Optimization of Distribution Network and Mobile Network with Interactive Balance of Flexibility and Power

Jianpei Han, Nian Liu, *Member, IEEE*, and João P. S. Catalão, *Fellow, IEEE*

***Abstract*—High proportions of renewable energy place higher requirements on the flexibility of the distribution network. Meanwhile, the communication network is striving to seek ways to save energy. In this regard, this paper proposes a novel collaborative optimization method with interactive balance of flexibility and power for distribution network operator (DNO) and mobile network operator (MNO). First, the flexibility balance mechanism is analyzed and the optimization model integrating flexibility balance and power balance is established for the distribution network. Secondly, a flexibility aggregation method of large-scale base stations with energy storage (ES) devices is proposed, and a virtual ES-based optimization model is built for the mobile network. Then, a Nash bargaining-based optimization method is proposed for the collaboration of DNO and MNO, and a decentralized solution algorithm is designed to obtain the Nash bargaining solution, preserving the personal privacy. Finally, through a comprehensive case study we can draw that, compared with the independent approach, the proposed collaborative optimization method with interactive balance of flexibility and power can improve the operating flexibility of the distribution network while reducing the electricity bills of the mobile network effectively, thus achieving a win-win result.**

***Index Terms*—Collaborative optimization; Flexibility balance; Distribution network; Mobile network; Power aggregation; Nash bargaining; Decentralized solution.**

I. Introduction

DEVELOPMENT and utilization of renewable energy (e.g., wind energy and solar energy) are effective means to reduce carbon emissions of the electric industry and promote energy transformation. Thus, high proportions of renewable energy will be an inevitable trend in the development of the future power system [1]. However, because of the significant volatility and uncertainty of the output of renewable energy, its large-scale penetration will bring huge challenges to the safe operation of the power system. One of them is to put forward higher requirements for system flexibility [2]. Meanwhile, with the development of 5G technology, the mobile network is consuming much more energy than that of 4G (about 3-6 times) with the employment of massive Multi Input Multi Output technology. The research shows that for the worst-case scenario, the information and communication technology (ICT) industry would use as much as 51% of global electricity and 23% of the carbon footprint in 2030 [3], in which the energy consumption of the mobile network accounts for a considerable proportion. Therefore, in the coming 5G or beyond 5G (B5G) era, the energy consumption of the mobile network will have an important impact on both the mobile network and distribution network. Fortunately, the base station (BS), main share of energy consumption of the mobile network (BSs consume around 80 percent of the energy [4]), is usually equipped with an energy storage (ES) device for energy-saving and reliable power supply, which can serve as a promising flexibility supplier for the distribution network if effective measures can be taken. Thus, the main work of this paper is to study how the distribution network and the mobile network can achieve a win-win result through energy coordination optimization.

For the distribution network, the system flexibility refers to the ability to deploy its resources to respond to changes in net load [5]. In addition, the application of advanced ICT promotes the evolution from traditional power grid to a Smart Grid [6], which provides possibilities for new technologies. Therefore, the existing research on distributed flexibility coordination can be summarized as the following six methods according to flexibility supply [7]-[9]: demand response-based approach, dispatchable distributed generators-based approach (e.g., micro-turbines (MT)), ES-based approach, grid interconnection-based approach, renewable energy curtailment-based approach, and load shedding-based approach. Note that the above first four approaches can be regarded as proactive methods while the last two are passive ones. Although existing flexibility coordination methods look rich, all these methods are implemented inside the distribution network, which are insufficient with a high penetration of renewables. Thus, it is necessary to leverage the external available flexibility to support power regulation of the distribution network.

For the mobile network, it is an urgent need to reduce its carbon footprints and energy consumption, because the implementation of 5G requires higher density of BSs than 4G, imposing serious concerns about the sustainability and the energy consumption of the mobile network in the future [10]. Now, significant efforts have being made to reduce the electricity bills of the mobile network, such as BSs equipped with ES devices, which could take decisions of consuming energy or storing it in response to price signals [11]. The mobile network is capable of switching off some of the BSs or

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offloading users to hot spots, or the mobile network can achieve energy cooperation among multiple BSs. The above endeavor is necessary but insufficient due to the soaring increase in the users' traffic. As shown in the Pilot C of the Horizon 2020 European project SmartNet, an aggregation of radio base stations have the potential of provision of ancillary services for power grids [12]. Thus, it is a wise choice to achieve the collaboration between the distribution network and the mobile network, which will be beneficial for the two.

Very few studies have focused on the collaboration between the distribution network and the mobile network, for example, [13] and [14] argue that the mobile network can provide ancillary services to the smart grid owing to flexible power adjustment capability, [15] proposes an optimal day-ahead and real-time energy group buying jointly approach with wireless load sharing. Yet, these studies only show the economic advantages for the mobile network and the effect on the smart grid is not included, so the collaboration operation between distribution and mobile networks still remains an open issue.

In the context of a high penetration of renewables, the difficulties of collaboration optimization between distribution and mobile networks can be summarized as three aspects:

1) For the distribution network, the generic optimization idea is to determine the least-cost schedules while meeting prevailing operational constraints (e.g., power balance constraint), which cannot reflect the flexibility coordination with a high penetration of renewables.

2) For the mobile network, it is computational intractable when co-optimizing it with the distribution network, because the number of BSs is quite large in the 5G or B5G era.

3) Since the distribution network operator (DNO) and the mobile network operator (MNO) are different entities, it is difficult to design a collaborative mechanism, which ensures that both parties can profit through collaborative optimization.

In this regard, this paper provides an innovative study of the collaborative optimization mechanism of DNO and MNO from the perspective of interactive balance of flexibility and power, which is totally new. A previous collaborative optimization approach of DNO and MNO can be found in our preliminary work [16], which explored the possibility of the collaborative optimization of distribution and 5G mobile networks.

Hence, different from all existing studies, the major contributions of this paper are threefold:

1) A collaborative optimization framework of the distribution network and the mobile network is proposed, which realizes the interactive balance of both by introducing a power balance and flexibility balance mechanism. Specifically, in addition to the traditional power balance, the mobile network can serve as a flexibility supplier, which can proactively provide flexibility support for the distribution network. To the best of our knowledge, this is the very first attempt to model the interactive process of both distribution and mobile networks from the perspective of both power and flexibility balance.

2) An approximate power aggregation method is suggested for mobile network optimization, which is practical for the optimization of the mobile network and the interaction with the distribution network. The high-density 5G base station leads to the soaring complexity of the power management of the mobile network. As a novel solution, the proposed power aggregation method can significantly reduce the variables and constraints of the original optimization problem, making the problem solving computational tractable, which is crucial in real-life applications.

3) A collaborative optimization approach of DNO and MNO with interactive balance of flexibility and power is proposed. Specifically, the Nash bargaining game model is adopted to describe the interactive process of DNO and MNO. Moreover, a decentralized solution algorithm based on the alternating direction method of multipliers (ADMM) is designed to reach the Nash bargaining solution (NBS), preserving the personal information of both DNO and MNO.

II. Collaborative Optimization Framework

A. *Collaborative Framework with Interactive Balance of Flexibility and Power*

In a Smart Grid environment, the collaborative optimization framework of the distribution and mobile networks with the interactive balance of flexibility and power is shown in Fig. 1, which contains two aspects of balance, i.e., power balance and flexibility balance. For the former, the distribution network serves as the power supplier, which aggregates the power from the neighboring grids, local PV generation and backup MT to meet the power demand of electricity users, while the mobile network works as the power consumer and the distribution network is its main power support. For the latter, in turn, the mobile network can serve as a potential flexibility supplier for the distribution network, because this paper considers the situation that each BS of the mobile network is equipped with a ES system for reliable power supply, and large scales of ES devices in the mobile network can provide flexibility for the distribution network. It should be noted that, this article focuses on the optimization of the feeder-level distribution network, i.e., the BSs of the mobile network are connected to the same distribution feeder. Thus, the core work mainly lies in the collaborative optimization of power and flexibility balance. The extended analysis of network constraints can be seen in Part C, Section III.

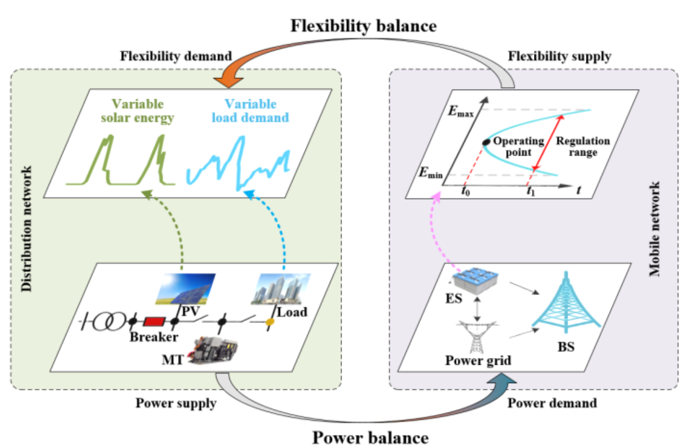

Fig. 1. The framework of the collaboration system.

B. *DNO and MNO strategies*

This paper focuses on the case that the scale of the considered distribution network is relatively small, such as park-level distribution network. In this case, all of the BSs and conventional electric load are assumed to be integrated into the distribution network through a unified distribution feeder. Thus, we have two assumptions: 1) the network constraints are ignored in this paper. 2) the voltage of the unified distribution feeder will not violate the limitations.

Therefore, the collaborative optimization of DNO and MNO with interactive balance of flexibility and power can be modeled as a two-player Nash Bargaining paradigm. For DNO, the mobile network could provide flexibility support through changing its optimal strategies (which might enhance the operating cost of the mobile network). Thus, the strategies of the DNO are not only the power purchase plan from neighboring grids and the outputs of MT, but also the incentive reimbursement for motivating the MNO to provide flexibility voluntarily. In response to the incentive signal from the DNO, the MNO minimizes its total energy consumption while meeting traffic load requirement. The optimal reimbursement and interactive power of the DNO and the MNO are determined through a Nash bargaining process, as shown in Section V.

III. Optimization Model of the Distribution Network with Flexibility Balance and Power Balance

A. Flexibility Balance Mechanism

1) Flexibility demand: High proportions of renewable energy (only photovoltaic (PV) generation is considered in this paper) make the net load profile of the distribution network fluctuate dramatically, which place strict requirements on the flexible regulation capability, i.e., flexibility. In general, the flexibility demand of the distribution network mainly stems from the fluctuations and uncertainties of loads and renewables [1]. But this paper only regards the variability of both loads and renewables as flexibility demand of the distribution network, and the flexibility modeling with uncertainties will be investigated in a follow up research.

Considering that the flexibility is directive, the flexibility demand of the distribution network can be divided into upward and downward flexibility demand respectively. Given $t\in \mathcal{T} \equiv \{t{:}t=1,2,\cdots,T\}$, where T is the number of time slots of the energy operation, let $\mathcal{T}_{-T} \equiv \{t{:}t=1,2,\cdots,T\text{-}1\}$, the up/down-ward flexibility demand, be calculated by

$$FD_t^{up} = \max\left\{\Delta L_{t+1}^{DN} - \Delta L_t^{DN}, 0\right\}, \forall t \in \mathcal{T}_{-T} \tag{1a}$$

$$FD_t^{down} = -\min\left\{\Delta L_{t+1}^{DN} - \Delta L_t^{DN}, 0\right\}, \forall t \in \mathcal{T}_{-T} \tag{1b}$$

where, FD_t^{up} , FD_t^{down} denote the up/down-ward flexibility demand of the distribution network at time slot t, and ΔL_t^{DN} is the net-load of the distribution network at time slot t.

2) Flexibility supply: The flexibility sources of the distribution network refer to the resources that can handle the volatility of loads and renewables. This paper assumes that the distribution network is equipped with distributed PV panels and backup MT, and can achieve power interaction with neighboring grids and the mobile network. Also, the flexibility sources can be divided into proactive measures (e.g., the power adjustment of MT, power interaction with neighboring grids and the mobile network) and passive measures (e.g., PV power curtailment and load shedding). Note that for ensuring the highly reliable power supply and facilitating the utilization of renewables, the passive measures are not included in this paper. Therefore, given $t\in \mathcal{T}$, the up/down-ward flexibility supply of the distribution network can be calculated by

$$FS_t^{up} = FS_{MT,t}^{up} + FS_{NG,t}^{up} + FS_{MN,t}^{up}, \forall t \in \mathcal{T} \tag{2a}$$

$$FS_t^{down} = FS_{MT,t}^{down} + FS_{NG,t}^{down} + FS_{MN,t}^{down}, \forall t \in \mathcal{T} \tag{2b}$$

where, FS_t^{up} , FS_t^{down} denote the up/down-ward flexibility supply of the distribution network at time slot t. And $FS_{MT,t}^{\mathrm{up}}$, $FS_{NG,t}^{\mathrm{up}}$, $FS_{MN,t}^{\mathrm{up}}$ are the upward flexibility supply of MT, power interaction with neighboring grids and the mobile network, while $FS_{MT,t}^{\mathrm{down}}$, $FS_{NG,t}^{\mathrm{down}}$, $FS_{MN,t}^{\mathrm{down}}$ denote the downward flexibility supply, respectively, which are determined by

$$FS_{MT,t}^{up} = \min\left\{P_{MT}^{\max} - P_{MT,t}, R_{MT}^{up}\Delta t\right\}, \forall t \in \mathcal{T} \tag{3a}$$

$$FS_{NG,t}^{up} = \min\left\{P_{NG}^{\max} - P_{NG,t}, \Delta P_{NG,t}^{\max}\right\}, \forall t \in \mathcal{T} \tag{3b}$$

$$FS_{MN,t}^{up} = \min\left\{P_{MN}^{\max} - P_{MN,t}, \Delta P_{MN,t}^{\max}\right\}, \forall t \in \mathcal{T} \tag{3c}$$

$$FS_{MT,t}^{down} = \min\left\{P_{MT,t} - P_{MT}^{\min}, R_{MT}^{down}\Delta t\right\}, \forall t \in \mathcal{T} \tag{3d}$$

$$FS_{NG,t}^{down} = \min\left\{P_{NG,t} - P_{NG}^{\min}, \Delta P_{NG,t}^{\max}\right\}, \forall t \in \mathcal{T} \tag{3e}$$

$$FS_{MN,t}^{down} = \min\left\{P_{MN,t} - P_{MN}^{\min}, \Delta P_{MN,t}^{\max}\right\}, \forall t \in \mathcal{T} \tag{3f}$$

where, $P_{MT}^{\max}$, $P_{NG}^{\max}$, $P_{MN}^{\max}$ are the upper limits of MT's output, interactive power with neighboring grids and the mobile network, while $P_{MT}^{\min}$, $P_{NG}^{\min}$, $P_{MN}^{\min}$ denote the upper limits of that, respectively. $P_{MT,t}$, $P_{NG,t}$, $P_{MN,t}$ are the output of MT, the interactive power with neighboring grids and the mobile network at time slot t. R_{MT}^{up}, R_{MT}^{down} are up/down-ward ramping ratios of MT with Δt the width of time slot t, and $\Delta P_{NG,t}^{\max}$, $\Delta P_{MN,t}^{\max}$ are the maximum allowable adjustments of the interactive power with neighboring grids and the mobile network at time slot t.

3) Flexibility balance: When the proportion of PV is small, the volatility of the net-load of the distribution network is not significant and the flexibility is not an urgent need in this case, which can be met by the regulation capability of the distribution network alone. While the penetration of PV is high, the fluctuation of the net-load of the system sometimes exceeds its own adjustment range. At this time, the optimization of the distribution network not only needs to ensure the real-time power balance, but also needs to satisfy the flexibility balance, i.e., to guarantee the flexibility supply of the system be more than the flexibility demand at any time slot t.

$$FS_t^{up} - FD_t^{up} \ge \beta, \forall t \in \mathcal{T}_{-T} \tag{4a}$$

$$FS_t^{down} - FD_t^{down} \ge \beta, \forall t \in \mathcal{T}_{-T} \tag{4b}$$

where, β is the given flexibility margin.

4) Evaluation indexes: Note that the purpose of introducing flexibility balance is to eliminate the net-load fluctuation of the distribution network with high penetration of PV power, thus, the Net-load Fluctuation Index (NFI) is adopted to quantify operational flexibility of the distribution network. Let $\mathcal{T}_{-1} \equiv \{t{:}t=2,3,\cdots,T\}$, the index NFI can be calculated by

$$NFI = \sum\nolimits_{t\in\mathcal{T}_{-1}} \left|\Delta L_t^{DN} - \Delta L_{t-1}^{DN}\right| \tag{5}$$

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B. Optimal Model of DNO with Flexibility Balance

For DNO, it has two operating modes, i.e., the independent optimization mode (which does not consider the collaboration of MNO and DNO, serving as a benchmark) and the collaborative optimization mode (between DNO and MNO).

1) Independent optimization mode: In the context of high PV penetration, this paper assumes that the DNO aims at minimizing the operating cost of the distribution network while satisfying the operational constraints and an additional flexibility balance constraint. The operating cost of the distribution network in independent optimization mode can be described as

$$\begin{aligned} C_{DNO}^{in} &= \sum\nolimits_{t\in\mathcal{T}} p_{buy,t} P_{NG,t}\Delta t \\ &+ \sum\nolimits_{t\in\mathcal{T}} [a(P_{MT,t})^2 + bP_{MT,t} + c] \\ &+ p_c \sum\nolimits_{t\in\mathcal{T}} \alpha_{MT} P_{MT,t}\Delta t \end{aligned} \tag{6}$$

where, the operating cost mainly contains two parts: the cost of purchasing electricity from neighboring grids, the electricity generation cost of distribution generators (note that PV ignores the cost of power generation), in which, $p_{buy,t}$ denotes the price of purchasing electricity from neighboring grids at time slot t. a, b, and c are cost coefficients, α_{MT} is the carbon emission factor of MT, and p_c represents the penalty price of carbon emissions produced by MT while generating electricity.

Thus, the optimization model of the DNO in independent mode can be described as

$$\text{minimize} \quad C_{DNO}^{in} \tag{7a}$$

subject to

$$P_{NG,t} + P_{MT,t} + P_{PV,t} = L_{DN,t} + P_{MN,t}, \forall t \in \mathcal{T} \tag{7b}$$

$$P_{NG}^{\min} \le P_{NG,t} \le P_{NG}^{\max}, \forall t \in \mathcal{T} \tag{7c}$$

$$P_{MT}^{\min} \le P_{MT,t} \le P_{MT}^{\max}, \forall t \in \mathcal{T} \tag{7d}$$

$$-\Delta P_{NG,t}^{\max} \le P_{NG,t} - P_{NG,t\text{-}1} \le \Delta P_{NG,t}^{\max}, \forall t \in \mathcal{T}_{-1} \tag{7e}$$

$$-R_{MT}^{down}\Delta t \le P_{MT,t} - P_{MT,t\text{-}1} \le R_{MT}^{up}\Delta t, \forall t \in \mathcal{T}_{-1} \tag{7f}$$

where, the variables are $\boldsymbol{P}_{MT}$, $\boldsymbol{P}_{NG}$ (Note that in independent mode, we assume the power consumption vector $\boldsymbol{P}_{MN}$ is provided by the MNO directly, which is known before the optimization for the DNO). To ensure the safety of the distribution network, the operational constraints must be met, in which, constraint (7b) is the power balance constraint of the distribution network, and constraints (7c)-(7d) are the limits of power purchase from neighboring grids or upper-level power grid, power outputs of MT at time slot t. Among them, the left side of the inequalities are the lower limits while the right side one are the upper limits. Considering that the power regulation capabilities of the neighboring grids, and MT are limited, the constraints (7e)-(7f) are considered in this paper, where the left sides of which are the downward limits of the power regulation while the left are the upward limits. Besides, the flexibility balance constraints defined by (4a)-(4b) should also be satisfied for ensuring sufficient power regulation capabilities to eliminate the fluctuations of net-load of the distribution network. Note that in the independent optimization case, the flexibility supply in (4a)-(4b) should be modified, i.e., $FS_t^{\mathrm{up}} = FS_{MT,t}^{\mathrm{up}} + FS_{NG,t}^{\mathrm{up}}$, $FS_t^{\mathrm{down}} = FS_{MT,t}^{\mathrm{down}} + FS_{NG,t}^{\mathrm{down}}$. Let C_{DNO}^{0} denote the optimal value of (7a), which is obtained by solving the above optimal problem defined by (7). It serves as the benchmark for comparison with the collaborative optimization mode in next sub-section.

2) Collaborative optimization mode: Now we consider the possibility of energy collaborative optimization between DNO and MNO, i.e., the MNO can rearrange its power consumption to provide flexibility for the DNO. However, it may enhance the electricity bills when the MNO changes its optimal strategy. Thus, it is necessary for the DNO to offer a reimbursement to the MNO. Therefore, the operating cost of the DNO in collaboration mode can be described by

$$C_{DNO}^{co} = C_{DNO}^{in} + \kappa \tag{8}$$

where, κ is the reimbursement to the MNO, then the optimization model of the DNO in collaboration mode can be defined as a cost reduction maximization problem.

$$\begin{aligned} &\text{maximize } \mathcal{U}_{DNO}(\boldsymbol{P}_{MT}, \boldsymbol{P}_{NG}, \kappa) = C_{DNO}^{0} - C_{DNO}^{co} \\ &\textit{subject to } \ (4\text{a})-(4\text{b}), (7\text{b})-(7\text{f}) \end{aligned} \tag{9}$$

In the collaborative optimization mode, the variables are $\boldsymbol{P}_{MT}$, $\boldsymbol{P}_{NG}$, and κ. It is assumed that the value of power limits P_{MN}^{min}, P_{MN}^{max}, and $\Delta P_{MN,t}^{max}$ in (3c) and (3f) can be provided by the MNO. And when the DNO does not cooperate with the MNO for the collaborative optimization (i.e., $\kappa = 0$), its optimal objective is $\mathcal{U}_{DNO} = 0$.

C. Extended Analysis of Network Constraints

As stated in Part A, Section II, this paper focuses on the optimization of feeder-level distribution network, and the network constraints didn't work in this case. In order to further analyze the extensibility of the proposed method with network constraints, such as a larger range of distribution network (e.g., region-level distribution network), the idea of checking after the optimization is introduced in this paper [17]. The implementation of the optimization with network constraints is expressed as follows:

1) In each distribution feeder m, the DNO and MNO determine the power purchase strategies with neighboring grids or higher level power grid collaboratively, i.e., $\boldsymbol{P}_{NG}$ in (7a).

2) The optimal results obtained by collaborative optimization of DNO and MNO will be utilized to check whether the power flow exceeds the power line transmission capacity. If there is overload in the power line, the power line transmission capacity will be a constraint added to the next optimization process to obtain the new power collaboration schedule.

The power line capacity constraints of higher level power grid can be expressed as follows:

$$-P_k^{\max} \le \sum_{m\in\mathcal{M}} \zeta_{k,m} P_{m,t} \le P_k^{\max}, \forall t \in \mathcal{T}, \forall k \in \mathcal{K} \tag{10}$$

where, $m \in \mathcal{M} \equiv \{m{:}m=1,2,\cdots,M\}$, M is the number of distribution feeders. $k \in \mathcal{K} \equiv \{k{:}k=1,2,\cdots,K\}$, K is the number of distribution power lines. $P_{m,t}$ is the injected power of feeder m at time slot t, and $\zeta_{k,m}$ is the power injection shift distribution factor of feeder m to branch power line k, which is determined by the distribution network topology and parameters.

IV. Mobile Network Optimization Model with Power Aggregation

We consider that the mobile network consists of N BSs, which are denoted by $\mathcal{N} \equiv \{n{:}n=1,2,\cdots,N\}$. It is assumed that each BS is equipped with an ES device for energy saving, and the MNO is willing to reduce its electricity bills through optimizing the operation strategies of all ES devices in the mobile network in response to MNO's incentive signal. However, the fact is that the power consumption of each BS and the capability of each ES devices are quite small (usually only a few kW's) while the numbers of BSs and ES devices are quite large, especially in the context of the current 5G technology with ultra-dense network. Thus, the fundamental task for the MNO before cooperative optimization with the DNO is to characterize the aggregate power of multiple BSs with ES devices over a considered time horizon effectively.

A. Power Aggregation Model

1) Model of Single BS with Energy Storage

a) Power consumption model: Given $t \in \mathcal{T}$, the power consumption of BS n at time slot t is described as follows [15], [18]:

$$L_{n,t}^{MN} = L_{n,stat}^{MN} + \rho_n \overline{D_{n,t}^{MN}}, \forall t \in \mathcal{T}, \forall n \in \mathcal{N} \tag{11}$$

where, $L_{n,stat}^{MN}$ is the static power consumption which is primarily used for the main basic circuit operation of the BS n. ρ_n denotes the consumed power per unit of load traffic of BS n, which is assumed to be fixed and uniform. Note that the parameters $L_{n,stat}^{MN}$ and ρ_n may typically vary over BSs. This paper, for simplification, assumes that those parameters of all BSs are the same; typical values can be referred to in [14]. $\overline{D_{n,t}^{MN}}$ is the average traffic profile of BS n during t^{th} time period and it can be obtained by

$$\overline{D_{n,t}^{MN}} = \frac{1}{\Delta t} \int_{(t-1)\Delta t}^{t\Delta t} D_n^{MN}(\tau) d\tau \tag{12}$$

where, D_n^{MN} is the traffic profile of the BS n, and Δt is the length of time slot t.

b) Energy storage model: we consider that each BS is equipped with an ES device in response to the price signals from the DNO. Thus, for each BS $n \in \mathcal{N}$, the feasible region of the ES device is approximately defined as the set of all admissible power profiles.

$$\mathcal{F}_n = \left\{ \boldsymbol{P}_n^{ES} \in \mathbb{R}^T \;\middle|\; \begin{array}{c} SOC_{n,t}^{ES} = \delta_n SOC_{n,t\text{-}1}^{ES} + P_{n,t}^{ES}\Delta t, \forall t \in \mathcal{T} \\ -P_{n,t}^{ES,-} \le P_{n,t}^{ES} \le P_{n,t}^{ES,+}, \forall t \in \mathcal{T} \\ SOC_n^{ES,-} \le SOC_{n,t}^{ES} \le SOC_n^{ES,+}, \forall t \in \mathcal{T} \end{array} \right\} \tag{13}$$

where, $\boldsymbol{P}_n^{ES}$ is the power vector of BS n, which is defined as $\boldsymbol{P}_n^{ES} = [P_{n,1}^{ES}, P_{n,2}^{ES}, \cdots, P_{n,T}^{ES}]$. For each time slot t, the power of BS n is bounded with $[-P_{n,t}^{ES,-}, P_{n,t}^{ES,+}]$, and $P_{n,t}^{ES} > 0$ denotes charging while $P_{n,t}^{ES} < 0$ denotes discharging. $SOC_{n,t}^{ES}$ is the state of charge (SOC) of the ES device at time slot t, which is limited within the interval $[SOC_n^{ES,-}, SOC_n^{ES,+}]$. δ_n denotes the self-discharge rate of BS n.

2) Aggregation Model of mobile network with multiple BSs

a) Load Power aggregation model: For the mobile network with $n \in \mathcal{N}$, its aggregate power consumption, i.e., the power consumption of total traffic load, can be calculated by

$$L_{agg,t}^{MN} = \sum_{n \in \mathcal{N}} L_{n,t}^{MN}, \forall t \in \mathcal{T} \tag{14}$$

where, $L_{agg,t}^{MN}$ is the aggregated power consumption of mobile network at time slot t.

b) Exact Power aggregation model: For N energy storage devices owned by the MNO, its aggregated power is given by

$$P_{agg,t}^{ES} = \sum_{n \in \mathcal{N}} P_{n,t}^{ES}, \forall t \in \mathcal{T} \tag{15}$$

The aggregate feasible region can be written as

$$\mathcal{F} = \bigcup_{n \in \mathcal{N}} \mathcal{F}_n \tag{16}$$

where, $\cup$ denotes the Minkowski sum [19].

3) Simplified Aggregation Model of multiple energy storage devices with inner-approximation

From (13) and (16), we can see that the expression of set F is quite abstract, which contains all the aggregate power profiles of N energy storage devices. Thus, the numerical complexity of calculating their Minkowski sum is prohibitively expensive when the number of energy storage devices is large. Although the feasible region defined by (13) can be described by a polytope, calculating the Minkowski sum of polytopes is NP-hard since the number of inequality constraints increases exponentially with the system dimension, e.g. the numbers of T and N. Therefore, it is necessary to search for a numerically tractable approach to obtain the Minkowski sum. An alternative way is to find the maximum inner approximation or minimum outer approximation [19]. While some outer approximation methods could be computed efficiently, the main concern is that they can contain some infeasible cases. Thus, this paper tries to find an inner approximation method of feasible region defined by (13). The detailed aggregation process and the $\mathcal{F}_0$ homothet-based aggregation approach are given in Appendix A.

Assume the aggregate model of N energy storage devices is given by a virtual battery model, i.e.,

$$\mathcal{F}_{agg} = \left\{ \boldsymbol{P}_{agg}^{ES} \in \mathbb{R}^T \;\middle|\; \begin{array}{c} SOC_{agg,t}^{ES} = \delta_{agg} SOC_{agg,t\text{-}1}^{ES} + P_{agg,t}^{ES}\Delta t, \forall t \in \mathcal{T} \\ -P_{agg,t}^{ES,-} \le P_{agg,t}^{ES} \le P_{agg,t}^{ES,+}, \forall t \in \mathcal{T} \\ SOC_{agg}^{ES,-} \le SOC_{agg,t}^{ES} \le SOC_{agg}^{ES,+}, \forall t \in \mathcal{T} \end{array} \right\} \tag{17}$$

The above aggregate model can be specified by parameter $\boldsymbol{\Theta}_{agg} = \{\boldsymbol{C}_{agg}, \boldsymbol{P}_{agg}^{ES,-}, \boldsymbol{P}_{agg}^{ES,+}, \boldsymbol{SOC}_{agg}^{ES,-}, \boldsymbol{SOC}_{agg}^{ES,+}\}$. Based on the parameters of the chosen $\boldsymbol{\mathcal{F}}_0$ obtained by the aggregation approach in Appendix A, we use $\beta_n \boldsymbol{\mathcal{F}}_0 + \boldsymbol{\chi}_n$ to approximate $\boldsymbol{\mathcal{F}}_n$ for each $n \in \mathcal{N}$, in which the optimal solutions are denoted by $\beta_{n,*}$ and $\boldsymbol{\chi}_{n,*}$. Let $\beta = \sum_{n \in \mathcal{N}} \beta_{n,*}$ and $\boldsymbol{\chi} = \sum_{n \in \mathcal{N}} \boldsymbol{\chi}_{n,*}$, the aggregate parameter $\boldsymbol{\Theta}_{agg}$ can be calculated by

$$\begin{cases} \boldsymbol{C}_{agg} = \beta \boldsymbol{C}_0 \\ \boldsymbol{P}_{agg}^{ES,-} = \beta \boldsymbol{P}_0^{ES,-} - \boldsymbol{\chi}, \boldsymbol{P}_{agg}^{ES,+} = \beta \boldsymbol{P}_0^{ES,+} + \boldsymbol{\chi} \\ \boldsymbol{SOC}_{agg}^{ES,-} = \beta \boldsymbol{SOC}_0^{ES,-} - \boldsymbol{A}^{-1}\boldsymbol{B}\boldsymbol{\chi}, \boldsymbol{SOC}_{agg}^{ES,+} = \beta \boldsymbol{SOC}_0^{ES,+} + \boldsymbol{A}^{-1}\boldsymbol{B}\boldsymbol{\chi} \end{cases} \tag{18}$$

Thus, we obtain the approximate flexibility region of N ES devices.

B. Optimal Model of MNO

After power aggregation of multiple BSs and ES devices depicted in Part A, the optimal model of MNO can be described as follows. We assume that the MNO is a rational decision maker, who minimizes its electricity bills through interaction

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with the DNO. Similarly, the optimal models of the MNO can also be divided into two modes: the independent optimization mode and the collaborative optimization mode.

1) Independent optimization mode: In the independent mode, we assume that the MNO optimizes its power purchase plan and local ES devices operational strategy by solving the following cost minimization problem.

$$\text{minimize} \quad C_{MNO}^{in} = \sum\nolimits_{t\in\mathcal{T}} p_{sell,t} P_{MN,t} \Delta t \tag{19}$$

subject to

$$P_{MN,t} + P_{agg,t}^{ES} = L_{agg,t}^{MN}, \forall t \in \mathcal{T} \tag{20a}$$

$$SOC_{agg,t}^{ES} = \delta_{agg} SOC_{agg,t\text{-}1}^{ES} + P_{agg,t}^{ES} \Delta t, \forall t \in \mathcal{T} \tag{20b}$$

$$-P_{agg,t}^{ES,-} \le P_{agg,t}^{ES} \le P_{agg,t}^{ES,+}, \forall t \in \mathcal{T} \tag{20c}$$

$$SOC_{agg}^{ES,-} \le SOC_{agg,t}^{ES} \le SOC_{agg}^{ES,+}, \forall t \in \mathcal{T} \tag{20d}$$

where, $p_{sell,t}$ is the power selling price to electricity users at time slot *t*. $L_{agg,t}^{MN}$ and $P_{agg,t}^{ES}$ for each time slot *t* are the variables, and the parameters in (20b)-(20d) can be calculated by (18). Let C_{MNO}^{0} denote the optimal value of the problem denoted by (19), which serves as the benchmark for comparison with the collaborative optimization mode in next sub-section.

2) Collaborative optimization mode: In the collaborative optimization mode, we assume that the MNO can reschedule its operating strategies to provide flexibility for the DNO, which can be rewarded by a reimbursement. Thus, the operating cost of the MNO in collaboration mode can be described by

$$C_{MNO}^{co} = C_{MNO}^{in} - \kappa \tag{21}$$

Then the optimization model of MNO can be defined as the following cost reduction maximization problem.

$$\begin{aligned} &\text{maximize} \quad \mathcal{U}_{MNO}(\boldsymbol{P}_{MN}, \boldsymbol{P}_{agg}^{ES}, \kappa) = C_{MNO}^{0} - C_{MNO}^{co} \\ &\textit{subject to} \quad (20\text{a}) - (20\text{d}) \end{aligned} \tag{22}$$

In collaboration mode, $\boldsymbol{L}_{agg}^{MN}$, $\boldsymbol{P}_{agg}^{ES}$, and κ are variables of the MNO. Similarly, when MNO does not cooperate with the DNO for collaborative optimization, its optimal objective is $\mathcal{U}_{MNO} = 0$. In addition, we assume that the ES device is the only source for power regulation of the mobile network, thus the up/down-ward flexibility supply of the mobile network at time slot *t*. (i.e., (3c) and (3f)) can be reconstructed as

$$FS_{MN,t}^{up} = \min\left\{(P_{agg,t}^{ES,+} - P_{agg,t}^{ES})\Delta t, SOC_{agg}^{ES,+} - SOC_{agg,t}^{ES}\right\}, \forall t \in \mathcal{T} \tag{23a}$$

$$FS_{MN,t}^{down} = \min\left\{(P_{agg,t}^{ES} - P_{agg,t}^{ES,-})\Delta t, SOC_{agg,t}^{ES} - SOC_{agg}^{ES,-}\right\}, \forall t \in \mathcal{T} \tag{23b}$$

Note that we assume that the up/down-ward flexibility supply $FS_{PV,t}^{\text{up}}$ and $FS_{PV,t}^{\text{down}}$ can be released to the DNO and the personal information of the MNO, such as $P_{agg,t}^{ES,-}$, is not leaked.

V. Nash Bargaining-Based Collaborative Optimization of DNO and MNO

Section III and IV presented the optimization models of DNO and MNO in different modes. As proposed in this paper, the decision-making processes of DNO and MNO are coupled closely, which makes the collaborative optimization problem between DNO and MNO hard to solve through standard commercial solvers. Moreover, it is not realistic that all the personal information are shared with each player to realize collaborative optimization, because the DNO and MNO are different entities who preserve their own privacy. Instead of the conventional Stackelberg game-based approach, the Nash bargaining game approach can both improve the benefits of the players and maximize the social welfare of the system [20]. Thus, a Nash bargaining game model is proposed in this section to facilitate mutually beneficial results between DNO and MNO through negotiation and collaboration. Then, the de-centralized solution algorithm based on ADMM is proposed to obtain NBS with limited information interaction.

A. Nash Bargaining Model

In the collaborative optimization problem, this paper assumes that both DNO and MNO are rational and self-interested decision-makers, who negotiate with each other to achieve a mutually beneficial agreement. Thus, this paper tries to find a solution that satisfies pareto efficiency, symmetry, invariance to affine transformations, and independence of irrelevant alternatives, i.e., NBS. Mathematically, for the collaboration problem of DNO and MNO, a pair of strategies $\{\boldsymbol{L}_{agg}^{MN,*}, \kappa^*\}$ is a NBS only if it is obtained by solving the following optimization problem [21], [22]:

$$\begin{aligned} &\text{maximize} \quad \left(\mathcal{U}_{DNO} - \mathcal{U}_{DNO}^{0}\right)\left(\mathcal{U}_{MNO} - \mathcal{U}_{MNO}^{0}\right) \\ &\textit{subject to} \quad (4\text{a})-(4\text{b}), (7\text{b})-(7\text{f}), (20\text{a})-(20\text{d}) \\ &\qquad\qquad \mathcal{U}_{DNO} \ge \mathcal{U}_{DNO}^{0}, \mathcal{U}_{MNO} \ge \mathcal{U}_{MNO}^{0} \end{aligned} \tag{24}$$

where, $\mathcal{U}_{DNO}^{0}$ and $\mathcal{U}_{MNO}^{0}$ are the disagreement points of DNO and MNO, respectively. Note that compared with the summation of performance improvements, the Nash product can guarantee that the benefits of cooperation are shared by each player in a fair manner [23]. Then, the NBS can be reached by solving the optimization problem denoted by (24) as the following theorem [24], [25].

Theorem 1: The Nash bargaining problem in (24) is feasible only if the social welfare of the collaboration system (which is obtained by solving the optimization problem denoted by (26)) is positive, and the NBS $\{\boldsymbol{L}_{agg}^{MN,*}, \kappa^*\}$ is as follow:

$$\kappa^* = \frac{1}{2}\left[\left(C_{DNO}^{0} - C_{DNO}^{in}\right) - \left(C_{MNO}^{0} - C_{MNO}^{in}\right)\right] \tag{25}$$

$\boldsymbol{L}_{agg}^{MN,*}$ is obtained through solving the social welfare maximization problem.

Proof: See the Appendix B.

Note that the social welfare considered in this paper is defined as the aggregate utilities of the DNO and the MNO, and the social welfare maximization problem is described by

$$\begin{aligned} \text{maximize} \quad \mathcal{W} &= \mathcal{U}_{DNO} + \mathcal{U}_{MNO} \\ &= \left(C_{DNO}^{0} - C_{DNO}^{in} - \kappa\right) + \left(C_{MNO}^{0} - C_{MNO}^{in} + \kappa\right) \\ &= \left(C_{DNO}^{0} - C_{DNO}^{in}\right) + \left(C_{MNO}^{0} - C_{MNO}^{in}\right) \\ \textit{subject to} \quad &(4\text{a})-(4\text{b}), (7\text{b})-(7\text{f}), (20\text{a})-(20\text{d}) \end{aligned} \tag{26}$$

where, the objective function and constraints are linear, thus, the proposed social welfare maximization model is a strictly convex.

B. Decentralized Solution to NBS

As stated in Appendix B, the Nash bargaining problem defined by (24) can be equivalently decomposed as two sub-problems: the social welfare maximization sub-problem (**P1**) and the payoff allocation sub-problem (**P2**). Theorem 1 provide a solution method for NBS of (24), but this approach can only be implemented in a centralized way, which cannot be applied directly in this paper's scenario (DNO and MNO commonly run as autonomous entities and it is impractical to share their own personal information). Since the convergence of the two blocks ADMM is guaranteed [23], this sub-section presents a decentralized method based on ADMM to obtain the NBS of (24). For the social welfare maximization sub-problem shown in (26), the constraint (7b) couples DNO and MNO together. In order to perform a decentralized solution, the auxiliary variable is introduced

$$\hat{P}_{MN,t} = P_{MN,t}, \forall t \in \mathcal{T} \quad (: \lambda_{MN,t}) \tag{27}$$

where, $\lambda_{MN,t}$ is the dual variable of the consensus constraint (26). Since C_{DNO}^{0} and C_{MNO}^{0} are constants, the problem (26) can be equivalently rewritten as

$$\begin{aligned} &\text{minimize} \quad C_{DNO}^{in} + C_{MNO}^{in} \\ &\textit{subject to} \quad (4\text{a})-(4\text{b}), (7\text{b})-(7\text{f}), (20\text{a})-(20\text{d}) \\ &\qquad \hat{P}_{MN,t} = P_{MN,t}, \forall t \in \mathcal{T} \end{aligned} \tag{28}$$

For the implementation of ADMM, the augmented Lagrangian function of the optimal problem (28) with respect to consensus constraint (26) is given by

$$\begin{aligned} L(\boldsymbol{P}_{MN}, \hat{\boldsymbol{P}}_{MN}, \boldsymbol{\lambda}_{MN}) &= C_{DNO}^{in} + C_{MNO}^{in} + \frac{\rho_1}{2} \sum\nolimits_{t\in\mathcal{T}} \left\| \hat{P}_{MN,t} - P_{MN,t} \right\|^2 \\ &+ \sum\nolimits_{t\in\mathcal{T}} \lambda_{MN,t} (\hat{P}_{MN,t} - P_{MN,t}) \end{aligned} \tag{29}$$

where, ρ_1 is the penalty parameter which satisfies $\rho_1 > 0$.

By leveraging the ADMM decomposition technique, the problem (28) be decomposed into a sub-problem for DNO as

$$\begin{aligned} &\text{minimize} \quad C_{DNO}^{in} \\ &\textit{subject to} \quad (4\text{a})-(4\text{b}), (7\text{b})-(7\text{f}) \\ &\qquad \hat{P}_{MN,t} = P_{MN,t}, \forall t \in \mathcal{T} \end{aligned} \tag{30}$$

and a sub-problem for MNO as

$$\begin{aligned} &\text{minimize} \quad C_{MNO}^{in} \\ &\textit{subject to} \quad (20\text{a})-(20\text{d}) \end{aligned} \tag{31}$$

Thus, the iterative procedure based on ADMM to obtain the optimal solutions of (26) is illustrated in **Algorithm 1**. Due to the convexity properties of (30) and (31), the convergence of **Algorithm 1** can always be guaranteed and a detailed proof process for ADMM algorithm is given in [24]. For the payoff allocation sub-problem (i.e., **P2**), the de-centralized solution procedure to obtain optimal κ^* is similar to the solution process of **P1** above, which is not presented here due to limited space.

Algorithm 1: Iterative procedure of solving **P1** based on ADMM.

1: Initialization: set iteration index *it*=0, error tolerance $\varepsilon > 0$, and ρ_1; initialize $\boldsymbol{\lambda}_{MN}(it)$, $\boldsymbol{P}_{MN}(it)$.
2: **Repeat**
At *it*-th iteration, do
3: **DNO:** Given ρ_1, $\boldsymbol{\lambda}_{MN}(it)$, $\boldsymbol{P}_{MN}(it)$
Solve $\min\ c_{DNO}^{in} + \frac{\rho_1}{2}\sum_{t\in\mathcal{T}}\left\|\hat{P}_{MN,t}(it+1) - P_{MN,t}(it)\right\|^2 + \sum_{t\in\mathcal{T}}\lambda_{MN,t}(it)\hat{P}_{MN,t}(it+1)$
s.t. (4a)-(4b), (7b)-(7f)
Obtain $\hat{P}_{MN,t}(it+1)$.
4: **MNO:** Given ρ_1, $\boldsymbol{\lambda}_{MN}(it)$, $\hat{\boldsymbol{P}}_{MN}(it+1)$
Solve $\min\ c_{MNO}^{in} + \frac{\rho_1}{2}\sum_{t\in\mathcal{T}}\left\|\hat{P}_{MN,t}(it+1) - P_{MN,t}(it+1)\right\|^2 - \sum_{t\in\mathcal{T}}\lambda_{MN,t}(it)P_{MN,t}(it+1)$
s.t. (20a)-(20d)
Obtain $\boldsymbol{P}_{MN}(it+1)$.
5: **Update:** $\boldsymbol{\lambda}_{MN}(it+1) = \boldsymbol{\lambda}_{MN}(it) + \rho_1\left(\hat{\boldsymbol{P}}_{MN}(it+1) - \boldsymbol{P}_{MN}(it+1)\right)$;
$it = it+1$.
6: **Until** the stopping criterion is met, i.e., $\sum_{t\in\mathcal{T}}\left\|\hat{P}_{MN,t}(it+1) - P_{MN,t}(it)\right\| < \varepsilon$.
7: **End**.

VI. Case Study

A. Basic Data

The collaborative system of the distribution network and the mobile network is constructed to verify the performance of the proposed optimization method. It is assumed that the coverage area of the target feeder-level distribution network in this paper is 1.2 km^2, and the conventional load peak of the distribution network in a typical day is 1.65MW.

We suppose that this area has completed the deployment of 5G BSs, according to the BS density in [26] (i.e., 40-50 BSs/km^2) and the average maximum power consumption of each BS (i.e., 3.0 kW [14]), the number of 5G BSs of the mobile network is set to 60. Thus, the original load curve of the distribution network (i.e., without considering the collaboration with MNO) and the normalized aggregate traffic load of mobile network are shown in Fig. 2. Note that the load pattern profile of the mobile network refers to [15].

The distribution network consists of 1.0 MW PV panels and 0.5 MW MT for flexibility supply, and the parameters of MT (e.g. ramping rates, cost coefficients, etc) are given in [27], [28]. Each BS in the mobile network is equipped with a 2.5kW/4kWh ES for energy-saving. Also, the power aggregation method described in Section III-A is utilized to obtain the approximate flexibility of multiple ES devices. Besides, this paper assumes that both DNO and MNO are rational decision-makers, who minimize their own cost through collaboration with each other. The price parameters of this paper adopt the feed-in tariff in most Chinese areas, which refer to [27].

B. Analysis of Power Aggregation of the Mobile Network

To verify the effectiveness of the proposed power aggregation method for energy optimization of the mobile network, two schemes are set for comparative analysis:

Scheme 1: Implement energy optimization of the mobile network without power aggregation, i.e., solve the optimization problem defined by (13) and (19). Scheme 2: Implement energy optimization of the mobile network with the proposed power aggregation method, i.e., solve the optimization problem defined (19)-(20). Given *N*=60, the optimized power interaction strategies with distribution network of the two schemes are depicted as Fig. 3, which demonstrates that the proposed approximate power aggregation method has good accuracy. Further, the trend of calculation time in solving the optimization problem of two schemes changing with the number of BSs (i.e., *N*) is shown in Fig. 4. The proposed power aggregation method has significant calculation advantage, especially when *N* is large. Although the cost increases slightly after power aggregation (since the obtained solution with power aggregation is sub-optimal and conservative in comparison with the optimal solution), the calculation time with power aggregation is reduced significantly, which is quite suitable for the application of a 5G mobile network with ultra-dense BSs.

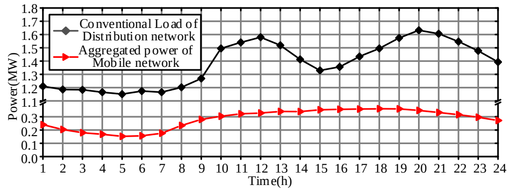

Fig. 2. The load curves of the distribution network and the mobile network.

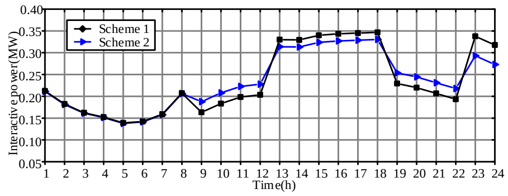

Fig. 3. The optimized power interaction strategies of two schemes.

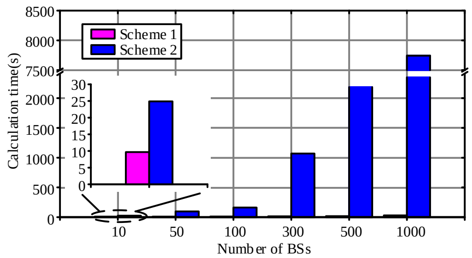

Fig. 4. The trend of calculation time changing with the number of BSs.

C. *Collaborative Optimization Results of DNO and MNO*

To verify the effectiveness of the proposed collaborative optimization method based on Nash bargaining, two optimization modes are employed for comparative analysis.

1) Independent mode: In this mode, we assume that the DNO and the MNO optimize their own objectives independently, i.e., the optimal problems defined by (6)-(7) and (19)-(20) are solved by DNO and MNO, respectively.

2) Collaborative mode: In this mode, the optimization method based on Nash bargaining is utilized for the collaborative optimization of DNO and MNO.

The optimized results of two operation modes are illustrated in Table I and Figs. 5-8. From Table I we can draw that, compared with the independent optimization mode, the collaborative mode can reduce the operating cost of DNO and MNO while alleviating net-load fluctuation of the distribution network, which is beneficial for both DNO and MNO.

In the independent mode, the high penetration of PV power makes the net load of the distribution network fluctuate dramatically, e.g., the net-load of the distribution network drops sharply during 10:00-14:00, then rises rapidly and reaches the peak at 20:00 (as shown in Fig. 6). The volatility of the net load put higher requirement on system flexibility; however, in independent mode, the flexibility of the distribution network is derived from the neighboring grid support and backup MT, which are restricted by transmission lines' capacity, probable network congestions, ramping abilities, etc. Thus, the flexibility supply is quite limited in independent mode, which can be demonstrated by Fig. 7, i.e., during the period 10:00-12:00, the downward flexibility of the distribution network is swallowed up, while during the period 15:00-16:00, the flexibility supply cannot satisfy the flexibility demand. In this case, it is inevitable to abandon PV power to ensure the flexibility balance of the distribution network.

In the collaborative mode, the flexibility sources of the distribution network include not only the neighboring grid support and backup MT, but also the power support from the mobile network. It can be seen from Fig. 5, Fig. 6 and Fig. 8 that with the proactive support of the mobile network, the volatility of the net-load of the distribution network is reduced (e.g., power increased during time period 13:00-15:00) and the operating flexibility is enhanced significantly, which is beneficial for utilization of high proportions of renewables.

D. *Optimization results with different PV penetration ratios*

In this sub-section, the capacity penetration index (e.g., the ratio of the maximum PV power to the peak of total load of the distribution network) is employed to qualify the PV power penetration ratio in the distribution network. The change of flexibility margin (which is defined by (4)) in different optimization modes with PV ratios is shown in Fig. 9.

TABLE I OPTIMIZED RESULTS IN DIFFERENT MODES

Comparison		Independent mode	Collaborative mode
Cost ($\times 10^3$CNY)	DNO	13.2605	13.1590
	MNO	4.4755	4.3740
NFI (MW)		3.0475	2.6456

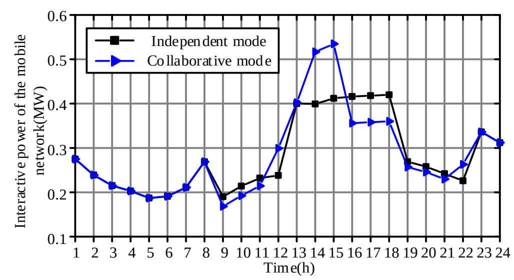

Fig. 5. The interactive power of the mobile network with the distribution network in different modes.

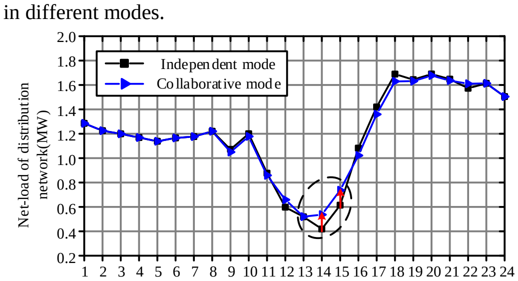

Fig. 6. The net-load curves of the distribution network in different modes.

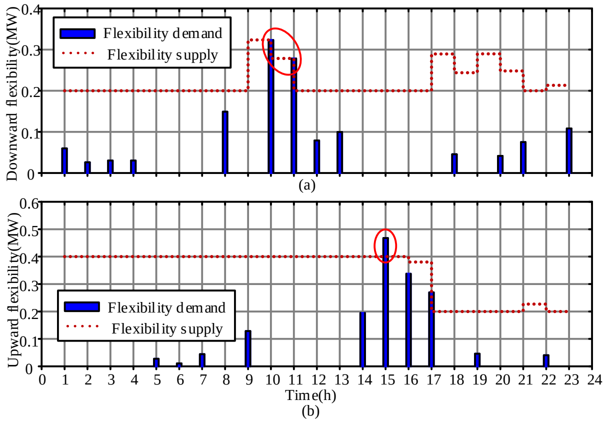

Fig. 7. The flexibility balance of the distribution network in independent mode. (a) The downward flexibility balance. (b) The upward flexibility balance.

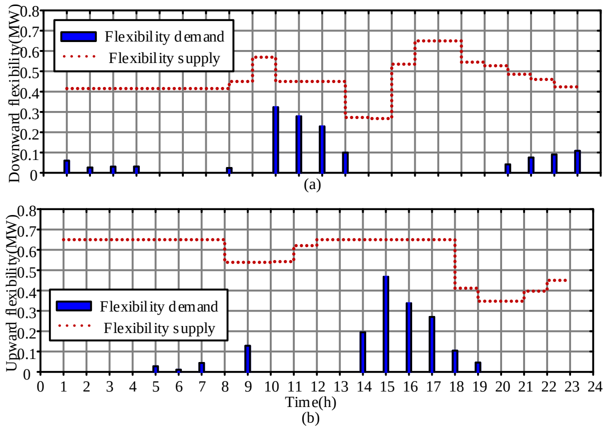

Fig. 8. The flexibility balance of the distribution network in collaborative mode. (a) The downward flexibility balance. (b) The upward flexibility balance.

In the independent mode, the flexibility margin of the distribution network decreases significantly with the increase of the penetration ratio, especially during time period 14:00-16:00 (as seen in Fig. 9 (b)). In this time period, the upward flexibility margin becomes negative (i.e., the upward flexibility is insufficient and it is inevitable to conduct PV power shedding) when the penetration ratio is greater than 0.35, and the greater the penetration ratio, the smaller the value of the flexibility margin (i.e., the more serious the flexibility insufficiency), which demonstrates that the ability of the distribution network to support PV penetration is very limited in the independent mode due to insufficient flexibility. In the collaborative mode, it can be seen from Fig. 9 (c) and (d) that the downward and upward flexibility margins are increased significantly compared with the independent mode, which is largely attributable to the proactive flexibility support from the mobile network in proposed Nash bargaining framework, which is helpful for utilizing high penetration of PV power rather than abandoning it (as done in the independent mode).

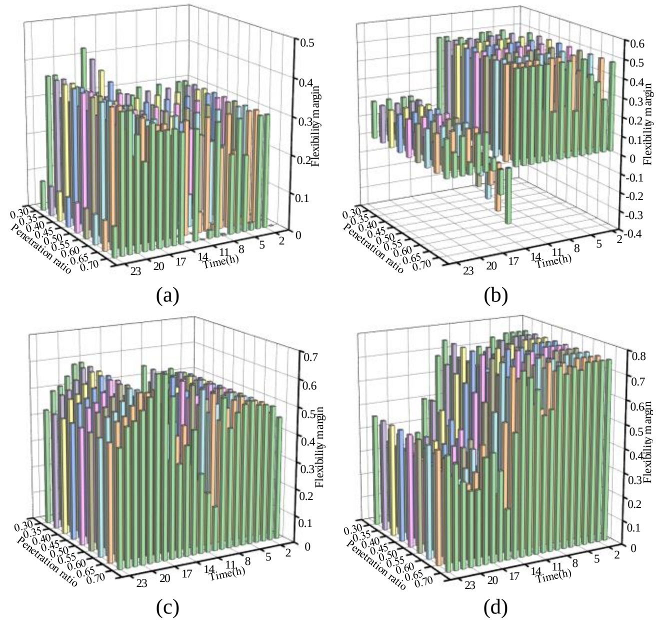

Fig. 9. The trend of flexibility margin changing with PV penetration without PV power abandonment. (a) The downward flexibility margin in independent mode. (b) The upward flexibility margin in independent mode. (c) The downward flexibility margin in collaborative mode. (d) The upward flexibility margin in collaborative mode.

E. *Extensibility Analysis of the Proposed Method*

1) Consideration of network constraints: Note that the case this paper mainly focuses on is the optimization of feeder-level distribution network, i.e., the BSs of the mobile network and distributed energy resources are connected to the same distribution feeder. To illustrate the extensibility of the proposed method considering network constraints, the modified radial distribution network in [16], [17] is adopted for demonstration, which contains three 10kV bus (shown in Fig. 10). Without loss of generality, the basic data (e.g., original load curves) presented in Part A are taken as the benchmark, multiplying the benchmark data by the amplitude coefficient (0.6, 0.8, 1.0 for bus 1, 2, 3 respectively) and adding a normal distribution disturbance (the standard deviation is 0.01, 0.015 and 0.02 respectively), the obtained data are utilized as inputs of the modified radial distribution network.

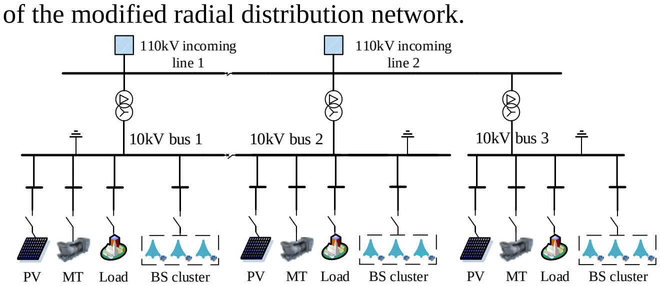

Fig. 10. The topology of modified radial distribution network.

After the implementation of the proposed Nash Bargaining-based collaborative optimization approach, the DNO and MNO obtain their optimal strategies. The operating cost of DNO and MNO are 31926CNY and 10504CNY, respectively. Because the line capacity constraints were not considered in the process of obtaining the DNO and MNO's optimal strategies, the power line capacity should be checked following the steps listed in Part C, Section III. Taking time slot 13 as an example, the

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power flow results of the distribution network are presented in Fig. 11. It is clear that the power flow on each power line satisfied the constraints, which demonstrates that the obtained strategies of DNO and MNO are feasible when considering the network constraints.

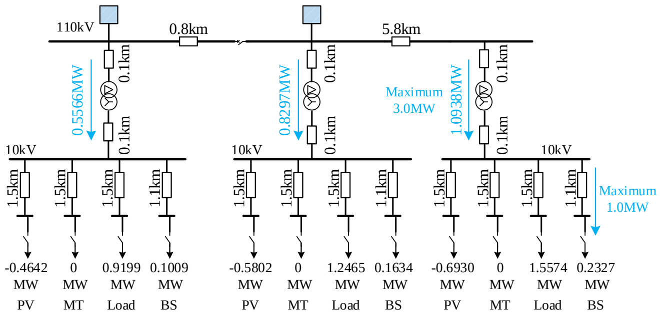

Fig. 11. Load distribution and mainly power flow at time slot 13.

2) Extensibility analysis on large-scale systems: To analyze the computational performance of the proposed decentralized solution algorithm and verify its extensibility on large-scale systems, three testing conditions are selected for comparison: i) The basic data of Part A are utilized as the benchmark (Case 1). ii) The proposed algorithm is tested on the aforementioned 3-feeder distribution network (Case 2). iii) The proposed algorithm is tested on the modified IEEE 33-bus distribution system (Case 3), and the network topology is not presented here due to page limits.

Furthermore, all numerical tests are carried out on a computer with an Intel(R) Core(TM) i5-5200 CPU at 2.20 GHz and 8 GB RAM, and the optimal problems were solved using Matlab software (ver. R2016a) by calling CPLEX solver (ver. 12.8). The testing results on different cases are shown in Table II, from which we can draw that, as the size of the testing systems grows, the calculation time of the proposed algorithm also increases correspondingly. But all the calculation times are acceptable in practical applications since the computation complexity is O(n).

TABLE II COMPARISON OF COMPUTATIONAL PERFORMANCE UNDER DIFFERENT CASES

Comparison	Variables number	Constraints number	Computation time
Case 1	96	284	6.812s
Case 2	288	852	16.492s
Case 3	3168	9372	173.623s

VII. CONCLUSION

In this paper, a collaborative optimization method of the distribution network and the mobile network with interactive balance of flexibility and power is proposed, as a new contribution to earlier studies. Through the comprehensive numerical case study, we can draw that: 1) For the MNO, the proposed approximate power aggregation approach can reduce the calculation time of the mobile network optimization significantly, especially when the number of BSs is large, which is suitable for some complex situations (e.g., collaborative optimization with distribution network) of the mobile network with ultra-dense BSs in 5G or B5G era. 2) Compared with the independent optimization mode, the proposed collaborative optimization method of DNO and MNO with flexibility balance and Nash bargaining is helpful to alleviate the fluctuation of the net-load of the distribution network and facilitate the utilization of PV power. In addition, the proposed collaborative optimization method integrates flexibility balance and power balance and can reduce the operating cost of both DNO and MNO, reaching a win-win result. Note that in this study, we assume that both DNO and MNO are perfectly rational decision makers, but in practical, this assumption is not always true. Future work will take the bounded rationality of DNO and MNO in decision-making into consideration. The flexibility demand considered in this paper focuses on the volatility of the net-load of the distribution network with high proportion of renewables, but the uncertainties of renewable generation and demand are also important parts of the flexibility demand, which could be evaluated further. Besides, the interaction between transmission system and distribution system is not included in this paper, thus the integrated optimization of transmission system and distribution system with interactive balance of flexibility and power should be investigated further.

APPENDIX A
AGGREGATION PROCESS OF MULTIPLE ES DEVICES

As depicted in [18], [28], given a compact convex set $\boldsymbol{\mathcal{F}}_0$, the homothet of $\boldsymbol{\mathcal{F}}_0$ can be defined as

$$\beta_n \mathcal{F}_0 + \boldsymbol{\chi}_n = \{\boldsymbol{y}_n \,|\, \boldsymbol{y}_n = \beta_n \boldsymbol{\xi} + \boldsymbol{\chi}_n, \forall \boldsymbol{\xi} \in \mathcal{F}_0\} \quad (32)$$

where, β_n is a scaling factor and meets $\beta_n > 0$, $\boldsymbol{\chi}_n$ is a translation factor with $\boldsymbol{\chi}_n \in \mathbb{R}^T$.

Then, the key problem becomes how to obtain the $\mathcal{F}_0$-homothet that optimally approximates $\mathcal{F}_n$, which contains two main tasks to be solved, i.e., how to choose the set $\boldsymbol{\mathcal{F}}_0$ and how to get the optimal factors β_n, $\boldsymbol{\chi}_n$. For the former, we choose $\boldsymbol{\mathcal{F}}_0$ to be in the same form as $\boldsymbol{\mathcal{F}}_n$ defined by (13), i.e.

$$\mathcal{F}_0 = \left\{ \boldsymbol{P}_0^{ES} \in \mathbb{R}^T \left| \begin{array}{c} SOC_{0,t}^{ES} = \overline{\delta} SOC_{0,t-1}^{ES} + P_{0,t}^{ES} \Delta t, \forall t \in \mathcal{T} \\ -\overline{P_{0,t}^{ES,-}} \le P_{0,t}^{ES} \le \overline{P_{0,t}^{ES,+}}, \forall t \in \mathcal{T} \\ \overline{SOC_0^{ES,-}} \le SOC_{0,t}^{ES} \le \overline{SOC_0^{ES,+}}, \forall t \in \mathcal{T} \end{array} \right. \right\} \quad (33)$$

where, the parameters $\overline{\delta}$, $\overline{P_{0,t}^{ES,-}}$, $\overline{P_{0,t}^{ES,+}}$, $\overline{SOC_0^{ES,-}}$, $\overline{SOC_0^{ES,+}}$ are obtained from the average of all ES parameters. And $\boldsymbol{\mathcal{F}}_0$ are determined by the parameter $\boldsymbol{\Theta}_0 = \{\boldsymbol{C}_0, \boldsymbol{P}_0^{ES,-}, \boldsymbol{P}_0^{ES,+}, \boldsymbol{SOC}_0^{ES,-}, \boldsymbol{SOC}_0^{ES,+}\}$, in which $\boldsymbol{C_0} = [\overline{\delta} \cdot \overline{SOC_{0,ini}^{ES}}, 0, \cdots, 0]^{\mathrm{T}}$, $\boldsymbol{P}_0^{ES,-} = [\overline{P_{0,t}^{ES,-}}]$, $\boldsymbol{P}_0^{ES,+} = [\overline{P_{0,t}^{ES,+}}]$, $\boldsymbol{SOC}_0^{ES,-} = [\overline{SOC_0^{ES,-}}]$, $\boldsymbol{SOC}_0^{ES,+} = [\overline{SOC_0^{ES,+}}]$ for each $t \in \mathcal{T}$. Note that $\overline{SOC_{0,ini}^{ES}}$ denotes the average initial SOC of all N energy storage devices, and $[\cdot]$ represents the $T \times 1$ dimensional vector.

For the convenience of problem description, (13) can be rewritten as

$$\mathcal{F}_n = \left\{ \boldsymbol{P}_n^{ES} \in \mathbb{R}^T \,\middle|\, \boldsymbol{K}_n \boldsymbol{P}_n^{ES} \le \boldsymbol{H}_n \right\} \quad (34)$$

where, $\boldsymbol{K}_n$ and $\boldsymbol{H}_n$ are calculated by

$$\boldsymbol{K}_n = (\mathrm{diag}(\boldsymbol{I}); \mathrm{diag}(-\boldsymbol{I}); \boldsymbol{A}_n^{-1}\boldsymbol{B}_n; -\boldsymbol{A}_n^{-1}\boldsymbol{B}_n) \quad (35a)$$

$$\boldsymbol{H}_n = (\boldsymbol{P}_n^{ES,+}; \boldsymbol{P}_n^{ES,-}; SOC_n^{ES,+}\boldsymbol{I} - \boldsymbol{A}_n^{-1}\boldsymbol{C}_n; -SOC_n^{ES,-}\boldsymbol{I} + \boldsymbol{A}_n^{-1}\boldsymbol{C}_n) \quad (35b)$$

where, $\boldsymbol{I} = [1,1,\cdots,1]^{\mathrm{T}}$ is a $T \times 1$ dimensional identity matrix, diag($\boldsymbol{I}$) means to generate a diagonal matrix with vector $\boldsymbol{I}$ as the main diagonal element, and $\boldsymbol{A}_n^{-1}$ denotes the inverse of $\boldsymbol{A}_n$. $\boldsymbol{A}_n$, $\boldsymbol{B}_n$, $\boldsymbol{C}_n$ are defined as

$$\begin{aligned} \boldsymbol{A}_n &= \begin{bmatrix} 1 & 0 & 0 & \cdots & 0 \\ -\delta_n & 1 & 0 & \cdots & 0 \\ 0 & -\delta_n & 1 & \cdots & 0 \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & 0 & \cdots & 1 \end{bmatrix} \\ \boldsymbol{B}_n &= \Delta t \cdot diag(\boldsymbol{I}) \\ \boldsymbol{C}_n &= \left[\delta_n SOC_{n,0}^{ES} \quad 0 \quad 0 \quad \cdots \quad 0 \right]^{\mathrm{T}} \end{aligned} \tag{36}$$

Thus, the above chosen set $\boldsymbol{\mathcal{F}}_0$ can be rewritten as

$$\mathcal{F}_0 = \left\{ \boldsymbol{P}_0^{ES} \in \mathbb{R}^T \,\middle|\, \boldsymbol{K}_0 \boldsymbol{P}_0^{ES} \le \boldsymbol{H}_0 \right\} \tag{37}$$

where, $\boldsymbol{K_0} = (\mathrm{diag}(\boldsymbol{I}), \mathrm{diag}(-\boldsymbol{I}), \boldsymbol{A_0}^{-1}\boldsymbol{B_0}, -\boldsymbol{A_0}^{-1}\boldsymbol{B_0})$ and $\boldsymbol{H} = (\overline{\boldsymbol{P}_0^{ES,+}}, \overline{\boldsymbol{P}_0^{ES,-}}, \overline{SOC_{max}^{ES}}\boldsymbol{I} - \boldsymbol{A_0}^{-1}\boldsymbol{C_0}, -\overline{SOC_{min}^{ES}}\boldsymbol{I} + \boldsymbol{A_0}^{-1}\boldsymbol{C_0})$, in which $\boldsymbol{B}_0 = \boldsymbol{B}_n$, and $\boldsymbol{A}_0$ can be calculated by

$$\boldsymbol{A}_0 = \begin{bmatrix} 1 & 0 & 0 & \cdots & 0 \\ -\bar{\delta} & 1 & 0 & \cdots & 0 \\ 0 & -\bar{\delta} & 1 & \cdots & 0 \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & 0 & \cdots & 1 \end{bmatrix} \tag{38}$$

Based on the chosen set $\boldsymbol{\mathcal{F}}_0$ denoted by (13), the parameters β_n and $\boldsymbol{\chi}_n$ can be obtained by solving the following optimal problem for each $n \in \mathcal{N}$. The detailed information for this equivalent conversion could be found in [29].

$$\begin{aligned} \underset{\beta_n, \boldsymbol{\chi}_n}{\text{maximize}} \quad & \beta_n \\ \text{subject to} \quad & \beta_n \mathcal{F}_0 + \boldsymbol{\chi}_n \subset \mathcal{F}_n \\ & \beta_n \ge 0 \end{aligned} \tag{39}$$

Let $\lambda_n = 1/\beta_n$ and $\boldsymbol{\theta}_n = -\lambda_n \boldsymbol{\chi}_n$, the above optimal problem can be rewritten as the linear programming problem.

$$\begin{aligned} \underset{\lambda_n, \boldsymbol{\theta}_n, \boldsymbol{G}}{\text{minimize}} \quad & \lambda_n \\ \text{subject to} \quad & \boldsymbol{G}\boldsymbol{K}_0 = \boldsymbol{K}_n \\ & \boldsymbol{G}\boldsymbol{H}_0 \le \lambda_n \boldsymbol{H}_n + \boldsymbol{K}_n \boldsymbol{\theta}_n \end{aligned} \tag{40}$$

Therefore, we can obtain λ_n and $\boldsymbol{\theta}_n$ through solving the above optimal problem, which can be used to calculate the parameters of aggregate feasible region directly.

APPENDIX B

PROOF OF THEOREM 1

Note that the NBS of (24) can also be obtained by solving the following problem:

$$\begin{aligned} \text{maximize} \quad & \ln\left(\mathcal{U}_{DNO} - \mathcal{U}_{DNO}^0\right) + \ln\left(\mathcal{U}_{MNO} - \mathcal{U}_{MNO}^0\right) \\ \textit{subject to} \quad & (4\text{a}) - (4\text{b}), (7\text{b}) - (7\text{f}), (20\text{a}) - (20\text{d}) \\ & \mathcal{U}_{DNO} \ge 0, \mathcal{U}_{MNO} \ge 0 \end{aligned} \tag{41}$$

Since the disagreement points of DNO and MNO satisfy $\mathcal{U}_{DNO}^0 = 0$ and $\mathcal{U}_{MNO}^0 = 0$, the optimization problem (41) can be rewritten as

$$\begin{aligned} \text{maximize} \quad & \ln\left(C_{DNO}^0 - C_{DNO}^{in} - \kappa\right) + \ln\left(C_{MNO}^0 - C_{MNO}^{in} + \kappa\right) \\ \textit{subject to} \quad & (4\text{a}) - (4\text{b}), (7\text{b}) - (7\text{f}), (20\text{a}) - (20\text{d}) \end{aligned} \tag{42}$$

According to the Nash's axioms, the bargaining problem (42) can be equivalently decomposed as two sub-problems: collaborative optimization sub-problem and payoff allocation sub-problem [23], [24].

For the payoff allocation sub-problem (Given $\{\boldsymbol{P}_{MT}, \boldsymbol{P}_{NG}, \boldsymbol{P}_{PV}, \boldsymbol{L}_{agg}^{MN}, \boldsymbol{P}_{agg}^{ES}\}$), the optimal reimbursement κ meets

$$\frac{-1}{C_{DNO}^0 - C_{DNO}^{in} - \kappa} + \frac{1}{C_{MNO}^0 - C_{MNO}^{in} + \kappa} = 0 \tag{43}$$

Then, we obtain the expression of optimal κ^*

$$\kappa^* = \frac{1}{2}\left[\left(C_{DNO}^0 - C_{DNO}^{in}\right) - \left(C_{MNO}^0 - C_{MNO}^{in}\right)\right] \tag{44}$$

For the collaborative optimization sub-problem, to guarantee the feasibility of problem (42), the following constraints should be met

$$C_{DNO}^0 - C_{DNO}^{in} - \kappa \ge 0, C_{MNO}^0 - C_{MNO}^{in} + \kappa \ge 0 \tag{45}$$

Substituting κ^* into (45), we have

$$\left(C_{DNO}^0 - C_{DNO}^{in}\right) + \left(C_{MNO}^0 - C_{MNO}^{in}\right) \ge 0 \tag{46}$$

which is equivalent to the social welfare of the system to be positive. Substituting κ^* into (42), the bargaining problem (42) can be rewritten as

$$\begin{aligned} \text{maximize} \quad & 2\ln\left[\frac{1}{2}\left(\left(C_{DNO}^0 - C_{DNO}^{in}\right) + \left(C_{MNO}^0 - C_{MNO}^{in}\right)\right)\right] \\ \textit{subject to} \quad & (4\text{a}) - (4\text{b}), (7\text{b}) - (7\text{f}), (20\text{a}) - (20\text{d}) \end{aligned} \tag{47}$$

The NBS of (47) can also be obtained by equivalently solving the following problem:

$$\begin{aligned} \text{maximize} \quad & \left(C_{DNO}^0 - C_{DNO}^{in}\right) + \left(C_{MNO}^0 - C_{MNO}^{in}\right) \\ \textit{subject to} \quad & (4\text{a}) - (4\text{b}), (7\text{b}) - (7\text{f}), (20\text{a}) - (20\text{d}) \end{aligned} \tag{48}$$

Thus, we can obtain the optimal solutions of $\boldsymbol{P}_{MT}$, $\boldsymbol{P}_{NG}$, $\boldsymbol{P}_{PV}$, $\boldsymbol{L}_{agg}^{MN}$ and $\boldsymbol{P}_{agg}^{ES}$ by solving problem (48).

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