Temporal and Spatial Optimization for 5G Base Station Groups in Distribution Networks

Silu Zhang, Nian Liu, and Jianpei Han

Abstract—**With the large-scale connection of 5G base stations (BSs) to the distribution networks (DNs), 5G BSs are utilized as flexible loads to participate in the peak load regulation, where the BSs can be divided into base station groups (BSGs) to realize inter-district energy transfer. A Stackelberg game-based optimization framework is proposed, where the distribution network operator (DNO) works as a leader with dynamic pricing for multi-BSGs; while BSGs serve as followers with the ability of demand response to adjust their charging and discharging strategies in temporal dimension and load migration strategy in spatial dimension. Subsequently, the presence and uniqueness of the Stackelberg equilibrium (SE) are provided. Moreover, differential evolution is adopted to reach the SE and the optimization problem in multi-BSGs is decomposed to solve the time-space coupling. Finally, through simulation of a practical system, the results show that the DNO operation profit is increased via cutting down the peak load and the operation costs for multi-BSGs are reduced, which reaches a win-win effect.**

Index Terms—**5G base station, dynamic pricing, demand response, energy storage, load migration, Stackelberg game, optimization.**

I. Introduction

WITH the development of the economy, the communication technology is improved. The 5th-generation (5G) mobile networks, which provide high bandwidth, high capacity, and low latency communication [1], are becoming widely used in recent years. Meanwhile, as the core of 5G mobile networks, the extensive deployment of 5G base stations (BSs) contributes to much more power consumption than previous generation of technology [2]. On the macro level, the proportion of the electricity consumption of 5G BSs in terminal electricity consumption will continue to increase. It is estimated that the electricity consumption of communication BSs will account for 2%-2.4% of the whole social electricity consumption by 2025. In the same period, the electricity consumption of transportation such as intercity high-speed rail, intercity rail transit, and electric vehicles is estimated to account for 1.4%-1.5% of the total social electricity consumption [3]. The load of 5G BSs will have an increasing impact on the load structure and operation optimization of the distribution networks (DNs). On the micro level, the influence of high energy consumption of 5G BSs is becoming more and more significant. In urban local DNs, such as office area, commercial area, and residential area DNs, 5G BSs could bring 6.43%-11.34% increase in peak load [4]. For the mobile network operator (MNO), the electricity costs rise exponentially with the deployment of massive 5G BSs [5]. Consequently, it is necessary for the MNO to find an effective way to reduce its payment. The large-scale access of 5G BSs to the DNs has a significant effect on the operation of the power system. For one thing, the power consumption of the 5G BS will increase the peak load of the DN, which affects the safety and stability of the power system [6]; for another, the dispersive installation of 5G BSs also provides potential flexibility resources which promote the grid resilience [7]. Therefore, the collaborative interaction of the distribution network operator (DNO) and the MNO considering the features of both sides deserves further exploration.

From the perspective of mobile networks, the main approaches for energy and cost control could be divided into two categories: ① internal optimization in the MNO; and ② interactive optimization with the DNO. Recent researches on the internal optimization related to 5G BSs include the energy consumption management, energy storage (ES) management, and the cooperative dispatch in the multiple 5G BSs [8], [9]. The BS sleeping strategy based on communication traffic is an effective method to reduce the energy consumption of 5G cellular networks [10]. A model considering multiple sleep modes is constructed to balance the energy consumption and quality of service [11]. The game theory is also applied to the BS sleeping problem [12] to deal with the conflicts and interactions among the distributed BS sleeping switching operations. The ES devices are usually installed in 5G BSs to maintain the BS power supply reliability at a required level [13], which could be utilized as dispatchable resources. The BS operation cost is reduced by evaluating the dispatchable capacity of the BS based on semi-Markov analysis and taking advantage of the spare capacity [14]. Besides, with the penetration of renewable energy resources, the on-grid power of BSs is saved by maximizing the utilization of green energy by decomposition of such joint optimi-

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S. Zhang, N. Liu (corresponding author), and J. Han are with the Department of Electrical and Electronic Engineering, North China Electric Power University, Beijing, China (e-mail: 18810931839@163. com; nianliu@ncepu. edu. cn; jianpei@ncepu.edu.cn).

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zation problem into several subproblems [15], [16]. Ulteriorly, the ES is imported to better adapt to the dynamic nature of renewable energy [17], which is realized by a low-complexity online control scheme based on Lyapunov optimization. However, the researches mainly focus on the optimization in the internal 5G base station groups (BSGs) and ignore the collaborative interaction with DNs.

There are some researches considering the interaction of the DNO and the MNO. Through direct load control based on incentive or guiding signal based on electricity price, the distributed energy resources participate in the energy interaction with the power grid. A mixed-integer nonlinear optimization model is proposed to allocate user associations according to real-time price differences among BSs [18]. Considering the influence of the real-time change of communication load on the backup power demand of BSs, the ES regulation strategy in 5G BS is established to reduce the operation cost of BSs [19]. However, the existing research mainly focuses on the characteristics of BS operators and considers the parameters of DNs as given inputs, which neglects the demand of DNs.

From the perspective of DNs, demand response is widely applied in the solution to energy management in DNs [20]. Demand response is divided into incentive demand response and price demand response. Time-of-use (TOU) pricing is a common demand-side management strategy for electricity prices, which involves charging consumers differently depending on the time they use energy services. As one branch of game theory, the Stackelberg game is extensively utilized in the demand response, especially in the electricity trading process due to the unequal status between power providers and users [21]. A multiparty energy management framework based on the Stackelberg game is proposed for the joint operation of combined heat and power and photovoltaic (PV) prosumers with the internal price-based demand response [22]. A Stackelberg-game-based energy sharing framework is recommended for the DN with dynamic pricing, whereas PV prosumers serve as followers with the ability to modify flexible loads through demand response [23]. A Stackelberg-game-based collaborative optimization approach is proposed for DNs and 5G mobile networks with renewable resources [24].

To realize the two-way interaction and efficient cooperation between the DNO and the MNO, 5G BSGs are served as dispatchable resources to participate in the demand response in the DN. In the temporal scale, ES devices installed in 5G BSGs implement wired energy exchange facilitated by the grid architecture through charging and discharging, which is guided by different prices over time. In the spatial scale, considering the broadcast nature of wireless communications, energy can be shared among multiple BSs through wireless energy transfer methods [25]. The behavior of load migration (LM) is affected by the price diversity in different areas in the same period.

To this end, this paper focuses on the collaborative optimization framework by making the following contributions.

1) An optimal model of 5G BS is proposed for peak load regulation in DNs. The proposed model considers the characteristics of ES and LM that correspond to temporal dimension and spatial dimension, then realizes the demand response of these two dimensions.

2) A collaborative optimization framework based on the Stackelberg game theory is constructed. The peak load regulation in the DN is realized by the ES dispatch strategy of 5G BSs and LM strategy among 5G BSGs guided by the dynamic pricing scheme. The optimization framework aims at reducing the peak load regulation pressure in the DN while reducing the 5G BS operation cost.

3) The differential evolution (DE) algorithm is utilized to reach the Stackelberg equilibrium (SE). The optimization in the MNO level is decomposed into two sub-problems, i.e., the time-scale charging and discharging problem and the space-scale multi-BSG energy sharing problem, and interacts until reaching the optimal results.

II. Demand Response in Multi-BSGs

A. Characteristics of 5G BS

The 5G BS is mainly composed of communication devices and ES devices (backup battery). The power consumption of communication devices in the 5G BS is divided into static power and dynamic power. The static power is usually fixed and related to the energy consumption of the baseband unit. Meanwhile, the dynamic power is adjustable, which depends on the communication traffic of served mobile users [26]. The coverage range of a 5G BS is mainly related to the BS transmission power, frequency, and installation position, and the signal coverage radius is about 250-400 m [27]. In a region equipped with 5G BSs, there is spatial coupling relationship among the BSs, thus the mobile users connected by one BS can be transferred to other BSs. By taking advantage of the ability of dynamic access, the MNO can regulate the number of mobile users connected with each 5G BS, realizing the LM in space dimension. To meet the demand for uninterrupted power supply in the case of power outages, the 5G BSs are equipped with ES. The rated power and the total energy capacity of the ES in 5G BS are the same as and triple that of the total power of the 5G BS at full load, respectively [14]. The reserved ES in 5G BSs is the potential dispatchable resource to participate in the demand response. The ES device in the 5G BS is utilized as flexibility resource, which exchanges power with the grid and realizes the dispatch in time dimension by the charging and discharging behaviors.

In practical situation, the dispatchable power in single 5G BS is little compared with total loads in the DN. In addition, the number of 5G BSs is large, which leads to higher model solving complexity and longer model solving time. Therefore, there is a local BSG agent in each area, which assembles dispersed adjustable resources in 5G BSGs. The transmission mode of power and information in communication networks is shown in Fig. 1.

In a vibrant electricity market, the BSGs in different areas receive different local prices. Each local 5G BSG agent collects the energy consumption of BSGs and the local electricity price and transmits them to the central MNO. The MNO rationally plans resource allocation according to information such as electricity price from each area. Then, the 5G BSGs take part in demand response in two ways: charging and discharging in ES and LM.

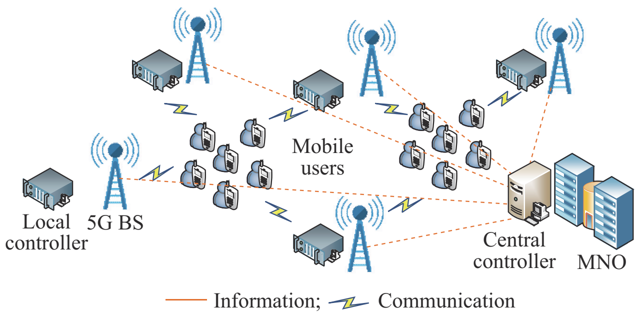

Fig. 1. Transmission mode of power and information in communication networks.

B. Framework of Multi-BSGs in DNs

In this paper, the framework of multi-BSGs in the DN is shown in Fig. 2. There are two general business agents (the DNO and the MNO) and multiple local BSG agents in the network. The DNO takes charge of the operation and security of the power grid. The MNO has the ownership and operation control of the flexibility resources in the 5G BSGs, which issues scheduling instructions to the local BSG agents. A region is commonly divided into various areas according to their functions, like residential area, industrial area, and commercial area. The load curves of DNs and communication networks in these areas are different and complementary. In one day, the peak and off-peak loads in different areas occur at different time slots. By dispatching flexible resources in space at one time slot, the peak loads in different areas are smoothed.

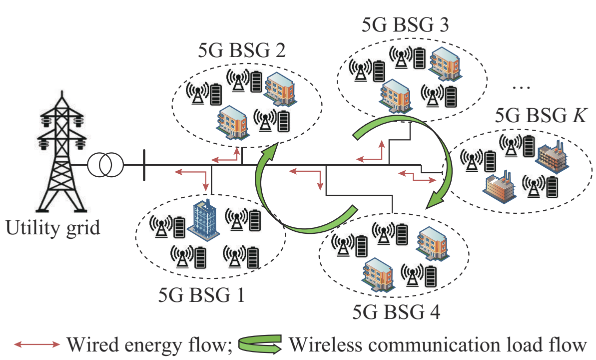

Fig. 2. Framework of multi-BSGs in DN.

The mobile users can change the connection in the overlapped 5G BS coverage areas. LM of BSs within a 5G BSG area could not change the power flow and reduce the cost by multi-area prices. The 5G BSG in various areas has the characteristics of local spatial LM, which means the 5G BSs at the boundary of an area could change the connection of the mobile users with the 5G BS at the boundary of other area, while the 5G BSs inside the area could not participate in the LM. Therefore, the dynamic load of the 5G BSG can be divided into spatial schedulable load and spatial non-schedulable load. In a typical distribution area, the number of evenly distributed 5G BSs is about 50-100 [18]. For a symmetrical plane area, the spatial schedulable dynamic load of the area accounts for about 19%-26%; for an asymmetric area, the spatial schedulable dynamic load will account for a larger proportion.

In terms of the temporal dimension, ES devices installed in 5G BSGs realize wired energy exchange with the DN through charging and discharging behaviors according to electricity price signals at different time. In terms of spatial dimension, mobile communication load is migrated among 5G BSGs through wireless communication load flow according to electricity price difference in different areas at the same time, so as to realize energy sharing among the BSGs [28].

C. Operating Strategy

The DNO serves as an intermediary agent, which purchases energy from the main grid at wholesale prices and then sells to consumers at retail prices. The price provided by the DNO reflects the degree of power supply shortage in the current period, and guides users' power consumption behavior. On the premise of the supply for energy demand of consumers, the DNO endeavors to obtain the highest possible operation profits. Meanwhile, the DNO also needs to provide more preferential dynamic pricing to incentivize flexible loads to actively respond and help ease the system's peak load pressure. In this framework, the DNO uses a multi-area pricing strategy that provides different prices to BSGs based on their load characteristics.

The MNO, as an independent general agent, aims at minimizing its total power costs while meeting the operation conditions. In the mechanism of multi-BSG price-incentive-based demand response, the MNO reduces its payments by the charging and discharging strategy in ES and the LM strategy. In the charging and discharging strategies, the ES device in 5G BSG is utilized as flexibility resource, whose charging and discharging behaviors in the time dimension are guided by the local electricity price. In the LM strategy, the MNO is stimulated to allocate communication traffic to different 5G BSGs based on their different loads and prices at one time slot. The interactive process of the DNO and MNO in Stackelberg game is shown in Fig. 3.

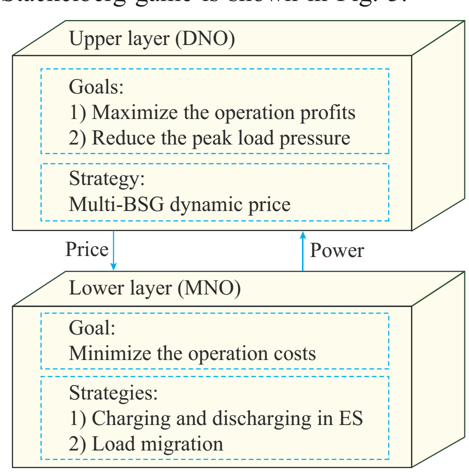

Fig. 3. Interactive process of DNO and MNO in Stackelberg game.

III. Optimal Models of 5G BSGs and DNs

A. Basic Model of 5G BSGs

Assuming that a region is divided into K areas, the 5G BSs in one area are considered as a group. In this study, the ES model and LM model of 5G BSGs are aggregated.

1) ES Model

The state of charge (SOC) of the ES in BSG i between two consecutive time intervals satisfies:

$$SOC_{ES,i,t} = SOC_{ES,i,t-1} + \frac{1}{C_{ES,i}}\left(\eta_{ES,i}^{cha} P_{ES,i,t}^{cha} \Delta t - \frac{P_{ES,i,t}^{dis} \Delta t}{\eta_{ES,i}^{dis}}\right) \quad \forall t \in T, \forall i \in K \tag{1}$$

where $SOC_{ES,i,t}$ and $SOC_{ES,i,t-1}$ are the average SOCs of the ES in BSG i at time slots t and $t-1$, respectively; $P_{ES,i,t}^{cha}$ and $P_{ES,i,t}^{dis}$ are the aggregated charging and discharging power of the ES in BSG i at time slot t, respectively; $\eta_{ES,i}^{cha}$ and $\eta_{ES,i}^{dis}$ are the average charging and discharging efficiencies of the ES in BSG i, respectively; T is the number of time slots; K is the number of BSGs; and $C_{ES,i}$ is the total capacity of the ES in BSG i.

The ES should not charge and discharge simultaneously due to the nature of the storage, which can be described as:

$$P_{ES,i,t}^{cha} P_{ES,i,t}^{dis} = 0 \quad \forall t \in T, \forall i \in K \tag{2}$$

The stored energy and the charging/discharging power are constrained by the ES capacity:

$$0 \le P_{ES,i,t}^{cha} \le P_{ES,i,\max}^{cha} \quad \forall t \in T, \forall i \in K \tag{3}$$

$$0 \le P_{ES,i,t}^{dis} \le P_{ES,i,\max}^{dis} \quad \forall t \in T, \forall i \in K \tag{4}$$

$$SOC_{ES,i,\min} \le SOC_{ES,i,t} \le SOC_{ES,i,\max} \quad \forall t \in T, \forall i \in K \tag{5}$$

where $P_{ES,i,\max}^{cha}$ and $P_{ES,i,\max}^{dis}$ are the aggregated maximum charging and discharging power of the ES in BSG i, respectively; and $SOC_{ES,i,\min}$ and $SOC_{ES,i,\max}$ are the average lower and upper limits of the SOCs in BSG i, respectively.

2) LM Model

The power consumption of the 5G BS consists of static power and dynamic power, which is proportional to the communication traffic connected to this 5G BS. It is defined as:

$$L_{bs,t} = L_{bs,t}^{s} + \alpha L_{bs,t}^{d} \quad \forall t \in T \tag{6}$$

where $L_{bs,t}$ is the total load of the 5G BS; $L_{bs,t}^{s}$ and $L_{bs,t}^{d}$ are the static and dynamic loads of the 5G BS, respectively; and α is the energy efficiency coefficient, which is the reciprocal of efficiency of the power amplifier.

At time slot t, there is communication traffic transfer among different 5G BSGs, the dispatchable load of 5G BSG i satisfies:

$$L_{i,t}^{trans} = \sum_{j=1, i \ne j}^{K} \left(\max\{L_{i,j,t}^{trans}, 0\} + \gamma_{i,j} \min\{L_{i,j,t}^{trans}, 0\}\right) \quad \forall i \in K, \forall t \in T \tag{7}$$

$$L_{i,j,t}^{trans} = -L_{j,i,t}^{trans} \quad \forall t \in T \tag{8}$$

where $L_{i,t}^{trans}$ is the transferred load in 5G BSG i at time slot t; $\gamma_{i,j}$ is the migration coefficient related to the transmission distance and path; and $L_{i,j,t}^{trans}$ is the transferred load between 5G BSGs i and j at time slot t. When the load is transferred from 5G BSG i to group j, $L_{i,j,t}^{trans} > 0$; otherwise, $L_{i,j,t}^{trans} < 0$. To guarantee the quality of service, when the distance between the 5G BS and customers increases, the transmitted power of signal emitter in the 5G BS is enhanced correspondingly, which contributes to more energy consumption.

With the limitation of equipment, the dynamic load of 5G BSG i satisfies:

$$0 \le L_{bs,i,t}^{d} \le L_{bs,i}^{d,\max} \quad \forall i \in K, \forall t \in T \tag{9}$$

where $L_{bs,i,t}^{d}$ is the dynamic load of 5G BSG i at time slot t; and $L_{bs,i}^{d,\max}$ is the upper limit of dynamic load in 5G BSG i .

Considering the LM among BSGs, constraint (9) could be rewritten as:

$$0 \le L_{bs,i,t}^{d} + L_{i,t}^{trans} \le L_{bs,i}^{d,\max} \quad \forall i \in K, \forall t \in T \tag{10}$$

B. Optimal Model of DNs

The selling prices provided by the DNO to 5G BSGs are defined as:

$$\boldsymbol{p}_{Bsell} = \begin{bmatrix} p_{Bsell,1,1} & \cdots & p_{Bsell,1,t} & \cdots & p_{Bsell,1,T} \\ \vdots & & \vdots & & \vdots \\ p_{Bsell,i,1} & \cdots & p_{Bsell,i,t} & \cdots & p_{Bsell,i,T} \\ \vdots & & \vdots & & \vdots \\ p_{Bsell,K,1} & \cdots & p_{Bsell,K,t} & \cdots & p_{Bsell,K,T} \end{bmatrix} \tag{11}$$

where $p_{Bsell,i,t}$ is the selling price of the electricity to 5G BSG i at time solt t.

To ensure the profit of the DNO and incentive for collaboration of BSGs, $p_{Bsell,i,t}$ satisfies:

$$p_{buy} \le p_{Bsell,i,t} \le p_{sell} \tag{12}$$

where p_{buy} and p_{sell} are the purchase and selling prices of the electricity provided by the power grid, respectively.

In this study, we assume that the price of purchasing electricity from BSGs is the same as that from the power grid, which is generally a constant within a day.

The profit of the DNO is formed by three parts: the profit traded with inflexible and flexible loads, the cost traded with power grid, and the penalty cost under peak load pressure. Accordingly, the profit function is formulated as:

$$F_{DNO} = F_{CL} + F_{exc} - C_{grid} - C_{pen} \tag{13}$$

$$F_{CL} = \sum_{i=1}^{K} \sum_{t=1}^{T} p_{Bsell,i,t} L_{c,i,t} \tag{14}$$

$$F_{exc} = \begin{cases} \sum_{i=1}^{K} \sum_{t=1}^{T} p_{Bsell,i,t} P_{exc,i,t} \Delta t & P_{exc,i,t} \ge 0 \\ \sum_{i=1}^{K} \sum_{t=1}^{T} p_{buy} P_{exc,i,t} \Delta t & P_{exc,i,t} < 0 \end{cases} \tag{15}$$

$$C_{grid} = \sum_{i=1}^{K} \sum_{t=1}^{T} p_{buy} P_{grid,i,t} \Delta t \tag{16}$$

$$C_{pen} = 24\lambda \sum_{i=1}^{K} \left[\max_{t \in T} \{L_{c,i,t} + P_{exc,i,t}\} \Big/ \sum_{t=1}^{T} (L_{c,i,t} + P_{exc,i,t}) \right] \tag{17}$$

where C_{grid} is the cost of purchasing electricity from the power grid; C_{pen} is the extra operation cost due to peak load pressure, which is affected by the penalty coefficient λ and the peak-to-average ratio; F_{CL} is the profit gained from the conventional load $L_{c,i,t}$; $P_{grid,i,t}$ is the electricity purchased from the power grid in 5G BSG i at time slot t; and F_{exc} is the profit of exchanging power $P_{exc,i,t}$ between the DNO and BSGs. When BSGs purchase electricity from the DNO, $P_{exc,i,t}>0$; whereas when BSGs sell electricity to the DNO, $P_{exc,i,t}<0$. The decision variables in (13) contain the exchanging power $P_{exc,i,t}$ and the selling prices provided by the DNO to 5G BSGs $p_{Bsell,i,t}$.

To guarantee the security of the DN, the constraints are as follows:

$$P_{grid,i,t}=L_{c,i,t}+P_{exc,i,t} \quad \forall i\in K, \forall t\in T \tag{18}$$

$$P_{grid,i,\min}\le P_{grid,i,t}\le P_{grid,i,\max} \quad \forall i\in K, \forall t\in T \tag{19}$$

where $P_{grid,i,\min}$ and $P_{grid,i,\max}$ are the lower and upper limits of purchasing power from the upper grid, respectively, which depend on the transmission capacity of the lines.

Constraint (18) denotes the energy balance in the DN at any time. Constraint (19) restricts the limits of purchasing power from the upper grid.

C. Optimal Model of 5G BSGs

The 5G BSG adjusts the charging and discharging strategies of ES and the LM strategy to affect the power exchang with the DNO to minimize its total cost.

Considering scheduling in time and space, the cost model of the 5G BS, which consists of the cost traded with the DNO and the changing and discharging loss, is established as:

$$F_{BSG}=F_{exc}+C_{ES} \tag{20}$$

$$C_{ES}=\sum_{i=1}^{K}\sum_{t=1}^{T}\varphi_i(P_{ES,i,t}^{cha}+P_{ES,i,t}^{dis})\Delta t \tag{21}$$

where C_{ES} is the charging and discharging loss; and φ_i is the dissipation coefficient of charging and discharging power of ES in BSG i.

The constraints of energy balance and power line capacity for 5G BSGs can be expressed as:

$$P_{exc,i,t}=L_{bs,i,t}+L_{i,t}^{trans}+P_{ES,i,t}^{cha}-P_{ES,i,t}^{dis} \quad \forall i\in K, \forall t\in T \tag{22}$$

$$P_{exc,i,\min}\le P_{exc,i,t}\le P_{exc,i,\max} \quad \forall i\in K, \forall t\in T \tag{23}$$

where $L_{bs,i,t}$ is the load of 5G BSG i at time slot t; and $P_{exc,i,\min}$ and $P_{exc,i,\max}$ are the minimum and maximum limits of the exchanging power for each BSG, respectively.

IV. Stackelberg Game Model and Solution Algorithm

A. Stackelberg Game Model

The non-cooperative games include multiple decision-making bodies, and each body attempts to maximize its own benefit. Considering the asymmetric competition among multi-participants, the Stackelberg game is applied to provide solutions. The leader gives its strategy first, and then, the follower gives the optimal response according to the leader's strategy and passes the strategy to the leader until the SE is reached, which is defined as the only fixed point where no player can improve its utility by changing its strategy unilaterally.

In this optimization framework, the DNO acts as the leader with multi-pricing strategy, which sets dynamic prices in the 5G BS areas to guide the reaction of BSGs to obtain the maximum operation income. The BSGs act as the followers, who minimize their operation costs in response to the prices set by the DNO. The strategies of BSGs include the charging and discharging of ES and the LM. Thus, the Stackelberg game between the DNO and BSGs can be formulated as (24), which contains the game players, game strategies, and payoffs.

$$G=\{DNO\bigcup BSG;\{\boldsymbol{p}_{sell}\};\{\boldsymbol{P}_{exc}\};F_{BSG};F_{DNO}\} \tag{24}$$

where $DNO\bigcup BSG$ is the set of players; $\boldsymbol{P}_{exc}$ is the power exchanging strategy among the DNO and each 5G BSG, which is affected by the charging and discharging power in ES and the LM among various areas; $\boldsymbol{p}_{sell}$ is the dynamic price based on the demand response of each BSG; F_{BSG} is the cost function of all 5G BSGs, which is based on their behaviors of charging/discharging and load transformation; and F_{DNO} is the profit function of DNs, which depends on the load consumption and peak load pressure.

The existence of the SE point can be proven by the following conditions.

1) The strategy set of each player is nonempty, convex, and compact.

2) The BSGs have a unique optimal best response strategy once informed of the pricing strategy of the DNO.

3) The DNO has a unique optimal strategy based on the identified demand response strategies of all BSGs.

Proof 1: because the strategy sets of $\boldsymbol{p}_{sell}$ and $\boldsymbol{P}_{exc}$ defined in this paper are the sets of linear inequality constraints (12) and (23) and linear equality constraint (22), respectively, these sets are readily defined as nonempty, convex, and compact.

Proof 2: assuming that N BSGs purchase electricity from the DNO, and other BSGs sell electricity to the DNO, by substituting (15) and (21) into (20), the cost function of the 5G BSGs at time slot t can be obtained as:

$$\begin{aligned}F_{BSG,t}=&\sum_{i=1}^{N}[p_{Bsell,i,t}(L_{bs,i,t}+L_{i,t}^{trans}+P_{ES,i,t}^{cha}-P_{ES,i,t}^{dis})+\\&\varphi_i(P_{ES,i,t}^{cha}+P_{ES,i,t}^{dis})]+\sum_{i=N+1}^{K}[p_{buy}(L_{bs,i,t}+L_{i,t}^{trans}+P_{ES,i,t}^{cha}-P_{ES,i,t}^{dis})+\\&\varphi_i(P_{ES,i,t}^{cha}+P_{ES,i,t}^{dis})]=\sum_{i=1}^{N}[p_{Bsell,i,t}L_{i,t}^{trans}+(p_{Bsell,i,t}+\varphi_i)P_{ES,i,t}^{cha}+\\&(\varphi_i-p_{Bsell,i,t})P_{ES,i,t}^{dis}+p_{Bsell,i,t}L_{bs,i,t}]+\sum_{i=N+1}^{K}[p_{buy}L_{i,t}^{trans}+\\&(p_{buy}+\varphi_i)P_{ES,i,t}^{cha}+(\varphi_i-p_{buy})P_{ES,i,t}^{dis}+p_{buy}L_{bs,i,t}]\end{aligned} \tag{25}$$

Given that the pricing strategy of the DNO $p_{Bsell,i,t}$ is known, it is obvious that the coefficient of the decision variable is a constant. That means the objective function is linear with respect to $L_{i,t}^{trans}$ and $P_{ES,i,t}^{cha}/P_{ES,i,t}^{dis}$, which has a unique optimal solution in the feasible domain.

According to the positive or negative value of each $p_{exc,i,t}$, the entire feasible domain $\boldsymbol{U}$ is divided into 2^K closed and convex subsets $\{\boldsymbol{U}_1,\boldsymbol{U}_2,\ldots,\boldsymbol{U}_{2^K}\}$. Define the unique optimal solution in $\boldsymbol{U}_m$ $(m=1,2,\ldots,2^K)$ is $S_m=\{L_{i,t}^{trans,m},P_{ES,i,t}^{cha,m}/P_{ES,i,t}^{dis,m}\}$, the unique optimal best response strategy is obtained as:

$$S_{uni}=\mathop{\arg\max}_{S=\{S_m,m=1,2,\ldots,2^K\}} F_{BSG}(S_m) \tag{26}$$

Consequently, the BSGs have a unique optimal best response strategy once informed of the pricing strategy of the DNO. The best response strategy in terms of (20) is guaranteed to be optimal and unique, so condition (2) is proven.

Proof 3: the objective function (13) at time slot t can be concretely rewritten as:

$$\begin{aligned} F_{DNO,t}= & \sum_{i=1}^{K} p_{Bsell,i,t} L_{c,i,t}+\sum_{i=1}^{K} p_{Bsell,i,t} \max \left\{P_{exc,i,t}, 0\right\}+ \\ & p_{buy} \min \left\{P_{exc,i,t}, 0\right\}-\sum_{i=1}^{K} p_{buy} P_{grid,i,t}- \\ & \lambda \sum_{i=1}^{K}\left[\max \left\{L_{c,i,t}+P_{exc,i,t}\right\} \Big/ \sum_{t=1}^{T}\left(L_{c,i,t}+P_{exc,i,t}\right)\right] \end{aligned} \tag{27}$$

The derivative of (27) with respect to $p_{Bsell,i,t}$ is calculated to be a constant. When the follower's strategy is given, the determined optimal pricing strategy is guaranteed to be exist and unique.

In conclusion, a unique SE exists in the proposed Stackelberg game model.

B. Solution Process for Stackelberg Game

Because of the incompleteness of the strategy information obtained by each agent, it is necessary to apply decentralized algorithm, which utilizes multiple iterations to stabilize the game and reach the optimal value of the system. The DE algorithm, a heuristic optimization algorithm, is an efficient and effective way to solve the distributed optimization problem [29]. The process of the algorithm is that the DNO randomly generates an initial price strategy at first; then, BSGs solve the optimization problem with respect to the given price strategy; finally, the DNO calculates its objective function based on the optimized strategy in each BSG. In the next round, the DNO generates the new price through mutation, crossover, and selection operations until the iteration approaches the optimal solution with the evolution of individual fitness. The implementation process executed by the DNO and BSGs are shown in Algorithms 1 and 2, respectively, where $\boldsymbol{L}_c$ is vector of the conventional loads; $\boldsymbol{p}_{Bsell}$ and $\boldsymbol{p}_{Bsell}^{op}$ are the vector of the selling prices provided by the DNO to 5G BSGs and its optimal value, respectively; $\boldsymbol{\gamma}$ is the vector of migration coefficients; $\boldsymbol{p}_{buy}$ is the vector of the purchase prices of the electricity provided by the power grid; $\boldsymbol{L}_{bs}$ is the vector of loads of 5G BSGs; $\boldsymbol{L}^{trans}$ is the vector of transferred loads of 5G BSGs; $\boldsymbol{P}_{ES}^{cha}$ and $\boldsymbol{P}_{ES}^{dis}$ are the vectors of aggregated charging and discharging power of the ES, respectively; $F_{BSG}^{ES,n}$ is the optimal cost of 5G BSGs at the n^{th} iteration in the ES charging and discharging subproblem; and $F_{BSG}^{LM,n}$ is the optimal cost of 5G BSGs at the n^{th} iteration in the LM subproblem.

The optimized variables of BSGs are coupled in time and space considering constraints (1) and (7) and, as a result, the optimization model of BSGs could not be solved directly. The original optimization problem is decomposed into ES charging and discharging optimization subproblem and the LM optimization subproblem. The optimal solution of the original optimization problem will be found by solving the two subproblems iteratively until they converge.

Algorithm 1

1. Input the initial data $\boldsymbol{L}_c$ and $\boldsymbol{p}_{Bsell}$, and set the parameters $\boldsymbol{\gamma}$, $\boldsymbol{p}_{buy}$, and $Iter=0$
2. **Repeat**:
3. $Iter=Iter+1$
4. **For** each BSG $i \in K$
    Send prices to BSG i
    Execute Algorithm 2
    Receive the optimized exchanging power of each BSG
5. **End for**
6. Calculate F_{DNO}^{Iter+1} based on (13)
7. Perform the mutation and crossover operations, and generate offspring prices $\boldsymbol{p}_{Bsell}^{Iter+1}$
8. **If** $F_{DNO}^{Iter+1}>F_{DNO}^{Iter}$
    $\boldsymbol{p}_{Bsell}^{op}=\boldsymbol{p}_{Bsell}^{Iter+1}$
  Else
    $\boldsymbol{p}_{Bsell}^{op}=\boldsymbol{p}_{Bsell}^{Iter}$
9. **End if**
10. **Until** iterative condition is satisfied

Algorithm 2

1. Input the initial data $\boldsymbol{L}_{bs}$, $\boldsymbol{L}^{trans}$, and $\boldsymbol{P}_{ES}^{cha}/\boldsymbol{P}_{ES}^{dis}$, and set the parameters λ, $\boldsymbol{\varphi}$, ε, $n=0$, $F_{BSG}^{ES,0}$, and $F_{BSG}^{LM,0}=0$
2. Receive $\boldsymbol{p}_{Bsell}$ from the DNO
3. **Repeat**:
4. Optimize $\boldsymbol{P}_{ES}^{cha}/\boldsymbol{P}_{ES}^{dis}$ in the ES charging and discharging subproblem by substituting $\boldsymbol{L}^{trans}=\boldsymbol{L}^{trans,n}$ into (20)
5. Calculate $F_{BSG}^{ES,n}$ based on (20)
6. **If** $\left|F_{BSG}^{ES,n}-F_{BSG}^{LM,n}\right|<\varepsilon$
    Break
7. **End if**
8. Optimize $\boldsymbol{L}^{trans}$ in the LM subproblem by substituting $\boldsymbol{P}_{ES}^{cha,n}/\boldsymbol{P}_{ES}^{dis,n}$ into (20)
9. Calculate $F_{BSG}^{LM,n}$ based on (20)
10. **If** $\left|F_{BSG}^{ES,n}-F_{BSG}^{LM,n}\right|<\varepsilon$
    Break
11. **End if**
12. Update iteration index $n=n+1$
13. **Until** iterative condition is satisfied

V. Case Study

A. Basic Simulation Setup

In this subsection, the topology of the DN shown in Fig. 4 is constructed to verify the availability of the proposed collaborative optimization framework and algorithm. There are three areas in the DN: Area 1 is the industrial area; Area 2 is the residential area; and Area 3 is the commercial area. The conventional load data in each area are shown in Fig. 5, which are taken from the smart meters in a typical DN in Henan, China. If one region has completed the deployment of 5G BSs, the BSs installed in this area are regarded as a group.

As is known in [25], apart from the static power consumption, the dynamic power consumption of 5G BSs is about 20% of the initial conventional load. The load data in each BSG are demonstrated in Fig. 6.

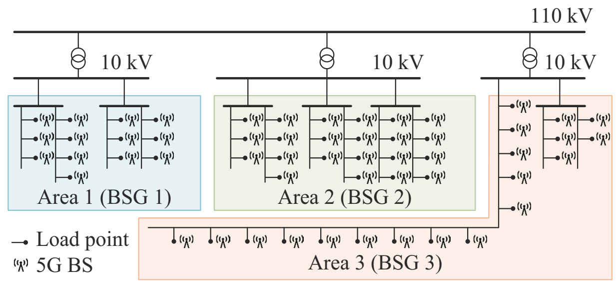

Fig. 4. Topology of constructed DN.

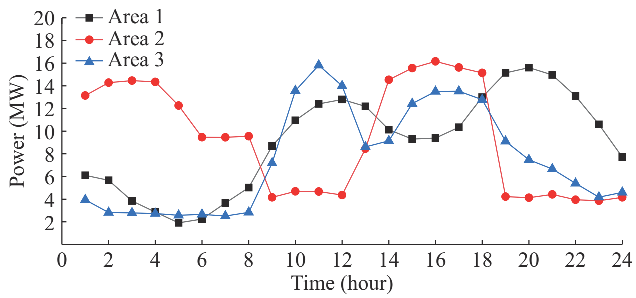

Fig. 5. Conventional load data in each area.

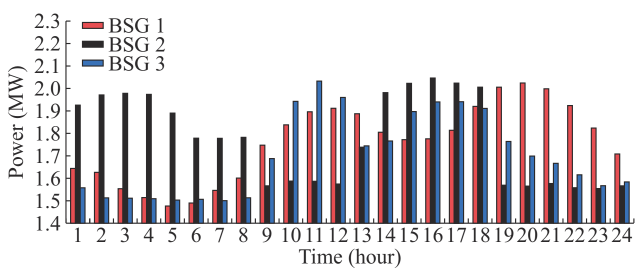

Fig. 6. Load data of each BSG.

The total power at full load of each 5G BSG is set to be 2.5 MW, which is limited by the hardware equipment, and the power at no load of each 5G BSG is set to be 1.4 MW, which is the basic power consumption of the BSG to maintain normal operation. At any time slot, the dispatchable power that a BSG could transfer to others is the differential value between its real-time load and its power at no load, and the power that a BSG could receive from others is the differential value between its power at full load and its real-time load. In this case, the spatial schedulable load is set to be 50% of the dynamic load of the 5G BSG. The aggregated rated power and total energy capacity of ES devices in each BSG are 2 MW and 6 MWh, respectively. The other related parameters in this DN are shown in Table I.

TABLE I
RELATED PARAMETERS IN CONSTRUCTED DN

Subject	Parameter	Value
DNO	λ	10 CNY/kW
BSG	φ_i	0.14 CNY/kW
	$\eta_{ES,i}^{cha}$, $\eta_{ES,i}^{dis}$	0.95
	$\gamma_{1,2}$, $\gamma_{1,3}$	1.1
	$\gamma_{2,3}$	1.2

The price of purchasing electricity from the upper grid adopts the feed-in tariff in most areas of China, which is set to be 0.3 CNY/kWh. Meanwhile, the price of purchasing electricity from BSGs is the same as 0.3 CNY/kWh. The TOU price of the power grid in Henan, China is shown in Table II.

TABLE II
TOU PRICE OF POWER GRID IN HENAN

Time period	Price (CNY/kWh)
19:00-22:00	1.076
08:00-13:00	0.960
13:00-19:00, 22:00-24:00	0.629
00:00-08:00	0.339

The main control parameters of the DE algorithm include population size (NP), mutation factor (MF), and crossover rate (CR) [30]. In this case, the NP is set to be 4, the MF is set to be 0.85, and the CR is set to be 0.8 to surely and rapidly calculate the global optimal solution.

B. Result Analysis

1) Results of Dynamic Prices

Figure 7 shows the optimized dynamic prices in different BSGs, which are tightly correlated with the original load curve characteristics of different areas.

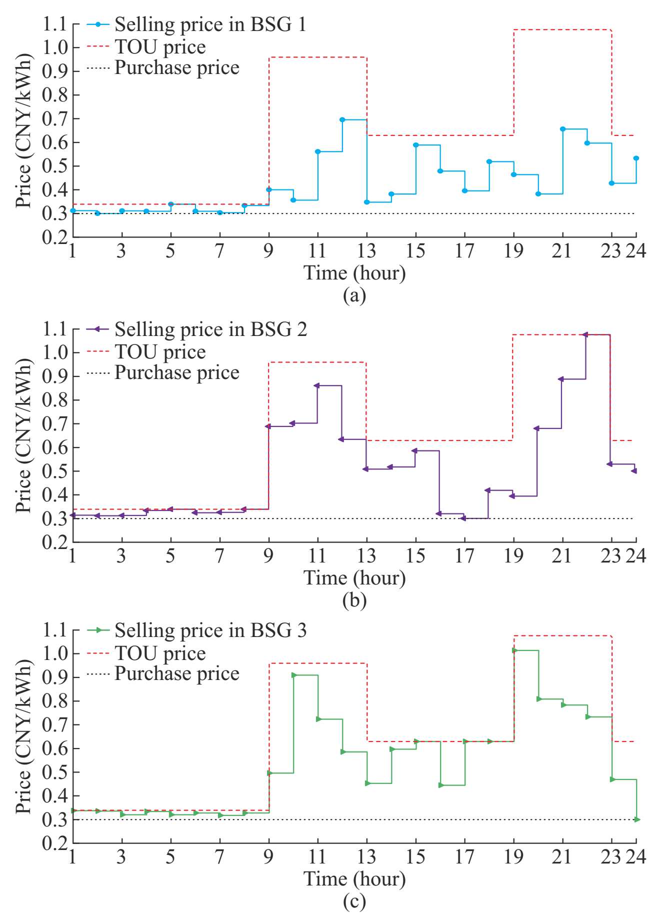

Fig. 7. Optimized dynamic prices in each BSG. (a) BSG 1. (b) BSG 2. (c) BSG 3.

To encourage the 5G BSGs to actively participate in the demand response, the selling prices of the electricity are lower than the original TOU prices. And the selling prices are higher than the wholesale prices of the upper power grid in order to ensure the interests of DNs. The industrial load in Area 1 is high at time slots 1-6 and 14-18, and the DNO intends to raise price to motivate BSG 1 to decrease the load consumption, whereas the TOU prices restrict the dynamic prices. Thus, the prices in BSG 1 maintain at a comparatively low level, as shown in Fig. 7(a). Known from Fig. 5, the load curve in Area 2 presents a small peak and a large peak at time slots 11-12 and 17-22, respectively. The dynamic prices in BSG 2 increase to stimulate the utilization of dispatchable loads and relieve the peak load pressure, which is coincident with the price trend in Fig. 7(b). Similarly, the prices in BSG 3 rise at time slots 10-12 and 15-18 to incentive the response of flexible resources.

2) Results of DNs and 5G BSGs

Guided by the multi-dynamic prices provided by the DNO, BSGs make strategies to minimize their operation costs in two means.

1) Strategies in ES. The charging and discharging strategies in each BSG are incentivized by price differences in temporal dimension. The price fluctuation is not obvious in BSG 1, so the behavior of ES in BSG 1 has little effects on the peak regulation. In BSG 2 and BSG 3, the ES devices charge at low prices and discharge at high prices, which cut down the peak load at time slots 19-21 in BSG 2 and at time slots 10-12 in BSG 3, respectively.

2) Strategies in LM. Due to the constraint of TOU prices, the dynamic prices in different BSGs are almost the same at time slots 0-8. Consequently, LM would not happen in this time period. At time slots 10-12, the prices in BSG 1 are lower than those in the other BSGs. The BSG 1 increases its load consumption by mobile users' connection transfer while other BSGs reduce their power consumption to lessen the total operation expenses. At time slots 16-18, the prices in BSG 2 are almost equal to those of utility grid. Therefore, the dynamic loads in BSG 1 and BSG 3 are transferred to BSG 2, which cuts down the peak load in BSG 1 and BSG 3. At time slots 20-22, the LM serves as an auxiliary means for further decreasing the peak loads as the charging and discharging play an important role in peak regulation at these time slots.

It is noted that at some time slots (e.g., time slot 21 in BSG 1), the behaviors of power consumption by two means are entirely opposite. It is not contradictory because the response of ES is guided by the price trend in time dimension while the LM is stimulated by the price difference among different areas at one time slot. For example, at time slot 21, the price in BSG 1 is higher than those at other time slots, so the ES discharges. Nevertheless, the price at that time slot in BSG 1 is lower than those in other BSGs, thus other BSGs transfer loads to BSG 1.

The comparison between the initial netload and the optimized netload in each area is shown in Fig. 8, and the ES strategy at 24 time slots and the LM strategy among BSGs are also illustrated.

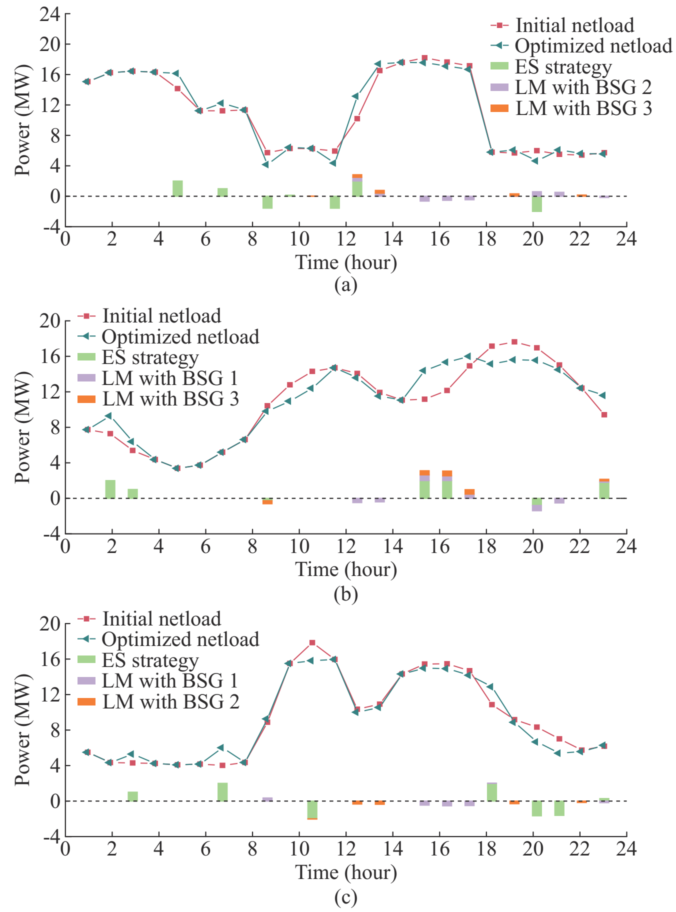

Fig. 8. Comparison between initial netload and optimized netload in each area and ES strategy and LM strategy in each BSG. (a) Area 1 (BSG 1). (b) Area 2 (BSG 2). (c) Area 3 (BSG 3).

As for the optimal electricity prices, the MNO utilizes the dispatchable resources in 5G BSGs to take part in the demand response due to the preferential electricity prices provided by the DNO. The effect of the proposed collaborative optimization for the guidance of the load is better than that of the independent optimization, which is shown in Table III.

TABLE III
COMPARISON OF PEAK LOAD IN EACH AREA

Area	Peak load (MW)		Decrease percentage (%)
	Independent optimization (MW)	Collaborative optimization (MW)	
Area 1	18.21	17.56	3.6
Area 2	17.63	15.61	11.5
Area 3	17.85	15.82	11.4

C. Comparison with Independent Optimization

1) Comparison of Peak Load Regulation in Different Scenarios

To demonstrate the effectiveness of the proposed collaborative optimization, the joint temporal and spatial optimization that combines the ES and LM is compared with the independent optimization that only considers the ES or LM.

Figure 9 shows the comparisons of optimized netload curves in each distributed area. It is clear that the joint temporal and spatial optimization performs better in peak load regulation than the independent optimization. As presented in Fig. 9(a), the effect of peak load regulation by means of LM is better than means of ES in Area 1. The ES could not fully utilize its ability to regulate the peak load due to the fact that the changing tendencies of price and load in time dimension are not similar. In Fig. 9(b) and (c), it is shown that the ES plays a more important role than LM in peak load shifting. In Areas 2 and 3, the ES of 5G BSGs charges at lower price and discharges at higher price following the guidance of dynamic price. The LM functions as an assistant role because the schedulable capacity of ES is more than that of LM.

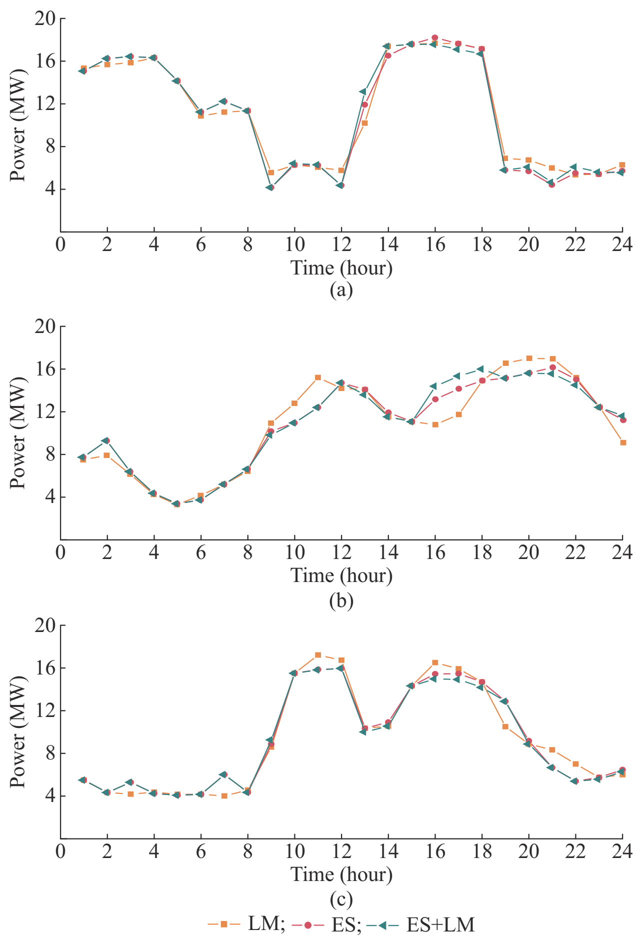

Fig. 9. Optimized netload curves in each distributed area. (a) Area 1. (b) Area 2. (c) Area 3.

In general, the proposed collaborative optimization integrates the characteristics of ES and LM, which could deal with various price strategies and load patterns and reduce the peak load regulation pressure.

2) Comparison of Economics in Different Scenarios

To show the advantage of multi-BSG pricing strategy, the economic comparisons in different scenarios are demonstrated in Table IV.

TABLE IV
ECONOMIC COMPARISONS IN DIFFERENT SCENARIOS

Scenario	Profit of DNO (CNY)	Cost of MNO (CNY)
Initial	245370	84030
LM	248210	68510
ES	255270	61940
ES + LM	260650	57010

The initial scenario represents the calculated results in independent operation pattern, while the other three scenarios present the results from the proposed collaborative optimization framework. According to Table III, the economic performance of the overall DN is improved when the proposed collaborative optimization is applied to the DNO and MNO, and the economic effectiveness considering the temporal and spatial dispatchable resources is better than only considering one of them. As for 5G BSGs, they adjust the charging and discharging strategies of ES and the LM strategy to fit in the optimized dynamic price to reduce their operation cost. Despite that the DNO gives up a part of benefits to incentive flexible loads to actively respond to its peak load regulation demand, the peak load penalty is decreased, which compensates for the economic losses on account of concessional price.

3) Comparison of Iterative Efficiency in Different Scenarios

The iterative solution algorithm is applied to the proposed collaborative optimization between the DNO and the MNO, and the convergency processes of DNO's profit are shown in Fig. 10. It is clear that with the increase of iteration number, the DNO's profit increases gradually and reaches the steady state after about 50 iterations. The convergence rate of the joint optimization is not slower than the independent optimization since the coupling model is decomposed into two sub-models. As a result, the proposed collaborative optimization has stable convergence performance.

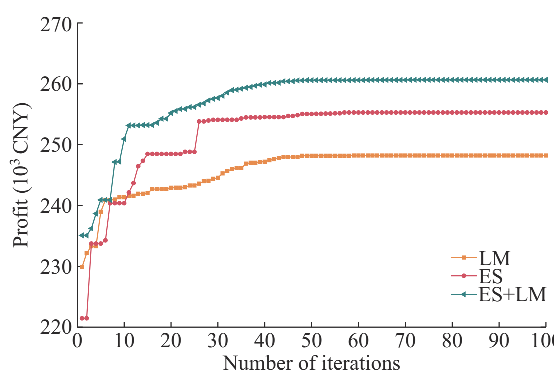

Fig. 10. Convergency processes of DNO's profit.

All numerical tests are carried out on a computer with an Intel Core i7-10710U CPU at 1.10 GHz and 16 GB RAM, and the optimal problems are solved using MATLAB software R2016b by calling CPLEX solver 12.8. The testing results of computation time with different numbers of areas are shown in Table V, from which we can draw that, as the number of areas grows, the computation time of the proposed collaborative optimization also increases correspondingly. Although the computation complexity is $O(N^2-N/2)$, the computation time is acceptable in practical applications since the number of areas N would not be very large and the variable matrix is a sparse matrix because the direct connections between areas will decrease with the increase in the number of areas.

TABLE V
COMPARISON OF COMPUTATIONAL PERFORMANCE WITH DIFFERENT NUMBERS OF AREAS

Number of areas	Number of variables	Computation time in each iteration (s)	Convergence time (s)
3	144	0.728	34.216
4	240	1.293	65.943
5	360	1.953	123.039

VI. CONCLUSION

In this paper, an optimization framework based on the Stackelberg game is proposed, where the DNO works as a leader with dynamic pricing for multi-BSGs, while BSGs serve as followers with the ability of demand response to adjust their charging and discharging strategies in temporal dimension and load migration strategy in spatial dimension. The existence and uniqueness of the SE of the proposed framework are proved and the problem reaches the optimal solution by DE algorithm. The results show that the DNO increases its total profits through electricity price regulation to encourage BSGs to assist with the peak load regulation, while the charging and discharging behaviors and LM responding to the dynamic price reduce the operation costs of multi-BSGs by 32.16%. The case study shows the effectiveness of the proposed framework which benefits both parties. Future work will relate to synergetic optimization considering 5G BS and other renewable resources and detailed consideration of the quality of service in both DNs and mobile networks.

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Silu Zhang is currently working toward the master's degree in electrical engineering with the School of Electrical and Electronic Engineering, North China Electric Power University, Beijing, China. Her current research interests include 5G base station and distribution system optimization.

Nian Liu received the B.S. and M.S. degrees in electric engineering from Xiangtan University, Xiangtan, China, in 2003 and 2006, respectively, and the Ph.D. degree in electrical engineering from North China Electric Power University, Beijing, China, in 2009. He is currently a Professor with the School of Electrical and Electronic Engineering, North China Electric Power University. He is also a Member of the State Key Laboratory of Alternate Electrical Power System with Renewable Energy Sources, Beijing, China, and a Member of the Standardization Committee of Power Supply and Consumption in Power Industry of China. He was a Visiting Research Fellow with the Royal Melbourne Institute of Technology (RMIT) University, Melbourne, Australia, from 2015 to 2016. He is an Editor of IEEE Transactions on Smart Grid, IEEE Transactions on Sustainable Energy, IEEE Power Engineering Letters, and an Associate Editor of Journal of Modern Power Systems and Clean Energy. His current research interests include multi-energy system integration, microgrids, cyber-physical energy system, and renewable energy integration.

Jianpei Han received the B.S. degree in electric engineering from North China Electric Power University, Baoding, China, in 2017. He is currently pursuing the Ph.D. degree in the School of Electrical and Electronic Engineering, North China Electric Power University, Beijing, China. His current research interests include game theory, power cyber-physical system, and distribution network optimization.