) and Eq.(9). To calculate annual average value of EENS of scenario $sc$, scenario $sc$ is repeated 365 times in each statistic year.

$$F_2^{\mathrm{U}} = \min \sum_{sc=1}^{N_{sc}}\left(\eta_{sc} I_{sc}^{\mathrm{EENS}}\right) \tag{8}$$

$$I_{sc}^{\mathrm{EENS}} = \frac{1}{N_{\mathrm{sy}}}\sum_{sy=1}^{N_{sy}}\left(I_{sy,sc}^{\mathrm{EENS}}\right) \tag{9}$$

The two-state Markov process model is adopted to simulate the transitions between operative and failed states of main system components, including WGs, PVs, ESSs and feeders. In the process of EENS calculation, the analytical method proposed in [20] is adopted to investigate the impacts of DGs and ESSs on the reliability improvement. When it comes to ESSs, the reserve capability of ESS is adopted to represent the maximum power that ESS can supply to ADS in the event of system failure, subjected to operation constraints, expressed as Eq.(10) and Eq.(11).

$$P_{k,sc,t}^{\mathrm{ava}} = \min\left\{P_k^{\mathrm{ESS,R}}, \left(\left(Soc_{k,sc,t} - Soc^{\min}\right) S_k^{\mathrm{ESS,R}}\eta_{\mathrm{D}}\right)/\Delta t\right\} \tag{10}$$

$$Soc_{k,sc,t} = E_{k,sc,t}/S_k^{\mathrm{ESS,R}} \tag{11}$$

Thus, in the process of EENS calculation, the features of uncertainty and contingency of RESs and ESSs are taken into account adequately.

##### c: THE OBJECTIVE OF RES PENETRATION

The optimization of network structure is beneficial for alleviating network congestion and improving allowable penetration of RESs. Therefore, to maximize the penetration of RESs is adopted as the third objective, shown as Eq.(12)-(14).

$$F_3^{\mathrm{U}} = \max \sum_{sc=1}^{N_{sc}} \left(\eta_{sc} RESP_{sc}\right) = \max \sum_{sc=1}^{N_{sc}} \left(\eta_{sc}\left(W_{sc}^{\mathrm{RES}} / W_{sc}^{\mathrm{LD}}\right)\right) \tag{12}$$

$$W_{sc}^{\mathrm{RES}} = \sum_{t=1}^{24} \left( \sum_{m\in\Omega_{\mathrm{WG}}} \left(P_{m,sc,t}^{\mathrm{WG}}\Delta t\right) + \sum_{n\in\Omega_{\mathrm{PV}}} \left(P_{n,sc,t}^{\mathrm{PV}}\Delta t\right)\right) \tag{13}$$

$$W_{sc}^{\mathrm{LD}} = \sum_{t=1}^{24}\left(\left(P_{sc,t}^{\mathrm{loss}} + \sum_{i\in\Omega_{\mathrm{bus}}} P_{i,sc,t}^{\mathrm{load}}\right)\Delta t\right) \tag{14}$$

### 2) OBJECTIVE FUNCTION OF MIDDLE LEVEL

The middle level serves to optimize the allocation of RESs and ESSs from the perspective of DGO. The planning target is to maximize the revenues by the sale of electricity by RESs and the arbitrage profit brought by ESSs. So, to maximize NPV of DGO is adopted to be the objective of middle level, shown as Eq.(15)-(25).

$$F^{\mathrm{M}} = \max \sum_{sc=1}^{N_{sc}} \left(\eta_{sc}\pi_{sc}^{\mathrm{DGO}}\right) \tag{15}$$

$$\pi_{sc}^{\mathrm{DGO}} = \sum_{m\in\Omega_{\mathrm{WG}}} \pi_{m,sc}^{\mathrm{WG}} + \sum_{n\in\Omega_{\mathrm{PV}}} \pi_{n,sc}^{\mathrm{PV}} + \sum_{k\in\Omega_{\mathrm{ESS}}} \pi_{k,sc}^{\mathrm{ESS}} \tag{16}$$

$$\pi_{n,sc}^{\mathrm{PV}} = B_{n,sc}^{\mathrm{PV}} - C_{n,\mathrm{d}}^{\mathrm{PV}} \tag{17}$$

$$\pi_{m,sc}^{\mathrm{WG}} = B_{m,sc}^{\mathrm{WG}} - C_{m,\mathrm{d}}^{\mathrm{WG}} \tag{18}$$

$$\pi_{k,sc}^{\mathrm{ESS}} = B_{k,sc}^{\mathrm{ESS}} - C_{k,sc}^{\mathrm{ESS}} \tag{19}$$

$$B_{n,sc}^{\mathrm{PV}} = EP^{\mathrm{PV}} \sum_{t=1}^{24} \left(P_{n,sc,t}^{\mathrm{PV}}\Delta t\right) \tag{20}$$

$$B_{m,sc}^{\mathrm{WG}} = EP^{\mathrm{WG}} \sum_{t=1}^{24} \left(P_{m,sc,t}^{\mathrm{WG}}\Delta t\right) \tag{21}$$

$$B_{k,sc}^{\mathrm{ESS}} = \sum_{t=1}^{24} \left(EP_t\left(-P_{k,Sc,t}^{\mathrm{ESS}}\right)\Delta t\right) \tag{22}$$

$$C_{n,\mathrm{d}}^{\mathrm{PV}} = \frac{1}{365}\left(\delta_{\mathrm{PV}} cc^{\mathrm{PV}} P_n^{\mathrm{PV,R}} + cm^{\mathrm{PV}} P_n^{\mathrm{PV,R}}\right) \tag{23}$$

$$C_{m,\mathrm{d}}^{\mathrm{WG}} = \frac{1}{365}\left(\delta_{\mathrm{WG}} cc^{\mathrm{WG}} P_m^{\mathrm{WG,R}} + cm^{\mathrm{WG}} P_m^{\mathrm{WG,R}}\right) \tag{24}$$

$$C_{k,sc}^{\mathrm{ESS}} = \frac{\delta_{\mathrm{ESS}}}{365}\left(cc^{\mathrm{PCS}} P_k^{\mathrm{ESS,R}} + cc^{\mathrm{B\&R}} S_k^{\mathrm{ESS,R}}\right) + \frac{1}{365} cm^{\mathrm{FOM}} P_k^{\mathrm{ESS,R}} + cm^{\mathrm{VOM}} P_k^{\mathrm{ESS,R}} h_{k,sc} \tag{25}$$

Thus, in the process of EENS calculation, the features of uncertainty and contingency of RESs and ESSs are taken into account adequately.

### 3) OBJECTIVE FUNCTION OF LOWER LEVEL

The lower level is the consideration of optimal scheduling of ESSs in typical scenarios. From the perspective of DGO, the main objective of each ESS is to obtain more arbitrage revenue by temporal shifting of energy from peak load periods to valley load periods, shown as Eq.(26).

$$F_{k,sc}^{\mathrm{L}} = \max\left(B_{k,sc}^{\mathrm{ESS}}\right) \tag{26}$$

## B. CONSTRAINTS

Because the proposed planning model is related to the planning of networks, the allocation of RESs and ESSs, and the optimal operation of ESS, respectively, the constraints are related to the radial network structure constraint, equipment investment constraint, operation constraints of network and ESS, and etc.

### a: RADIAL NETWORK STRUCTURE CONSTRAINT

Due to operation requirements in open loop, each candidate topology of distribution network should be a radial network without any isolated load bus, isolated load chain, or ring net. For this propose, the graph theory based method proposed in [21] is adopted in this paper, where the branch-bus incidence matrix serves to check and guarantee the radial and unabridged network structure.

### b: INSTALLED CAPACITY CONSTRAINT

In order to alleviate the harmful influences brought by bi-directional power flow, the integration proportion of RESs should be smaller than a permissible value, shown as Eq.(27).

$$\left(\sum_{m\in\Omega_{\mathrm{WG}}} P_m^{\mathrm{WG,R}} + \sum_{n\in\Omega_{\mathrm{PV}}} P_n^{\mathrm{PV,R}}\right) \le \lambda_{\mathrm{I}} S^{\mathrm{sub}} \tag{27}$$

### c: OPERATION CONSTRAINTS OF NETWORK

Operation constraints of networks are shown as Eq.(28)-(33), including active/ reactive power balance equations, power flow equations, and security constraints of current and voltage.

$$P_{sc,t}^{\mathrm{sub}} = \sum_{i\in\Omega_{\mathrm{bus}}} P_{i,sc,t}^{\mathrm{load}} + \sum_{k\in\Omega_{\mathrm{ESS}}} P_{k,sc,t}^{\mathrm{ESS}} + P_{sc,t}^{\mathrm{loss}} - \sum_{m\in\Omega_{\mathrm{WG}}} P_{m,sc,t}^{\mathrm{WG}} - \sum_{n\in\Omega_{\mathrm{PV}}} P_{n,sc,t}^{\mathrm{PV}} \tag{28}$$

$$Q_{sc,t}^{\mathrm{sub}} = \sum_{i\in\Omega_{\mathrm{bus}}} Q_{i,sc,t}^{\mathrm{load}} + \sum_{k\in\Omega_{\mathrm{ESS}}} Q_{k,sc,t}^{\mathrm{ESS}} + Q_{sc,t}^{\mathrm{loss}} - \sum_{m\in\Omega_{\mathrm{WG}}} Q_{m,sc,t}^{\mathrm{WG}} - \sum_{n\in\Omega_{\mathrm{PV}}} Q_{n,sc,t}^{\mathrm{PV}} \tag{29}$$

$$P_{i,sc,t} = U_{i,sc,t} \times \sum_{i,j\in\Omega_{\mathrm{bus}}} U_{j,sc,t}\left(G_{ij}\cos\theta_{ij,sc,t} + B_{ij}\sin\theta_{ij,sc,t}\right) \tag{30}$$

$$Q_{i,sc,t} = U_{i,sc,t} \times \sum_{i,j\in\Omega_{\mathrm{bus}}} U_{j,sc,t}\left(G_{ij}\sin\theta_{ij,sc,t} - B_{ij}\cos\theta_{ij,sc,t}\right) \tag{31}$$

$$U_i^{\min} \le U_{i,sc,t} \le U_i^{\max} \tag{32}$$

$$\begin{cases} \left|I_{a,sc,t}\right| \le I_a^{\max} \\ \left|I_{b,sc,t}\right| \le I_b^{\max} \\ \left|I_{c,sc,t}\right| \le I_c^{\max} \end{cases} \tag{33}$$

### d: OPERATION CONSTRAINTS OF ESSs

The operation of ESS should be strictly under the constraints of the periodical behaviors, the permissible ranges of state of charge (SOC) and charging/ discharging power, shown as Eq.(34)-(37).

$$E_{k,sc,t}^{\mathrm{ESS}} = \begin{cases} E_{k,sc,t-1}^{\mathrm{ESS}} + P_{k,sc,t}^{\mathrm{ESS}} \eta_{\mathrm{C}} \Delta t, & P_{k,sc,t}^{\mathrm{ESS}} \ge 0 \\ E_{k,sc,t-1}^{\mathrm{ESS}} + \left(P_{k,sc,t}^{\mathrm{ESS}} \Delta t\right)/\eta_{\mathrm{D}}, & P_{k,sc,t}^{\mathrm{ESS}} < 0 \end{cases} \tag{34}$$

$$\sum_{t=1}^{24} \left( P_{k,sc,t}^{\mathrm{ESS}} \eta_{\mathrm{C}} \Delta t + \left(P_{k,sc,t}^{\mathrm{ESS}} \Delta t\right)/\eta_{\mathrm{D}} \right) = 0 \tag{35}$$

$$Soc^{\min} \le Soc_{k,sc,t} \le Soc^{\max} \tag{36}$$

$$\left|P_{k,sc,t}^{\mathrm{ESS}}\right| \le P_k^{\mathrm{ESS,R}} \tag{37}$$

## IV. OPTIMIZATION METHOD FOR PLANNING MODEL

### A. ESTABLISHMENT OF TYPICAL DAILY SCENARIOS

Currently, probabilistic models, such as Weibull distribution, Beta distribution, and Normal distribution, are always adopted to model wind speed, solar illumination, and load demand, respectively. However, these probabilistic models have no ability to represent the time-sequence. Hence, the operation scheduling of ESS based on these profiles may be not correct due to strict timing sequence constraints of ESS. In addition, time-sequence complementarity between multi-RESs and load demand may escape researchers' notice.

To tackle these problems and take these uncertainties into account, typical scenarios are established with the corresponding probabilities by K-mean clustering algorithm based on the annual forecasted data of wind speed, solar illumination, and load demand. The detailed process is described as follows.

(1) Uniformization: The annual forecasted data are uniformized by the respective maximums and minimums. Then the normalized annual time-dependent data are segmented into 365 daily intervals to establish the initial daily scenario matrix $S_{\text{initial}}$.

(2) K-mean clustering: These 365 daily patterns are clustered into typical daily profiles by K-means clustering. In order to take the quality and diversity of these selected typical daily scenarios into account adequately, the number of clustering is determined by the validity index of Davies Bouldin $I_{\mathrm{DB}}$ [22]. Hence, the matrix $S_{\text{initial}}$ is converted to be the typical daily scenario matrix $S_{\text{clustered}}$. $I_{\mathrm{DB}}$ can be calculated by Eq.(38)-(41).

$$I_{\mathrm{DB}}\left(N_{\mathrm{C}}\right) = \frac{1}{N_{\mathrm{C}}} \sum_{g=1}^{N_{\mathrm{C}}} \left( \max_{h=1,\ldots,N_{\mathrm{C}},h\ne g} R_{gh} \right) \tag{38}$$

$$R_{gh} = \left(S_g + S_h\right)/d_{gh} \tag{39}$$

$$S_g = \frac{1}{N_g} \sum_{x \in c_g} d\left(x, c_g\right) \tag{40}$$

$$d_{gh} = \left\| c_g - c_h \right\| \tag{41}$$

(3) Restoration of variables' bounds: Then, the variables of matrix $S_{\text{clustered}}$ are restored to the original bounds, which can be used to optimize the planning schemes.

Thus, typical daily scenarios are extracted from annual prediction profiles and assumed to be sufficiently representative of the time-variable natures and inherent simultaneity between multiple RESs and load demand.

### B. SOLVING ALGORITHMS

The proposed model is a problem of multi-objective, multi-level, multi-constraint, non-linear optimization with mixed-integers. To satisfy the demands of efficiency and convergence, particle swarm optimization (PSO) is adopted to address this problem. PSO is an effective intelligent algorithm to solve non-linear, multi-extrema optimization problems, and it has widely served for power system analyses including power system planning problems. In this paper, several improvement measures are adopted to further improve the performance of PSO in solving the proposed planning problem, shown as follows.

(1) Tent chaos mapping: To avoid pseudo-random number sequence, the tent chaos mapping is applied to generate the initial population, which has better features of ergodicity and randomness than the logistic mapping [23].

(2) Combination of genetic algorithm and PSO: The fast non-dominated sorting approach, which is used in fast non-dominated sorting genetic algorithm [24], is introduced in the modified PSO. Meanwhile, the global best solution in each iteration is selected according to the crowding-distance assignment of the non-dominated solutions.

(3) Integer programming based on roulette algorithm: In view of the integer programming of upper level and middle level, the position of each particle in the solution space has to be converted to an integer variable. Instead of rounding off the value to the nearest integer, the roulette algorithm is adopted based on the distances between the non-integer variable and all the candidate integer variables.

### C. SOLUTION FLOW

There are three different optimization procedures to deal with these three levels, respectively. The optimization procedure of lower level is embedded in the middle level, and the optimization procedure of middle level is embedded in the upper level, shown as Fig. 2.

In the beginning, the initial population of upper level is generated by tent mapping for Pareto-based multi-objective PSO. Then, the first particle of upper level, representing a candidate network structure, is sent to the middle level. In this specified network, the initial population of middle level is generated for chaos PSO. Then, the particle of middle level, representing a candidate allocation scheme of RESs and ESSs, is sent to the lower level together with the specified

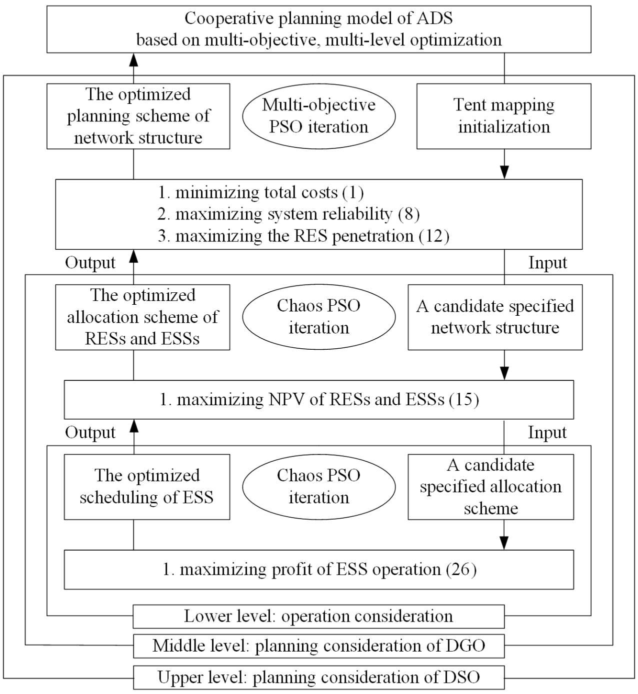


**FIGURE 2.** Optimization procedure of finding optimal planning schemes.

network. Thus, the short time scale optimal power flow is executed by chaos PSO to optimize the scheduling of each ESS in the condition of the specified network and the specified allocation of RESs and ESSs. Then, the obtained operation scheduling of each ESS is fed back to the middle level to calculate the optimization objective of this candidate allocation scheme. After the optimization of middle level, the optimized allocation scheme and operation scheduling are fed back to the upper level to calculate the planning objectives of DSO. The same steps are iterated until Pareto-based multi-objective PSO converges.

There is no doubt that the three-level optimization iteration requires more computational time, but for a long-term planning problem the computational time is not a very critical issue.

## V. CASE STUDY

### A. PARAMETERS OF TEST SYSTEM

To investigate effectiveness of the proposed planning model, three computational cases are executed based on IEEE 33-bus distribution system, shown as Fig. 3.

The system serves the peak demand of 3715+j2300 kVA currently, and the planning scheme is implemented in 10 years with the load growth of 3%. Besides the basic networks, 5 new load points and 11 candidate feeders are depicted by star-shape nodes and dashed lines, respectively. Three types of feeder are considered as candidate solutions for new feeders and upgrade of the basic system, shown as Table 1.

The contract prices of WGs and PVs are 65 and 78 ($/MW), respectively [16]. The time of use (TOU) electricity prices are shown in Fig. 4, extracted in [26].

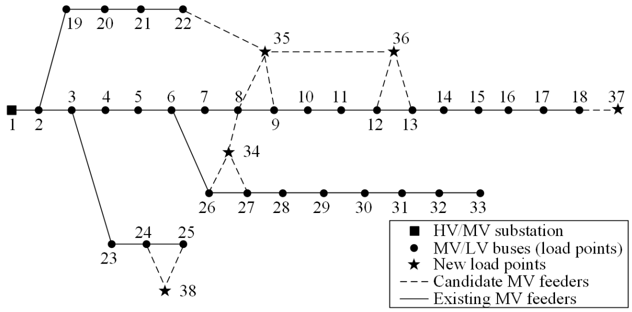


**FIGURE 3.** The modified 33-bus distribution test system.

**TABLE 1.** Candidate feeders' specifications [25].

| | Feeder 1 | Feeder 2 | Freeder 3 |
|---|---|---|---|
| Nominal current (A) | 158 | 250 | 453 |
| R (Ω/km) | 0.10145 | 0.52050 | 0.2006 |
| X (Ω/km) | 0.4679 | 0.4428 | 0.4026 |
| Failure rate (fail/km year) | 0.2 | 0.2 | 0.2 |
| Repair time (hour/fail) | 0.33 | 0.33 | 0.33 |
| Capital cost($/km) | 29089.18 | 29502.73 | 29990.00 |
| Replacement cost ($/km) | 5188.22 | 5601.78 | 7090.00 |
| Fixed cost ($) | 3232.13 | 3278.08 | 3110.00 |

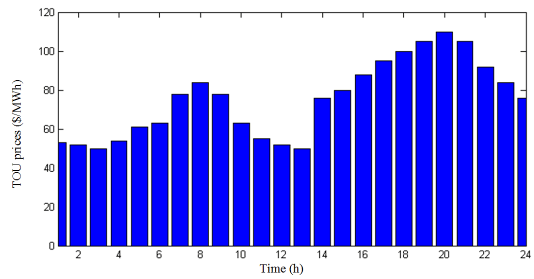


**FIGURE 4.** TOU electricity prices of non-renewable energy.

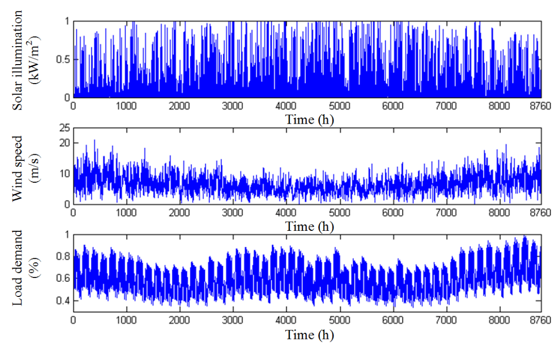


**FIGURE 5.** Annual data of wind speed, solar irradiance, and load demand.

To ease the computational burden, we assume that the atmospheric conditions are similar in the candidate locations for RESs. The different atmospheric conditions can be handled easily by means of the extension of daily scenario matrix dimension if necessary. Fig. 5 shows these predicted annual profiles.

The candidate locations, technical and economic parameters of RESs and ESSs are provided in Table 2.

**TABLE 2. Parameters of RESs and ESSs [12], [27], [28].**

| | WG | PV | ESS |
|---|---|---|---|
| Candidate buses | 24,31,32,37,38 | 8,14,18,22,30 | 7,25 |
| Capital cost | 1220 (\$/kW) | 1750 (\$/kW) | 175 (\$/kW)<br>225 (\$/kWh) |
| O&M cost | 33 (\$/kW·y) | 16 (\$/kW·y) | 4 (\$/kW·y)<br>2 (\$/MWh) |
| Lifetime | 25(y) | 25(y) | 20(y) |

For comparison purposes, three cases are presented to investigate the availability and effectiveness of the proposed planning model, shown as Table 3.

**TABLE 3. Case arrangement.**

| | Case 1 | Case 2 | Case 3 |
|---|---|---|---|
| Network planning | ✓ | ✓ | ✓ |
| Allocation of RESs | × | ✓ | ✓ |
| Allocation of ESSs | × | × | ✓ |
| Planning model | Single-level model | Bi-level model | Proposed model |

## B. RESULTS OF TYPICAL DAILY SCENARIOS

The typical daily scenarios are extracted from predicted annual profiles by means of K-means cluster shown as Fig. 6, respectively.

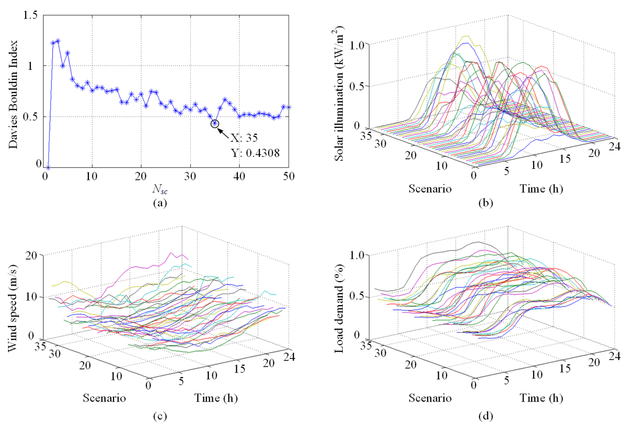


**FIGURE 6. Results of typical daily scenarios. (a) Variation trend of $I_{DB}$. (b) Typical scenarios of solar illumination. (c) Typical scenarios of wind speed. (d) Typical scenarios of load demand.**

In order to balance the computational burden and accuracy of planning calculation, the number of cluster is determined by Davies Bouldin index in the interval of [2, 50]. As shown in Fig. 6 (a), the value reaches the minimum when the clustering number equals to 35, which is the proper number for typical daily scenarios with high quality and diversity. Thus, these 35 typical daily scenarios are assumed to be sufficiently representative of the time-variable natures and inherent simultaneity between multiple RESs and load demand.

## C. RESULTS OF PLANNING PROBLEMS

In each case, seven alternative non-dominated solutions are provided for decision-makers, shown as Fig. 7.

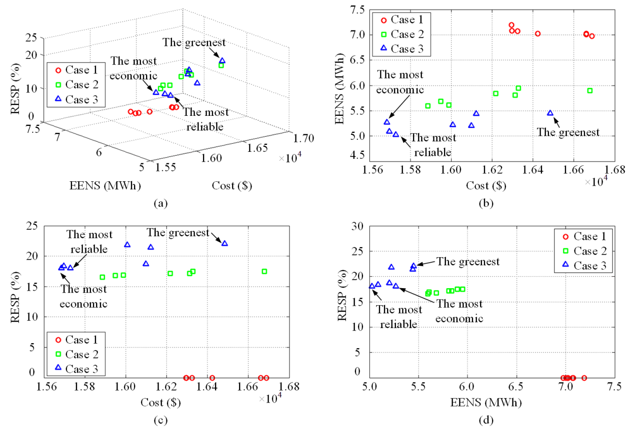


**FIGURE 7. Comparison of Pareto-approximation fronts. (a) Planning results (Cost, EENS, RESP). (b) Planning results (Cost, EENS). (c) Planning results (Cost, RESP). (d) Planning results (EENS, RESP).**

It is observed that the decision-makers have the flexibility to choose the appropriate planning schemes based on different perspectives of economy, reliability, and environment. As shown in Fig. 7, the average level of total costs and EENS depicted by these blue triangles obtained by Case 3 are smaller than others, and the values of RES penetration are also bigger than others. It means that the Pareto-based solutions of Case 3 have a better overall performance than the solutions of other two cases, especially in terms of reliability and RES penetration.

**TABLE 4. Optimal solution of different cases.**

| | Case 1 | Case 2 | Case 3 |
|---|---|---|---|
| **DSO** | | | |
| Cost iterms | | | |
| Inv. & Mai. (\$/d) | 8811.55 | 8415.93 | 8391.20 |
| Operation (\$/d) | 7848.30 | 7573.28 | 7306.58 |
| Total costs (\$/d) | 16659.85 | 15989.22 | 15697.79 |
| EENS (MWh) | 7.01 | 5.60 | 5.08 |
| RESP (%) | – | 16.90% | 18.37% |
| **DGO** | | | |
| Cost iterms | | | |
| Investment (\$) | – | $2.89\times10^6$ | $3.61\times10^6$ |
| Annual NPV (\$/y) | – | 13671.07 | 15021.21 |
| Diurnal NPV (\$/d) | – | 374.55 | 411.54 |
| WG (MW) | – | Bus 24: 0.30<br>Bus 31: 0.20<br>Bus 32: 0.20<br>Bus 37: 0.30<br>Bus 38: 0.30 | Bus 24: 0.40<br>Bus 31: 0.20<br>Bus 32: 0.20<br>Bus 37: 0.30<br>Bus 38: 0.40 |
| PV (MW) | – | Bus 08: 0.20<br>Bus 14: 0.15<br>Bus 18: 0.10<br>Bus 22: 0.10<br>Bus 30: 0.20 | Bus 08: 0.20<br>Bus 14: 0.05<br>Bus 18: 0.10<br>Bus 22: 0.10<br>Bus 30: 0.25 |
| ESS (MW, MWh) | – | – | Bus 07: 0.25; 0.75<br>Bus 25:0.40; 1.20 |

For the purpose of further analyses, the well-balanced solutions of these three cases are selected by fuzzy satisfaction-maximizing [23]. The corresponding cost items, reliability indexes, and RES penetration are demonstrated in Table 4.

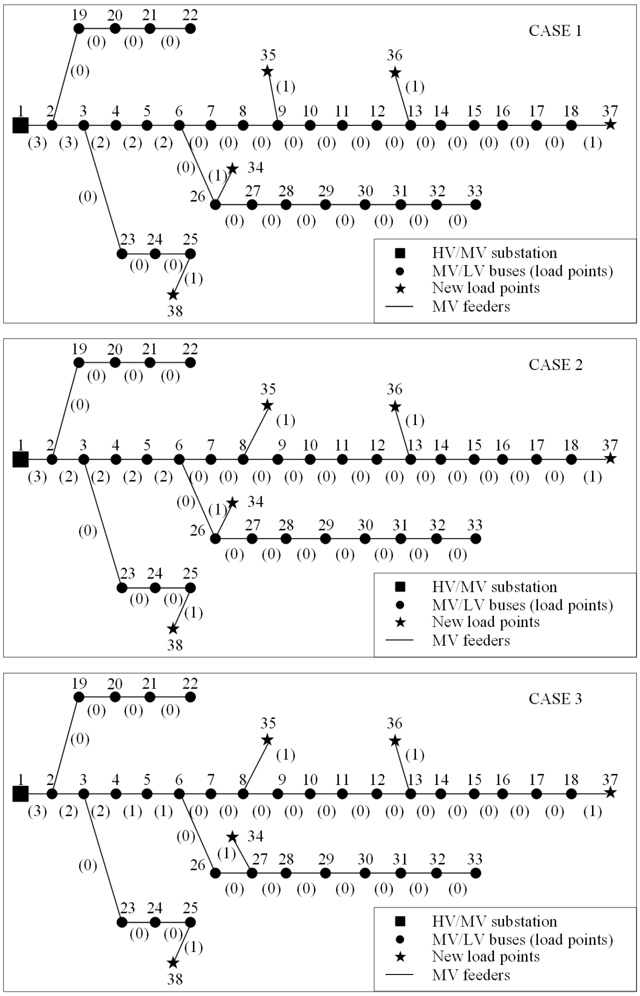


**FIGURE 8. Alternative planning schemes of networks.**

Fig. 8 provides these three planning solutions of networks, where the bracketed numbers imply the types of these feeders and zero means the feeders without being upgraded.

From the comparisons between Case 1 and Case 3, it can be seen that the total diurnal costs of DSO experience a decrease from 16659.85 ($) to 15697.79 ($). Thus the cost saving can reach more than $351\times10^3$ ($) for each year. It also can be found that the optimal integration of RESs and ESSs brings monetary benefits not only in ADS investment but also in ADS operation. As shown in Table 4, the costs related to ADS investment and ADS operation for DSO decrease by 4.78% and 6.91%, respectively.

In the meanwhile, the reliability items indicate that the planning scheme with RESs and ESSs possess a better reliability performance than the network planning scheme without RESs and ESSs; the resultant reduction of reliability index reaches 20%. Furthermore, clean RESs share more than 18.37% of the total power supply in Case 3.

It is also interesting to compare the results between Case 2 and Case 3. From the perspective of DGO, with the integration of ESSs and more RESs, the diurnal average net revenue of DGO experience an increase from 374.55 ($) to 411.54 ($). The expensive capital costs, and O&M costs contribute to the slow growth of revenue, but more net revenues can be obtained in Case 3 due to more share of RESs and peak load temporal shifting by operation of ESSs. Therefore, the optimal integration of ESSs brings about almost 10% increment in net revenues, and the planning scheme with ESSs has a more desirable investment attraction.

From the perspective of DSO, with the integration of ESSs, DSO also can obtain some benefits. Firstly, DSO spends less money on the feeders' investment and maintenance. The reason is that the operation of ESSs has desirable effects on peak load shaving and valley load filling, which brings about investment reduction to upgrade two existing feeders. Moreover, ADS with ESSs possesses a better reliability performance; the integration of ESSs brings about more than 9.3% reduction in EENS.

To illustrate operation conditions, operation profiles of the ADS and ESSs in the typical scenario 23 with the largest probability of occurrence, are shown in Fig. 9, respectively.

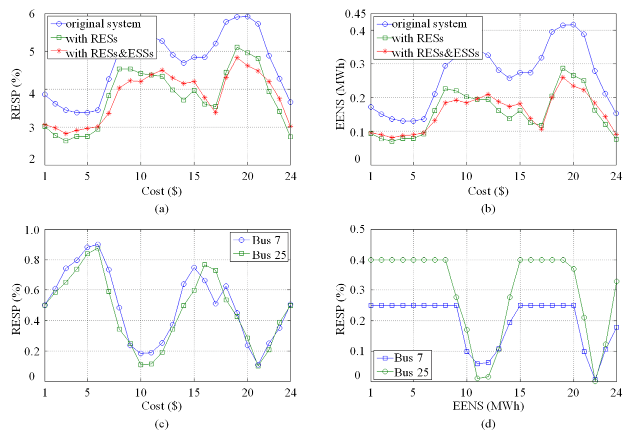


**FIGURE 9. Curves of operation situations of ADS and ESSs. (a) Curves of net load demands. (b) Curves of active losses. (c) Curves of SOC conditions. (d) Curves reserve capability.**

As can be seen from curves of net load demand and power losses, optimal operation of ESSs has recommendable effects on peak load shaving and valley load filling, which reflects on both upgrade deferral and reduction of operation costs as mentioned above. It is also worthy to mention that the similar fluctuation trends between load demands and TOU electricity prices contribute to the desirable effects.

The reserve capability curves of ESSs, shown as Fig. 9 (d), indicate that ESSs can provide power supply to the essential load and be ready to participate in system service restoration in most of the day.

Furthermore, the operation of ESSs has positive effects on alleviating the mismatch between power outputs of RESs and load demands, which relieves feeders' congestion and voltage over-limit. As a result, the harvest of RESs is also improved as shown in Table 5.

Fig. 10 depicts the active power profiles of load demands and power outputs during typical scenario 23 in case 3.

**TABLE 5. Profiles of renewable energy resources.**

| | Case 2 | Case 3 | Growth rate |
|---|---|---|---|
| RES penetration | 16.90% | 18.37% | 8.69% |
| Capacity penetration | 32.69% | 35.00% | 7.06% |

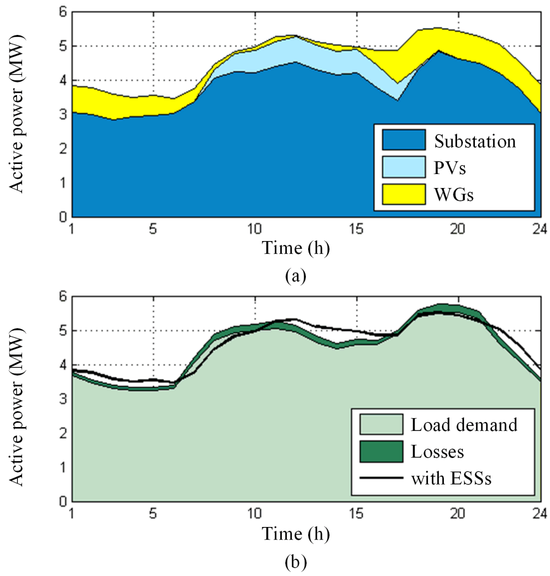


**FIGURE 10. Curves of operation situations of ADS and ESSs. (a) Active power profiles of power supply. (b) Active power profiles of load demand.**

It can be observed that, more than 18.81% of the load demands are supplied by RESs. Meanwhile, it is significantly noticeable that the sequential complementarity between PVs and WGs can be taken into account adequately in the proposed planning model.

From the analyses above, it is obvious that optimal operation of ESSs has significant effects on ADS planning, and the proposed multi-level planning mode has the ability to take optimal operation of ESSs into account adequately. Meanwhile, the proposed planning model enables us to take different stakeholders into account and create a win-win situation.

## VI. CONCLUSIONS

In this paper, a cooperative planning model of ADS is proposed based on multi-objective, multi-level optimization methodology. The availability and effectiveness of the proposed model are well demonstrated by the case studies with several final remarks and conclusions.

Results shows that the optimal allocation and coordinated operation of the RESs and ESSs are beneficial for both DGO and DSO to increase economic efficiency, improve system reliability, and promote green energy utilization.

Based on the multi-level optimization, the proposed planning model enables the ADS operation to be explicitly represented in the ADS planning calculations. In addition, the planning of networks, and the allocation of RESs and ESSs are optimized cooperatively considering the different perspectives of multiple stakeholders.

Based on K-means clustering and the multi-scenario tool, annual time-dependent data are processed into typical daily scenarios effectively, which can capture the time-variable natures and uncertainties related to RESs and load demand, while easing the computational burden.

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