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Two-Stage Hierarchical Congestion Management Method for Active Distribution Networks With Multi-Type Distributed Energy Resources

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ABSTRACT More and more distributed energy resources (DERs) are being integrated into the distribution networks raising the new concerns of secure and economic operations. Some traditional distribution networks are upgraded to active distribution networks (ADNs) which can communicate with and control the DERs. A microgrid connected to an ADN can be coordinated with the ADN. In this paper, a two-stage hierarchical congestion management mechanism is proposed for an ADN connected with multi-type DERs and microgrids. At the first stage, a hierarchical optimization model is built considering the dispatch of direct control resources (DCRs) and microgrids. An analytical target cascading (ATC) method is employed to optimize the microgrid autonomy model and the ADN optimization model simultaneously. A second stage optimization is designed to deal with the case when the control of DCRs and microgrids is not enough to completely eliminate the congestion. A congestion management model calling for the ancillary services provided by DERs is established, with an objective of minimizing the operational cost of distribution system operator (DSO). Case studies are carried out on modified IEEE 33 and PG&E 69 bus systems. The simulation results show that the proposed method can balance the interests of different stakeholders and eliminate the network congestion efficiently.

INDEX TERMS Active distribution network, distributed energy resources, congestion management, hierarchical optimization, analytical target cascading.

NOMENCLATURE

A. ABBREVIATIONS

DER	Distributed energy resource
ADN	Active distribution network
DCR	Direct control resource
ATC	Analytical target cascading
DSO	Distribution system operator
PV	Photovoltaic
EV	Electric vehicle
REG	Renewable energy generation
RCS	Remotely controlled switch
SOP	Soft open point
MT	Micro-turbine
DESS	Distributed energy storage system
SOCP	Second-order cone programming

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B. INDICES AND SETS

i, j	Index of nodes
k/M	Index and set of microgrid units
d/D	Index and set of renewable energy power stations
e/E	Index and set of EV charging stations
l/L	Index and set of flexible load aggregators
g/G	Index and set of DGs in the microgrid
Φ_i	Set of branch head nodes with node i as the end node
Ψ_i	Set of branch end nodes with node i as the head node
R	Set of network radial topologies

C. PARAMETERS

T	Total number of periods, T = 24
Δt	Time interval, $\Delta t = 1$h
$\lambda_{t,i}^{MG}$	Price of electricity transaction between distribution network and the microgrid connecting to node i at time t
λ_t^{grid}	Electricity purchasing price from the grid at time t
$Q_{\min i}^{SOP}$	Minimum reactive power output of SOP at node i
$Q_{\max i}^{SOP}$	Maximum reactive power output of SOP at node i
S_i^{SOP}	Capacity of SOP at node i
R_{ji}	Resistance of branch ji
X_{ji}	Reactance of branch ji
$P_{t,i}^{LOAD}$	Active power of base load at node i at time t
$Q_{t,i}^{LOAD}$	Reactive power of base load at node i at time t
$U_{i\min}$	Minimum voltage magnitude of node i
$U_{i\max}$	Maximum voltage magnitude of node i
$I_{ij\max}$	Maximum current of branch ij
$S_{ji,\max}$	Maximum action number of a single remotely controlled switch
$S_{\max}$	Maximum action number of all remotely controlled switches
N_0	Total number of nodes in the network
$P_{t,\min}^{grid}$	Lower limits of the power purchased from the grid at time t
$P_{t,\max}^{grid}$	Upper limit of the power purchased from the grid at time t
$P_{t,i,\min}^{MG}$	Lower limit of the interaction power between distribution network and the microgrid at node i at time t
$P_{t,i,\max}^{MG}$	Upper limit of the interaction power between distribution network and the microgrid at node i at time t
a/b/c	Corresponding cost coefficients of DGs
λ_t^{dis}	Cost coefficients of energy storages when discharging
λ_t^{ch}	Cost coefficients of energy storages when charging
$P_{g,t,\min}^{mDG}$	Minimum output of DG g in the microgrid at time t
$P_{g,t,\max}^{mDG}$	Maximum output of DG g in the microgrid at time t
Ru_g^{mDG}	Upward ramp rate of DG g in the microgrid
Rd_g^{mDG}	Downward ramp rate of DG g in the microgrid
$E_{\min}^{BA}$	Lower limit of energy storage's residual energy
$E_{\max}^{BA}$	Upper limit of energy storage's stored energy
$P_{\max}^{dis}$	Maximum discharge power of energy storage
$P_{\max}^{ch}$	Maximum charge power of energy storage
$\omega_{k,t}/\gamma_{k,t}$	First and second multipliers of the Lagrangian penalty function of microgrid k at time t
$\lambda_{t,d}^{DG}$	Transaction price between renewable energy power station d and the distribution network at time t
$\lambda_{t,d}^{DGpay}$	Congestion management bidding price of renewable energy power station d at time t
$P_{t,d,\max}^{DG}$	Scheduled output of renewable energy power station d at time t
$\lambda_{t,e}^{EVpay}$	Congestion management bidding price of EV charging station e at time t
$\tilde{P}_{t,e}^{EV}$	Scheduled charging demand of EV charging station e at time t
$\lambda_{t,l}^{ILpay}$	Congestion management bidding price of flexible load aggregator l at time t
$\tilde{P}_{t,l}^{IL}$	Scheduled load demand of flexible load aggregator l at time t
α	Loading coefficient of branches
$P_{t,e,\min}^{EV}$	Minimum charging demand of EV charging station e at time t
$P_{t,e,\max}^{EV}$	Maximum charging demand of EV charging station e at time t
$P_{t,d,\min}^{DG}$	Minimum output of renewable energy power station d at time t
$P_{t,d,\max}^{DG}$	Maximum of renewable energy power station d at time t
$P_{t,l,\min}^{IL}$	Minimum load demand of flexible load aggregator l at time t
$P_{t,l,\max}^{IL}$	Maximum load demand of flexible load aggregator l at time t

D. FUNCTIONS AND VARIABLES

C_t^{MG}	Revenue of distribution network from microgrids at time t
C_t^{grid}	Power purchase cost from the grid at time t
C_t^{DG}	Interaction cost between distribution network and renewable energy power stations at time t
C_t^{EV}	Interaction cost between distribution network and EV charging stations at time t
C_t^{IL}	Interaction cost between distribution network and flexible load aggregators at time t
$P_{t,i}^{MG}$	Power exchange between distribution network and the microgrid at node i at time t
P_t^{grid}	Active power purchased from the grid at time t
$P_{t,i}^{SOP}$	Active power of SOP at node i
$Q_{t,i}^{SOP}$	Reactive power of SOP at node i
$P_{t,ji}$	Active power of the branch from node j to node i at time t
$Q_{t,ji}$	Reactive power of the branch from node j to node i at time t
$P_{t,i}$	Total active power injection at node i at time t
$Q_{t,i}$	Total reactive power injection at node i at time t
$P_{t,i}^{DG}$	Active power of renewable energy power station at node i at time t
$Q_{t,i}^{DG}$	Reactive power of renewable energy power station at node i at time t
$P_{t,i}^{MG}$	Active power of microgrid at node i at time t

$Q_{t,i}^{\mathrm{MG}}$	Reactive power of microgrid at node i at time t
$P_{t,i}^{\mathrm{EV}}$	Active power of EV charging station at node i at time t
$Q_{t,i}^{\mathrm{EV}}$	Reactive power of EV charging station at node i at time t
$P_{t,i}^{\mathrm{IL}}$	Active power of flexible load aggregator at node i at time t
$Q_{t,i}^{\mathrm{IL}}$	Reactive power of flexible load aggregator at node i at time t
$U_{t,i}$	Voltage amplitudes of node i at time t
$I_{t,ji}$	Current amplitude from node j to node i at time t
$\alpha_{ji,t}$	RCS state of branch ji at time t, $\alpha_{ji,t} = 0$ means open, and $\alpha_{ji,t} = 1$ means closed
g	Topology after reconfiguration of distribution network
F^{MG}	Total operation cost of microgrid
C_t^{G}	Cost of power generation of DGs at time t
C_t^{buy}	Cost of purchasing power from the distribution network at time t
C_t^{BA}	Operation cost of energy storage at time t
$P_{g,t}^{\mathrm{mDG}}$	Output of DG g in the microgrid at time t
P_t^{dis}	Discharge power of energy storage at time t
P_t^{ch}	Charging power of energy storages at time t
E_t^{BA}	Residual energy of energy storage at time t
$u_t^{\mathrm{ch}}/u_t^{\mathrm{dis}}$	Charging/Discharging states of energy storages at time t, binary variables
$P_{t,d}^{\mathrm{DG}}$	Power from renewable energy power station d to the distribution network at time t
$P_{t,e}^{\mathrm{EV}}$	Actual charging demand of EV charging station e at time t
$P_{t,l}^{\mathrm{IL}}$	Actual load demand of flexible load aggregator l at time t

I. INTRODUCTION

In recent years, the rapid development of customer-side distributed energy resources (DERs) in distribution networks has played a positive role in the development and utilization of renewable energy, fossil energy consumption reduction and carbon emission decrease. However, the output plans or load demands of DERs often reflect a spatial or temporal aggregation effect, due to the natural characteristics of renewable energy or social behavior regularity. For example, distributed photovoltaic (PV) outputs often reach peaks at noon, and electric vehicles (EVs) are usually charged at night in residential areas [1], [2]. These phenomena will probably cause power flow overload and distribution networks will be congested [3]. For distribution system operator (DSO), the congestion will threaten system security, increase dispatch and operation difficulty and limit the penetration of renewable energy generations (REGs). For consumers, the congestion will restrict electricity transactions, generate congestion costs and increase their expenditure on purchasing electricity [4], [5].

In terms of the distribution network congestion, DSO generally solves it by direct control methods such as distribution network reconfiguration [6]. The reconfiguration based on remotely controlled switches (RCSs) can alter power flow distribution by changing the network topology. It is possible to solve the distribution network congestion problem without affecting user's power consumption and the output of DERs [7], [8]. Nevertheless, there are some problems in distribution network reconfiguration, such as closed loop current and long operation time. Based on this, SOPs (soft open points) instead of RCSs were adopted to solve the network congestion problem in [9], which has flexible regulation characteristic and more efficient management effects.

Microgrids can play a supporting role in the operation and management of distribution networks. For the distribution network management problem with microgrids, there are centralized [10], [11] and distributed [12]–[14] control and optimization methods. The centralized method needs a control center to collect all the operational data of the DERs and microgrids, which leads to a high computational burden. And the centralized method usually aims at optimizing the economic benefits of the distribution network without considering the specific interests of each microgrid. In [12], a distributed hierarchical cooperative control strategy was proposed for a cluster of islanded microgrids with intermittent communication. While in [13], a cluster-oriented cooperative control strategy for multiple ac MG clusters was proposed, and the power sharing among multiple MG clusters can be achieved. For the secondary power management of multiple microgrid system, a novel strategy with cluster-oriented two-layer cooperative framework was proposed in [14]. However, these methods are mainly applied to distributed real-time voltage/frequency control for multiple microgrid systems, which are not applicable to the problem of the coordinated scheduling for the distribution network connected with microgrids.

In addition, although extensive integration of multi-type DERs increases the risk of distribution network congestion, the flexibility owned by microgrids and DERs, such as EV charging demands and flexible load aggregators, also enhance the capability of network congestion management. [15] considers that aggregators and energy suppliers provide flexible resources at a certain cost or price, and establishes an optimal dispatch model which aims at reaching the minimum total cost of DSO and solving the network congestion problem by dispatching the flexible resources. In [16], a load reduction method based on mixed integer programming is proposed to solve the distribution network congestion problem when flexible resources are insufficient, which can effectively improve the selection process of the buses for active power curtailment and ensure the users' equity.

In order to solve the network congestion problem more efficiently, direct control resources (DCRs) of distribution network should be fully considered for optimal network operation, and the ancillary services provided by DERs can also be utilized. The DCRs, such as RCSs and SOPs, have limited regulation capabilities with lower usage costs [17]. The flexible regulation capabilities provided by DERs require higher costs from DSO, but it can make up for the lack of DCR regulation capacity in the periods of severe congestion [18]. Currently, DCRs and DERs are usually considered to address the network congestion problem separately. It is likely that the penetration of REGs is limited due to insufficient regulation capabilities of DCRs, or excessively high operation and management costs are resulted in due to totally relying on ancillary services of flexible resources [19], [20].

The main challenging problem on network congestion management with the coordinated optimization of DCRs and DERs is how to design a reasonable management mechanism and optimization method to achieve more efficient solutions. The controllable resources for DSO including RCSs, SOPs, microgrids, REGs, EV charging stations and flexible load aggregators, have different stakeholders, operational characteristics and adjustment costs. The network congestion management mechanism should achieve the goal of balancing the interests of all stakeholders and increasing DER penetration while eliminating congestion. Moreover, the proposed problem including both continuous (DERs, SOPs) and discrete (RSCs) variables in multi periods, is complex and difficult to be solved, which needs a more efficient optimization method.

Based on the above, this paper proposes a two-stage hierarchical congestion management mechanism for active distribution networks (ADNs) with multi-type distributed energy resources. This method relies on the power flow control capabilities of DCRs and microgrids, and the ancillary services for congestion management provided by DERs. At the first stage, a hierarchical optimization model is built considering the dispatch of DCRs and microgrids. An analytical target cascading (ATC) method is employed to optimize the microgrid autonomy model and the ADN optimization model simultaneously. A second stage optimization is designed to deal with the case when the control of DCRs and microgrids is not enough to completely eliminate the congestion. A congestion management model calling for the ancillary services provided by DERs is established, with an objective of minimizing the operational cost of DSO. Finally, two systems, i.e. modified IEEE 33 and PG&E 69 bus systems, are adopted to verify the validity of the proposed method.

The contributions of this work are as follows:

1) A two-stage hierarchical congestion management formulation is built, which can reduce the management costs of ADN and simultaneously coordinate the benefits of the AND, microgrids and DERs.

2) A solution method based on analytical target cascading method is proposed to solve the two-stage hierarchical congestion management problem, which solves the optimization subproblems of the microgrid and the distribution network separately and iteratively to improve efficiency and avoid the problem of dimensional disasters.

The rest of this paper is organized as follows: Section 2 presents a two-stage hierarchical congestion management mechanism for ADNs. Section 3 addresses a hierarchical coordinated dispatch model of ADNs and microgrids at the first stage. Network congestion management model of DERs at the second stage is provided in Section 4. Case studies and numerical results are given in Section 5. Finally, the paper is concluded in Section 6.

II. TWO-STAGE HIERARCHICAL CONGESTION MANAGEMENT MECHANISM FOR ADNS

Fig. 1 is a schematic diagram of active distribution network management framework with multi-type controllable resources. It can be seen that the controllable resources of ADNs include DCRs such as RCSs and SOPs, microgrids, and DERs such as EV charging stations, renewable energy power stations, and flexible load aggregators. There has been some published works on the operation optimization model of active distribution networks using these controllable resources. The ADN operation model that optimizes DCRs usually aims at minimizing the cost of active power losses [21], [22]. The feeder load unbalance is mitigated by optimizing a multi-terminal SOP-based model of ADN in [23]. For the ADN with microgrids, the energy management model needs to balance the economic benefits of distribution networks and microgrids [24]. In [25], the ADN management system targets to minimize the day-ahead total operation cost by means of optimally controlling active elements of the network, microgrids and DERs.

Among these three types of resources, DCRs belong to DSO, so the adjustment costs of DCRs is very low. Microgrids have micro-turbines (MTs), distributed energy storage systems (DESSs) and other control equipment, which can provide regulation capabilities for ADN congestion management while realize microgrid self-optimization operation

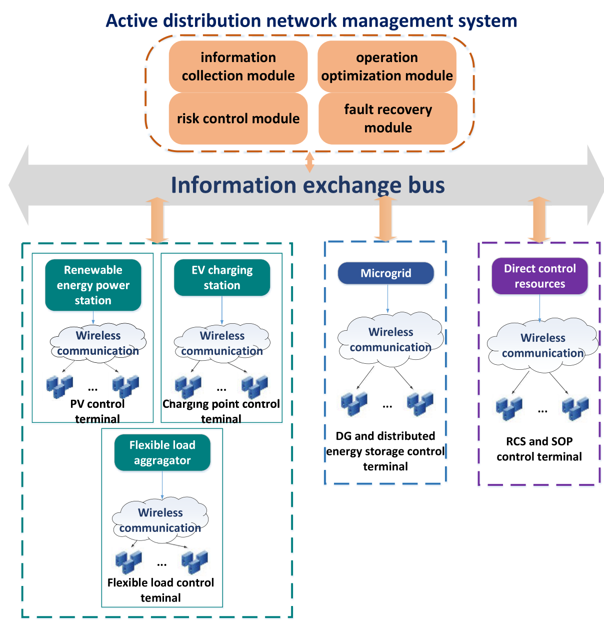

FIGURE 1. Active distribution network management framework with multi-type controllable resources.

when grid-connected [26]. Therefore, in the distribution network congestion management, DCRs and microgrids are given priority as regulation resources. At the same time, because microgrids and DCRs have different operating entities, the two types of resources need to be optimized separately. DERs generally operate in accordance with their output plans or load demands and it will incur high costs if the schedule outputs of DERs are changed. Therefore, they are used as the second-stage candidate control options when priority control resources cannot eliminate network congestion.

Based on the above analysis, we design a two-stage hierarchical congestion management mechanism for the DSO to solve the congestion problem of distribution network. The proposed mechanism includes two stages.

At the first stage, the regulation capability of DCRs and microgrids are used to solve the congestion problem with lower costs, while self-economic optimization of microgrids can be achieved. At this stage, DERs are operated according to their output plans or load demands, which avoids the impact of congestion on consumers. Considering the benefit balance between ADN and microgrids, an economic optimization model based on DCRs is established at ADN level, and an internal economic dispatch model of the microgrid is established at microgrid level. ATC is adopted to achieve the parallel coordinated optimization of the hierarchical model. When the congestion is severe, the regulation capabilities of DCRs and microgrids may be insufficient and network congestion cannot be fully removed at the first stage. In this case, DERs will be used to provide the ancillary services for congestion management, DSO sends signals to each DER, and DERs respond to the signals by uploading their congestion management bidding prices to DSO. Based on the prices, a congestion management model is set up with an objective of minimizing the operational cost of DSO, then optimization results are sent to each DER. In order to further reduce congestion management costs and ensure solving the congestion problem completely, the first stage is re-optimized with the DER optimization results of the second stage. The framework and flowchart of the two-stage hierarchical active distribution network congestion management approach is shown in Fig. 2.

III. HIERARCHICAL DISPATCH MODEL FOR ADNS AND MICROGRIDS AT THE FIRST STAGE

A. ECONOMIC OPTIMIZATION MODEL OF ACTIVE DISTRIBUTION NETWORK

At the first stage, it is preferred to utilize the direct control resources of ADNs and microgrids for network congestion management. ADNs and microgrids have different optimization objectives and a hierarchical coordinated dispatch model of ADNs and microgrids is established. DSO are responsible for the operation of ADNs, thus the optimization objective of ADN level is to minimize the total operation and management cost of DSO. The objective function is given as follows:

$$\min F^{\mathrm{co}}=\sum_{t=1}^{\mathrm{T}}(C_t^{\mathrm{grid}}+C_t^{\mathrm{DG}}+C_t^{\mathrm{EV}}+C_t^{\mathrm{IL}}-C_t^{\mathrm{MG}}) \tag{1}$$

At the first stage, DERs including renewable energy power stations, EV charging stations, and flexible load aggregators do not participate in congestion management, but operate optimally according to their output plans or power demands. Therefore, their costs have no effect on the objective function, and the objective function can be simplified as:

$$\min F^{\mathrm{co}}=\sum_{t=1}^{\mathrm{T}}(C_t^{\mathrm{grid}}-C_t^{\mathrm{MG}}) \tag{2}$$

$$C_t^{\mathrm{MG}}=\sum_{i\in \mathrm{M}}\lambda_{t,i}^{\mathrm{MG}}\Delta t P_{t,i}^{\mathrm{MG}} \tag{3}$$

Constraints include SOP operation constraints, network power flow constraints, and operational constraints of the other controllable resources. They are given as follows:

$$\begin{cases} P_{s,i}^{\mathrm{SOP}}+P_{s,j}^{\mathrm{SOP}}=0\\ Q_{\min i}^{\mathrm{SOP}}\le Q_{s,i}^{\mathrm{SOP}}\le Q_{\max i}^{\mathrm{SOP}}\\ Q_{\min j}^{\mathrm{SOP}}\le Q_{s,j}^{\mathrm{SOP}}\le Q_{\max j}^{\mathrm{SOP}}\\ (P_{s,i}^{\mathrm{SOP}})^2+(Q_{s,i}^{\mathrm{SOP}})^2\le (S_i^{\mathrm{SOP}})^2\\ (P_{s,j}^{\mathrm{SOP}})^2+(Q_{s,j}^{\mathrm{SOP}})^2\le (S_j^{\mathrm{SOP}})^2 \end{cases} \tag{4}$$

$$\begin{cases} \sum_{k\in\Psi_i}^{P_{t,ik}}=\sum_{j\in\Phi_i}(P_{t,ji}-R_{ji}(I_{t,ji})^2)+P_{t,i}\\ \sum_{k\in\Psi_i}^{Q_{t,ik}}=\sum_{j\in\Phi_i}(Q_{t,ji}-X_{ji}(I_{t,ji})^2)+Q_{t,i}\\ P_{t,i}=P_{t,i}^{\mathrm{DG}}+P_{t,i}^{\mathrm{SOP}}+P_{t,i}^{\mathrm{MG}}+P_{t,i}^{\mathrm{EV}}+P_{t,i}^{\mathrm{IL}}-P_{t,i}^{\mathrm{LOAD}}\\ Q_{t,i}=Q_{t,i}^{\mathrm{DG}}+Q_{t,i}^{\mathrm{SOP}}+Q_{t,i}^{\mathrm{MG}}+Q_{t,i}^{\mathrm{EV}}+Q_{t,i}^{\mathrm{IL}}-Q_{t,i}^{\mathrm{LOAD}}\\ (U_{t,i})^2=(U_{t,j})^2-2\left(R_{ji}P_{t,ji}+X_{ji}Q_{t,ji}\right)\\ \quad+\left(R_{ji}^2+X_{ji}^2\right)\left(I_{t,ji}\right)^2 \end{cases} \tag{5}$$

$$\begin{cases} U_{i\min}<U_{t,i}<U_{i\max}\\ I_{t,ij}\le I_{ij\max}\\ g\in \mathrm{R}\\ \sum_{t=1}^{\mathrm{T}}\left|\alpha_{ji,t}-\alpha_{ji,(t-1)}\right|\le S_{ji,\max}\\ \sum_{i=1}^{\mathrm{N_o}}\sum_{j\in\Phi_i}^{\sum_{t=1}^{\mathrm{T}}\left|\alpha_{ji,t}-\alpha_{ji,(t-1)}\right|}\le S_{\max}\\ P_{t,\min}^{\mathrm{grid}}\le P_t^{\mathrm{grid}}\le P_{t,\max}^{\mathrm{grid}}\\ P_{t,i,\min}^{\mathrm{MG}}\le P_{t,i}^{\mathrm{MG}}\le P_{t,i,\max}^{\mathrm{MG}} \end{cases} \tag{6}$$

B. ECONOMIC DISPATCH MODEL OF MICROGRID

At microgrid level, the optimization objective is to minimize the total operation cost of the microgrid, which can be

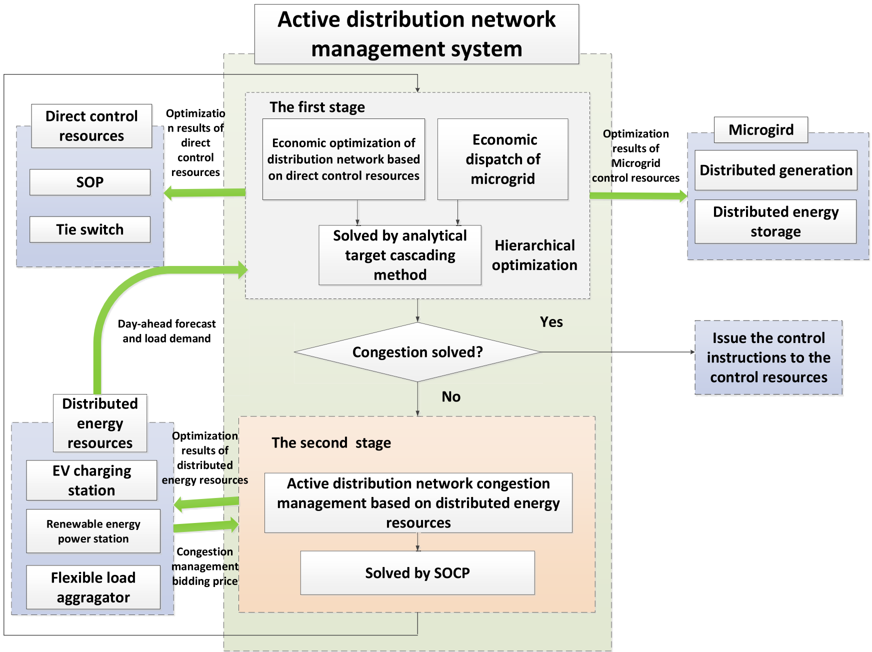

FIGURE 2. Framework and flowchart of the two-stage hierarchical active distribution network congestion management approach.

expressed as follows:

$$\min F^{\mathrm{MG}} = \sum_{t=1}^{\mathrm{T}} (C_t^{\mathrm{G}} + C_t^{\mathrm{buy}} + C_t^{\mathrm{BA}}) \tag{7}$$

$$C_t^{\mathrm{G}} = \sum_{g\in \mathrm{G}} \left(a(P_{g,t}^{\mathrm{mDG}})^2 + b(P_{g,t}^{\mathrm{mDG}}) + c \right) \tag{8}$$

$$C_t^{\mathrm{buy}} = \lambda_t^{\mathrm{MG}} \Delta t P_t^{\mathrm{MG}} \tag{9}$$

$$C_t^{\mathrm{BA}} = \lambda_t^{\mathrm{dis}} \Delta t P_t^{\mathrm{dis}} + \lambda_t^{\mathrm{ch}} \Delta t P_t^{\mathrm{ch}} \tag{10}$$

Operational constraints of microgrid and energy storage system are given below.

$$\begin{cases} P_t^{\mathrm{MG}} + \sum\limits_{g\in \mathrm{G}} P_{g,t}^{\mathrm{mDG}} = P_t^{\mathrm{load}} + P_t^{\mathrm{ch}} - P_t^{\mathrm{dis}} \\ P_{g,t,\min}^{\mathrm{mDG}} \le P_{g,t}^{\mathrm{mDG}} \le P_{g,t,\max}^{\mathrm{mDG}} \\ \left| P_{g,t}^{\mathrm{mDG}} - P_{g,t-1}^{\mathrm{mDG}} \right| \le \mathrm{Ru}_g^{\mathrm{mDG}} \\ \left| P_{g,t-1}^{\mathrm{mDG}} - P_{g,t}^{\mathrm{mDG}} \right| \le \mathrm{Rd}_g^{\mathrm{mDG}} \\ P_{t,\min}^{\mathrm{MG}} \le P_t^{\mathrm{MG}} \le P_{t,\max}^{\mathrm{MG}} \end{cases} \tag{11}$$

$$\begin{cases} E_{\min}^{\mathrm{BA}} \le E_t^{\mathrm{BA}} \le E_{\max}^{\mathrm{BA}} \\ u_t^{\mathrm{ch}} + u_t^{\mathrm{dis}} \le 1 \\ E_t^{\mathrm{BA}} = E_{t-1}^{\mathrm{BA}} - P_t^{\mathrm{dis}} \Delta t + P_t^{\mathrm{ch}} \Delta t \\ 0 \le P_t^{\mathrm{dis}} \le P_{\max}^{\mathrm{dis}} u_t^{\mathrm{dis}} \\ 0 \le P_t^{\mathrm{ch}} \le P_{\max}^{\mathrm{ch}} u_t^{\mathrm{ch}} \end{cases} \tag{12}$$

C. SOLUTION METHOD OF HIERARCHICAL MODEL BASED ON ANALYTICAL TARGET CASCADING

Analytical target cascading (ATC) is a method that adopts a parallel idea to solve the optimization problem of complex systems. ATC can effectively deal with the problems with a hierarchical structure by decomposing complex system and establishing the models of the master system and subsystem [27], [28]. The first stage model contains distribution network level and microgrid level, which can be decoupled into two independent sub-problems by ATC. The two sub-problems are optimized separately, then coordinate with each other until convergence conditions are met.

The dispatch models of the distribution network and each microgrid are mutually coupled through exchanging power $P_{t,i}^{\mathrm{MG}}$ and cannot be solved independently. Therefore, the exchanging power can be considered as a virtual load and a virtual generator at the two levels, respectively. Then the decomposition of distribution network and microgrid optimization problem can be realized. At distribution network level, $P_{t,i}^{\mathrm{MG}}$ is equivalent to a virtual load $P_{k,t}^{\mathrm{vl}}$; at microgrid level, $P_{t,i}^{\mathrm{MG}}$ is equivalent to a virtual generator $P_{k,t}^{\mathrm{vg}}$. The schematic diagram of model decoupling of the distribution network and microgrids is shown as Fig. 3.

There will be a deviation between the virtual load $P_{k,t}^{\mathrm{vl}}$ optimized from the distribution network side and the virtual generation $P_{k,t}^{\mathrm{vg}}$ optimized from the microgrid side. The Lagrangian penalty function is introduced into the distribution network model, which is expressed as:

$$\min \tilde{F}^{\mathrm{co}} = F^{\mathrm{co}} + \sum_{t=1}^{\mathrm{T}} \sum_{k=1}^{\mathrm{K}} \omega_{k,t} \left| P_{k,t}^{\mathrm{ul}} - P_{k,t}^{\mathrm{vg}} \right| + \sum_{t=1}^{\mathrm{T}} \sum_{k=1}^{\mathrm{K}} \gamma_{k,t} \left(P_{k,t}^{\mathrm{vl}} - P_{k,t}^{\mathrm{vg}} \right)^2 \tag{13}$$

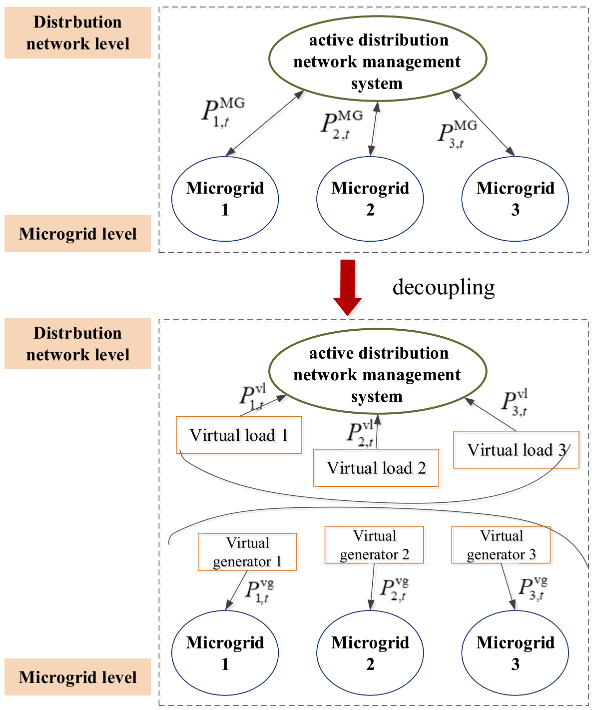

FIGURE 3. Model decoupling of the distribution network and microgrids.

Similarly, the Lagrangian penalty function is also introduced in the microgrid side model, which can be expressed as:

$$\min \tilde{F}_k^{\mathrm{MG}} = F_k^{\mathrm{MG}} + \sum_{t=1}^{\mathrm{T}} \omega_{k,t} \left| P_{k,t}^{\mathrm{vg}} - P_{k,t}^{\mathrm{vi}} \right| + \sum_{t=1}^{\mathrm{T}} \gamma_{k,t} \left(P_{k,t}^{\mathrm{vg}} - P_{k,t}^{\mathrm{v1}} \right)^2 \quad (14)$$

Therefore, the decoupled distribution network optimization model is composed of equations (14) and (4)-(6), and the microgrid optimization model is composed of equations (15) and (11)-(12). The two models can be solved independently. The distribution network optimization model is a complex multi-period mixed integer nonlinear optimization problem, which is solved by the mixed integer second-order cone programming (SOCP) method [29]. The microgrid optimization model is directly solved by SOCP method. The convergence conditions and the updating method of the Lagrangian penalty function multiplier can be found in [28]. The flowchart of the proposed algorithm to solve the hierarchical model based on ATC is illustrated in Fig. 4.

IV. NETWORK CONGESTION MANAGEMENT MODEL OF DERS AT THE SECOND STAGE

When network congestion is severe and the first stage model cannot eliminate the congestion, the second stage will enable the ancillary services for congestion management provided by DERs. DSO sends adjustment signals to each DER, and each DER responds to the signals by uploading its congestion management bidding price to DSO. To minimize the adjustment cost, a congestion management model for ADN can be established as follows considering all the bidding prices from DERs.

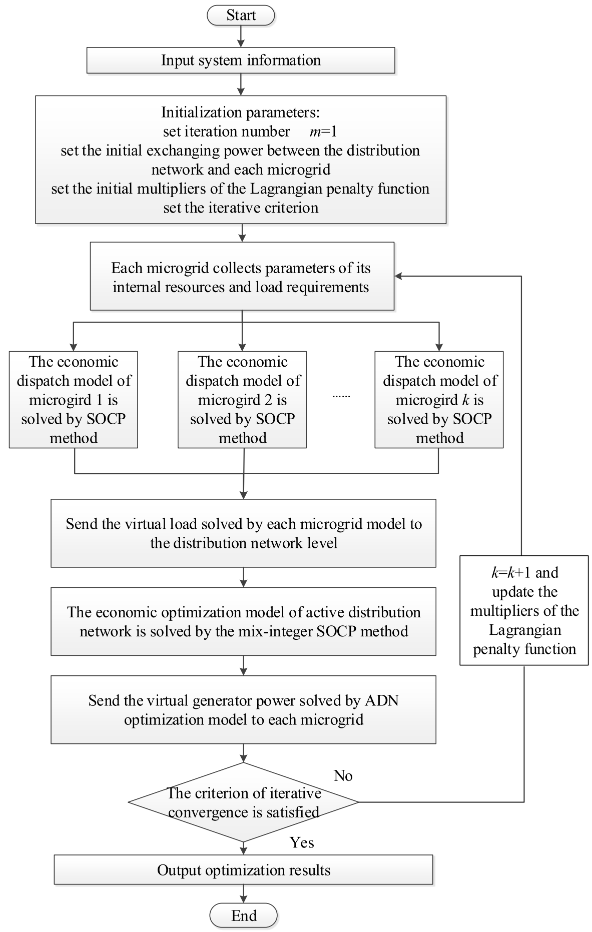

FIGURE 4. Block diagram of the proposed algorithm.

$$\min F^{\mathrm{cm}} = \sum_{t=1}^{\mathrm{T}} \left(C_t^{\mathrm{grid}} + C_t^{\mathrm{DG}} + C_t^{\mathrm{EV}} + C_t^{\mathrm{IL}} \right) \quad (15)$$

$$C_t^{\mathrm{DG}} = \sum_{d \in \mathrm{D}} \left(\lambda_{t,d}^{\mathrm{DG}} \Delta t P_{t,d}^{\mathrm{DG}} + \lambda_{t,d}^{\mathrm{DGpay}} \Delta t \left(P_{t,d,\max}^{\mathrm{DG}} - P_{t,d}^{\mathrm{DG}} \right) \right) \quad (16)$$

$$C_t^{\mathrm{EV}} = \sum_{e \in \mathrm{E}} \left(\lambda_{t,e}^{\mathrm{EVPay}} \Delta t \left(\tilde{P}_{t,e}^{\mathrm{EV}} - P_{t,e}^{\mathrm{EV}} \right) \right) \quad (17)$$

$$C_t^{\mathrm{IL}} = \sum_{l \in \mathrm{L}} (\lambda_{t,l}^{\mathrm{ILpay}} \Delta t (\tilde{P}_{t,l}^{\mathrm{IL}} - P_{t,l}^{\mathrm{IL}})) \quad (18)$$

The constraints of this problem include power flow equations and system operation constraints. The power flow equations are the same as equation (5). The system operation

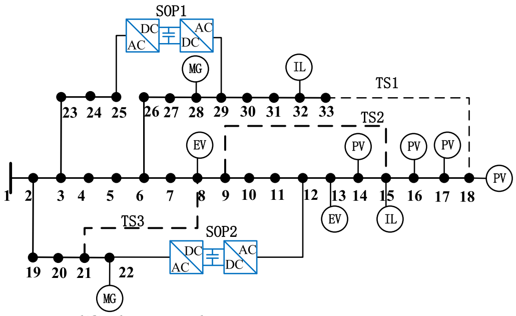

FIGURE 5. A modified IEEE 33 bus system.

constraints are:

$$\begin{cases} U_{i\min} < U_{t,i} < U_{i\max} \\ P_{t,ij} \leq \alpha P_{ij\max} \\ P^{EV}_{t,e,\min} \leq P^{EV}_{t,e} \leq P^{EV}_{t,e,\max} \\ \sum_{t=1}^{T} P^{EV}_{t,d} = \sum_{t=1}^{T} \tilde{P}^{EV}_{t,d} \\ P^{grid}_{t,\min} \leq P^{grid}_{t} \leq P^{grid}_{t,\max} \\ P^{DG}_{t,d,\min} \leq P^{DG}_{t,d} \leq P^{DG}_{t,d,\max} \\ P^{IL}_{t,l,\min} \leq P^{IL}_{t,l} \leq P^{IL}_{t,l,\max} \end{cases} \tag{19}$$

V. CASE STUDIES

A. IEEE 33 BUS SYSTEM

1) TEST SYSTEM SPECIFICATIONS

A modified IEEE 33 bus system is used to verify the proposed method, as shown in Fig. 5. There are three RCSs and SOPs are installed between nodes 25 and 29, 22 and 12, with a capacity of 600kVA. There are two microgrids connected at node 22 and 28 respectively. Each microgrid has two micro-turbines with a capacity of 0.8MW and 0.6MW. The specific parameters of micro-turbines are shown in Table 1. Both microgrids are equipped with an energy storage system whose capacity is 0.5MW / 2MWh. There are four distributed PV power stations at node 14, 16, 17, 18, all of them have an active power capacity of 500kW and a power factor of 0.9. There are two EV charging stations at nodes 8 and 13, and their daily charging demands are obtained from [30]. There are two flexible load aggregators at node 15 and 32, whose daily load demands are referenced from [25].

2) RESULT ANALYSIS

In order to analyze and verify the effectiveness of the proposed congestion management method for ADNs in this paper, three different optimization schemes are presented:

Case 1: Only the first-stage hierarchical coordinated optimization model is adopted to utilize DCRs and microgrids for distribution network congestion management.

Case 2: Only the second-stage optimization model is adopted to utilize the ancillary services provided by DERs for distribution network congestion management.

Case 3: The two-stage hierarchical coordinated optimization model proposed in this paper is adopted to utilized DCRs, microgrids and DERs for distribution network congestion management.

Before optimization, the network is simulated without any congestion management schemes, and it can be found that in two scenarios, the power flow will be off-limit. One scenario is 1 p.m., when PV output is large. At this time, the reverse power flow will occur on some branches, and the power of these branches may violate the lower limit. In Fig. 6, the red dashed lines are the upper and lower limits of branch power. It can be found that at 1 p.m., the power of branch 10, 11, and 12 violates the limit before optimization. The second scenario is 8 p.m., when PV output is 0, and the residential load and the EV charging load are large. At this time, the power of some branches may violate the upper limit. In Fig. 7, it can be found that the branch 18 and 19 are off-limit. Therefore, the three optimization schemes are mainly compared under these two scenarios.

It can be seen that through the coordinated optimization of DCRs and microgrids, network congestion can be effectively eliminated under both scenarios from Fig. 6 and Fig. 7. Then, we consider 80% of the maximum branch power as the limit of heavy-load branches, which is the blue dashed line in Fig. 8 and Fig. 9. And it can be found that some branches of Case 1 violate the heavy-load limit under the two scenarios from Fig. 8 and Fig. 9. Due to the random characteristics of DER output, in actual operation, there is a great risk that the heavy-load branches will be off-limit. Therefore, at this time, it is necessary to utilize the regulation capacities of DERs to

TABLE 1. Micro-turbine parameters of microgrids.

	Microgrid at node 22		Microgrid at node 28	
	MT1	MT2	MT1	MT2
P_{max}/MW	0.8	0.6	0.8	0.6
P_{min}/MW	0.1	0	0.1	0
a	0.002	0.004	0.003	0.005
b	0.3	0.21	0.27	0.18
c	40	30	70	32
Upwards ramp rate (MW/h)	0.2	0.18	0.2	0.18
Downwards ramp rate (MW/h)	0.15	0.1	0.15	0.1

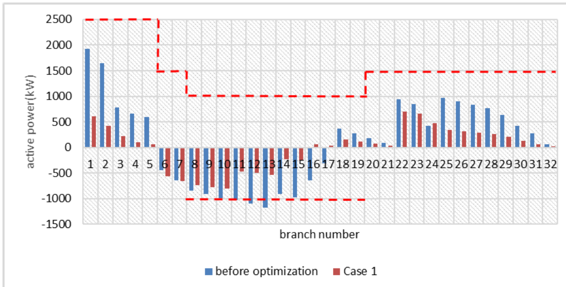

FIGURE 6. Comparison of the power flow distribution of each branch between before optimization and Case 1 at 1 pm under PV high output scenario.

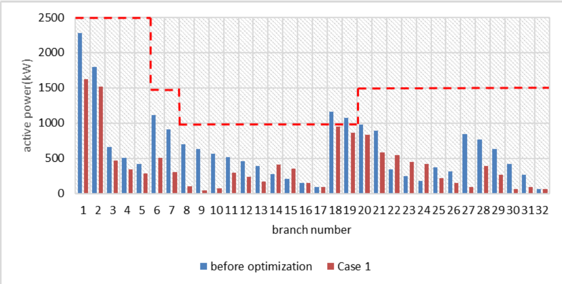

FIGURE 7. Comparison of the branch power flow between before optimization and Case 1 at 8 pm under heavy load scenario.

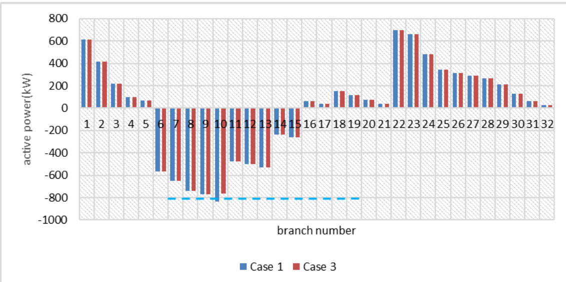

FIGURE 8. Comparison of the branch power flow between Case 1 and Case 3 at 1 pm under PV high output scenario.

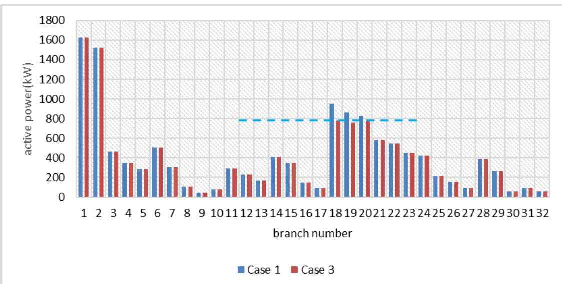

FIGURE 9. Comparison of the branch power flow between Case 1 and Case 3 at 8 pm under heavy load scenario.

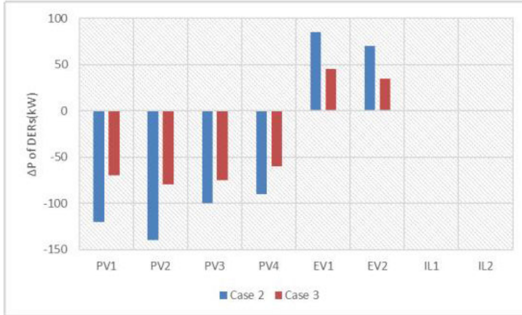

FIGURE 10. Comparison of various types DER output changes between Case 2 and Case 3 at 1 pm under PV high output scenario.

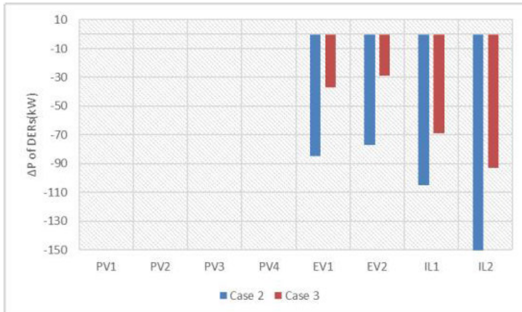

FIGURE 11. Comparison of various types DER output changes between Case 2 and Case 3 at 8 pm under heavy load scenario.

TABLE 2. Economic comparison between Case 2 and Case 3.

Scheme	Total cost of congestion management (Yuan)	Adjustment cost of DERs (Yuan)
Case 2	92506	18550
Case 3	87895	10385

eliminate the congestion risk. It can be found t.hat Case 3 can reduce the risk of branch power flow overload and meet the requirements of active distribution network congestion management with high penetration of DERs from Fig. 8 and Fig. 9.

Fig. 10 and Fig. 11 are comparisons of various types DER output changes between Case 2 and Case 3 under two scenarios. In Fig. 10, the congestion mainly comes from the high output of PV, so PV output reduction is the main measure to eliminate congestion in Case 2. In Fig. 11, the congestion mainly comes from heavy loads, so EV charging load shift and flexible load reduction are the main measures to eliminate congestion in Case 2. It can be found that the DER output changes of Case 2 are significantly higher than that of Case 3 (shown in Fig. 10 and Fig. 11), which causes that the adjustment costs of DERs are significantly higher than that of Case 3 (shown in Table 2). The above analysis illustrates that the proposed method in this paper can increase DER penetration, reduce the load reduction of consumer side and achieve higher economic benefits.

3) ALGORITHM PERFORMANCE ANALYSIS

In order to verify the performance of the algorithm, more microgrids are connected in the IEEE 33 bus system. The bi-level optimization method [31] and ATC method proposed in this paper are adopted to solve the first-stage congestion management model respectively. The comparison results are shown in Table 3.

The proposed method in this paper is close to the bi-level optimization method in terms of optimization effect, but the calculation time of the proposed method is significantly shorter than that of the bi-level optimization method. With the increase of the number of microgrids, the calculation time of the bi-level optimization method increases exponentially, while the growth rate of ATC method is relatively slow. The above analysis illustrates that the hierarchical coordinated optimization method based on ATC can decompose large-scale optimization problems, reduce the dimension of each sub-system and realize superior solution performance.

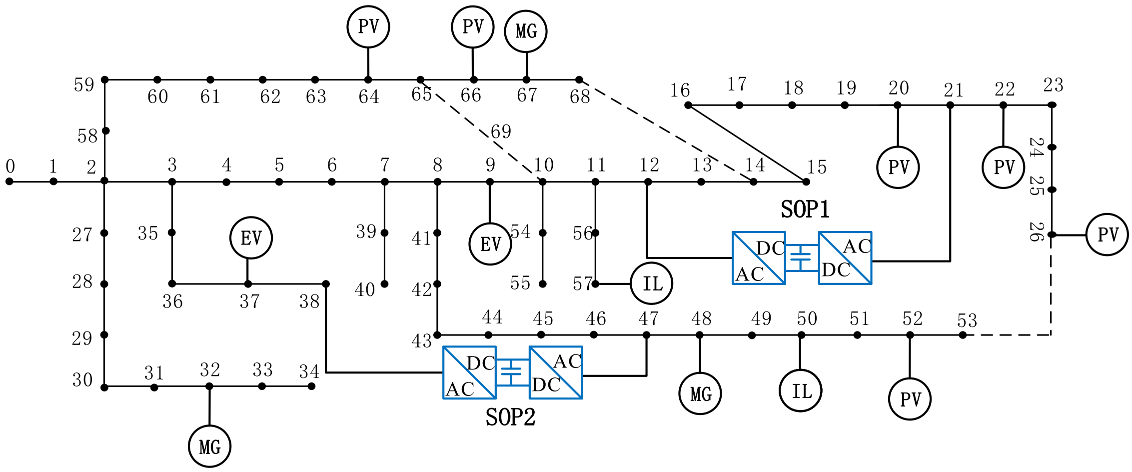

FIGURE 12. Diagram of the modified PG&E 69 bus system.

TABLE 3. Algorithm performance comparison.

		Number of microgrids			
		2	3	4	5
Total cost at the first stage (Yuan)	Bi-level optimization method	77402	88209	104665	117965
	The proposed method	77510	88375	104822	118393
CPU time (s)	Bi-level optimization method	580	1740	3300	5750
	The proposed method	69	95	132	160

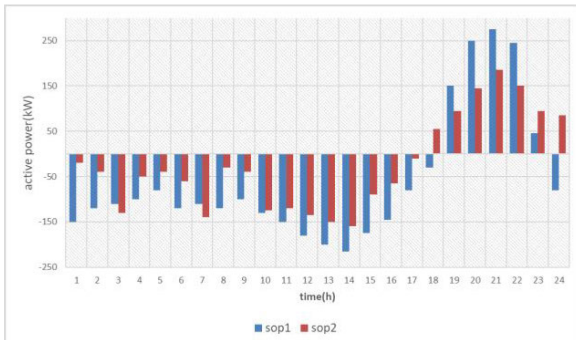

FIGURE 13. Active power profiles of the two SOPs at the first stage.

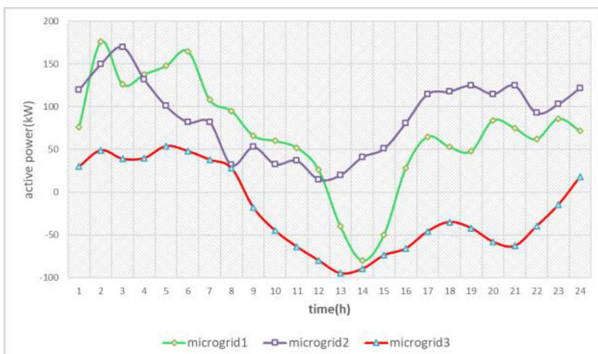

FIGURE 14. Active power exchange between the distribution network and the microgrids at the first stage.

B. PG&E 69 BUS SYSTEM

A modified PG&E 69 bus system is used as another test system to further verify the validity of the proposed method. Fig. 12 shows the diagram of this test system. There are three RCSs, which are installed between the dotted lines, and two SOPs, which are installed between nodes 12 and 21, 38 and 47, each with a rated capacity of 600kVA. There are three microgrids connected at nodes 32, 48 and 67, respectively. The parameters of the generators and energy storage system in the microgrids are from the same as those given in [32]. Nodes 20, 22, 26, 52, 64 and 66 are connected with PVs, each with a rated capacity of 500 kVA. Nodes 9 and 37 are connected with EV charging stations, whose daily charging demands are obtained from [30]. Nodes 50 and 57 are connected with flexible load aggregators, whose daily load demands are gotten from [25]. The dispatch results of various controllable resources optimized by the proposed optimization method are shown in Figs. 13-15.

As can be seen from Figs. 13 and 14, in the afternoon (12:00-14:00) under PV high output scenario, the active power outputs of SOPs are increased, and each microgrid reduces its DG output to consume more PV power. In the evening (19:00-21:00) under heavy load scenario, the DG outputs of microgrids and the output of SOPs are increased to mitigate the effect of heavy loads. However, through the first stage optimization, distribution network congestion occurs at 1 pm, 2 pm, 8 pm and 9 pm. This is mainly because the adjustment capabilities of SOPs and microgrids are limited at the first stage: under the PV high output scenario, microgrid 2 also has PVs, so it feeds power back to the distribution grid and cannot help the distribution network to consume PV

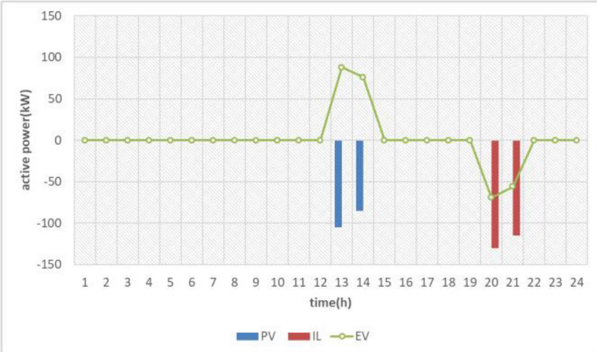

FIGURE 15. Optimization results of DERs' active power at the second stage.

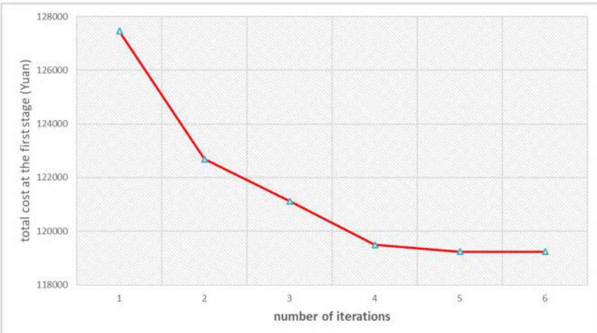

FIGURE 16. Iterative process of the ATC method.

TABLE 4. Comparison of optimization results between Case 2 and Case 3 for the modified PG&E 69 bus system.

Case	Number of overloaded branches	Total PV output curtailment (kW)	Total cost of congestion management (Yuan)	Adjustment cost of DERs (Yuan)
Case 2	0	275	138,671	24,735
Case 3	0	190	132,413	13,179

output; under the heavy load scenario, the load in Microgrid 3 is also large, so the distribution grid needs to transfer power to Microgrid 3, which increases the system load. The results of Fig. 15 show that flexible regulation capabilities provided by DERs at the second stage can make up for the lack of DCR adjustment capacity in the periods of severe congestion.

We also compare the optimization results between Case 2 and Case 3 with the modified PG&E 69 bus system, and the results are shown in Table 4. The distribution network congestion problem can be solved by the two methods corresponding to Case 2 and Case 3. However, the total PV output curtailment and total cost of congestion management of Case 2 are both larger than those of Case 3. The results show that the proposed method can increase PV power injection and improve the economic benefits of DSO for this test system.

For the modified PG&E 69 bus system, the convergence of the first-stage model can be achieved after six iterations using the ATC method, and the total computation time is about 180 s. By contrast, the computation time of the bi-level optimization method is 2640 s with 20 iterations. The simulation results from the two test systems show that the proposed method can effectively obtain the optimal solution with shorter CPU time, which proves the effectiveness and adaptability of the proposed method.

TABLE 5. Algorithm performance comparison.

Method	Number of iterations	CPU time (s)	Total cost at the first stage (Yuan)
Bi-level optimization method	20	2640	121152
Proposed method	6	180	119234

VI. CONCLUSION

Integration of multi-type DERs into distribution networks is an inevitable trend. However, if the DERs are not effectively controlled, they will likely cause network congestion and threaten the security of distribution networks. This paper proposes a two-stage hierarchical congestion management approach for ADNs with multi-type DERs, which can enable the power flow regulation capabilities provided by DCRs and the ancillary services provided by DERs to solve the congestion problem. Simulation results show that the proposed congestion management mechanism can utilize both DCRs and microgrids to avoid the impact of congestion on consumers and reduce the congestion management costs of DSO. At the same time, as candidate control scheme, flexible regulation capabilities provided by DERs can reduce the risk of branch power flow overload and meet the requirements of active distribution network congestion management with high penetration of DERs.

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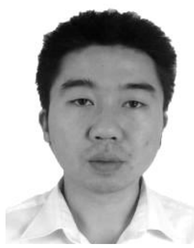

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