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Coordinated Energy Dispatch of Autonomous Microgrids with Distributed MPC Optimization

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***Abstract*—With the increased penetration of Renewable Energy Sources (RESs) and plug-and-play loads, MicroGrids (MGs) bring direct challenges in energy management due to the uncertainties in both supply and demand sides. In this paper, we present a coordinated energy dispatch based on Distributed Model Predictive Control (DMPC), where the upper level provides an optimal scheduling for energy exchange between Distribution Network Operator (DNO) and MGs while the lower level guarantees a satisfactory tracking between supply and demand. With the proposed scheme, not only we maintain a supply-demand balance in an economic way, but also improve the renewable energy utilization of distributed microgrid systems. To describe the dynamic process of energy trading, a novel conditional probability distribution model is introduced, which can characterize randomness of charging/discharging and uncertainties of energy dispatch. Moreover, we formulate a two-layer optimization problem and the corresponding algorithm is given. Finally, simulation results show the effectiveness of the proposed method.**

***Index Terms*—Autonomous Microgrids, Coordinated Energy Dispatch, Distributed Model Predictive Control, Renewable Energy Sources.**

I. INTRODUCTION

MICROGRIDS provide a promising solution to integrate distributed Renewable Energy Sources (RESs), storage devices and interconnected loads into a common distribution network [1]. However, due to the intermittent and randomness characteristics of RESs and the load demand across MicroGrids (MGs), there is an urgent need to coordinate energy between each other to achieve a reliable supply-demand balance in an economic way [2].

MGs can operate in an autonomous mode and are subject to environmental and technical constraints, such as lack of power supply from the utilities due to cascading failures or offshore islands [3], etc. Research efforts have been made to enhance system operation and guarantee the power supply security [4]. Some crucial issues related to Autonomous MicroGrids (AMGs) include, but are not limited to, controllable loads which may be curtailed without adequate power supply, surplus energy which cannot be utilized by neighbouring MGs, etc. To balance the demand-supply gap and improve the global resource utilization efficiency, performing cooperative energy management strategy within interconnected microgrids has shown significant benefits [5].

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A. Literature Review

Latest literature on coordinated energy management of AMGs, includes centralized control [6]–[10], decentralized control [11]–[14], hierarchical control [15]–[18] and distributed control [19]–[22]. The centralized control framework is based on global optimization of interconnected MGs to maintain the energy balance and maximize the overall benefits. However, it is vulnerable to single-point failures that can compromise the operation of the system. On the other hand, in a decentralized control, DNO and MGs are regarded as different entities which are self-managed and operated with distinct objectives to minimize their own operation costs [23], [24]. Nevertheless, due to a higher penetration of demand loads, there exists a conflict between price risks and cost savings because of lacking of coordination among AMGs. This means that each microgrid controls local appliance operations to minimize its own cost without considering other microgrids' surplus renewable energy. To this regard, the control of AMGs is needed to achieve system-level objectives.

Hierarchical control and distributed control have attracted much attention recently. Xu et al. [15] propose a hierarchical energy management strategy in order to save generation cost and maintain the system in sustainable operation. A hierarchical iterative control algorithm is presented to balance grid load while meeting consumers' power demand in smart grids [16]. Most of existing works focus on uncertainties either from supply-side or load-side. Recently, distributed control has become a trend in the development of AMGs energy management. In [19] an energy dispatch solution through a DMPC technique is presented to improve the optimal utilization of RESs and to reduce the operation cost. A networked and distributed control model for isolated MGs is proposed in [20], which can obtain a near-optimal dispatch of active and reactive power. The coordinated DMPC algorithm has also been applied to smart electrical grids, which use the "price-driven" decomposition-coordination method to adjust the system operation [25]–[27]. The aforementioned studies

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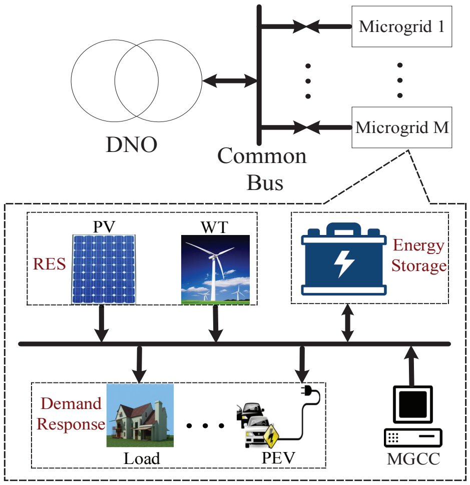

Fig. 1. Schematic of microgrid system considered in this work.

are presented with the assumption that the AMGs can communicate directly, namely, in a distributed manner. Each AMG is directly connected to the common bus in practical scenarios, allowing the power to be traded with neighbours. Individual interconnected power lines among AMGs are not required. That stimulates our energy management scheme through a coordinated DMPC technique.

B. Main Contributions

The main contributions of this paper are:

1) A coordinated energy management scheme for AMGs, which is interfaced to the DNO at the point of common coupling. Through the proposed infrastructure, each microgrid has the option to trade energy with DNO or a local battery according to the profit.
2) A DMPC strategy to deal with the uncertainties in both supply and demand sides. Not only does the strategy improve global distributed generation utilization efficiency, but also enhances the supply-demand matching performance and guarantees the overall benefit.
3) A conditional probability distribution model to describe randomness of charging/discharging and uncertainties of RESs scheduling, which can characterize the operation status of each microgrid dynamically.

C. Outline

The paper is organized as follows. Section II introduces the system structure and the energy dispatch scheme. Section III presents the system modeling framework. Section IV proposes coordinated distributed MPC-based energy management for AMGs. In Section V, validation results are provided. Section VI concludes the paper summarizing major findings.

II. PROPOSED ENERGY DISPATCH STRATEGY OUTLINE

A. General Structure

A cooperative network of M AMGs is illustrated in Fig. 1. Each microgrid is equipped with RESs (PhotoVoltaic (PV) and Wind Turbines (WT)), Energy Storage Systems (ESSs) and loads. In the case that each microgrid is operated in autonomous mode, the load demand can only be supplied by RESs and ES units. Through the advanced metering infrastructure, each microgrid can receive the published data from the DNO, and have the options to share its own information with DNO. It is assumed that all AMGs are connected to the same DNO and the power exchange can take place in both directions.

Figure 1 displays a distributed control architecture, where each microgrid has its own controller and shares information with other subsystems. Each AMG achieves energy coordination only through the DNO since there are no extra power lines among AMGs in practical cases. Moreover, the power generation in the network of AMGs is mainly based on RESs.

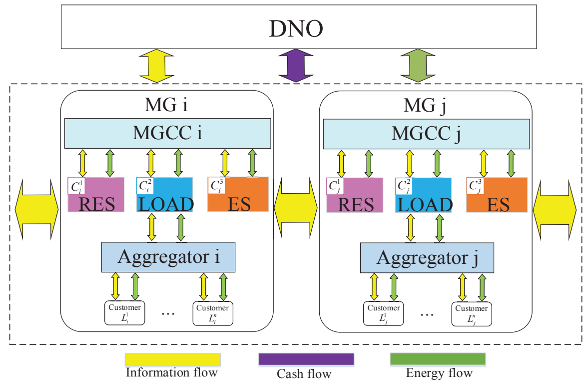

Fig. 2. Coordinated energy management scheme.

B. Proposed Energy Dispatch Strategy

In this paper, our main objective is to maintain the system-wide supply and demand balance as well as minimizing the operation cost. To achieve this target, a two-layer coordinated energy dispatch among AMGs is considered as shown in Fig. 2. The upper layer generates suitable set points for power exchanges among AMGs so that the total benefits of the network are optimized. At the lower layer, the trajectory of the optimal solution derived in upper DNO optimization is executed within each AMG. It is easy to see that the upper layer, namely DNO optimization, has higher priority in dispatching surplus renewable energy than the lower layer, on the other hand, which focuses more on tracking the derived set points. MG component has its own objective and intends to minimize its local cost through MicroGrid Central Controller (MGCC) coordination. Each microgrid with users are served by a load aggregator, which can compensate the disturbances caused by variant elastic loads and reduce demand peak. Moreover, there are demand-supply uncertainties, which not only relate to offers/demands by any given MG, but also relate to energy trading with DNO.

III. SYSTEM MODELLING

In this section, we provide the constraints of MG components and the models of autonomous microgrid systems.

Furthermore, we introduce a novel conditional probability model to characterize the dynamic operation mode.

A. Dynamics and Constraints of MG Components

1) Load Demand: We classify loads into two categories [28]:

- Critical loads: Refers to be always met because demand levels are related to essential processes, e.g., refrigerator, freezer and cooking, loads which are defined as $P_i^{UL}(k)$;
- Controllable loads: Let $\Delta P_i^L(k)$ denote the type of loads that can be flexibly scheduled in order to achieve peak shaving and peak shifting, e.g., electric heating whose power consumption can be changed if the resulting thermal comfort is within a range specified by the consumer, and Plug-in Hybrid Electric Vehicles (PHEV), whose battery charging rate can be adjusted as long as the charging process is completed before the vehicle departure.

Let $P_i^L(k)$ denote the total users' demand information in the ith microgrid at time k, which is modelled as the follow:

$$P_i^L(k) = P_i^{UL}(k) + \Delta P_i^L(k) \tag{1}$$

$$\underline{P}_i^L \le P_i^L(k) \le \overline{P}_i^L, \forall i \in M \tag{2}$$

$$0 \le \Delta P_i^L(k) \le \Delta \overline{P}_i^L, \forall i \in M \tag{3}$$

where $\underline{P}_i^L$ is the minimum active power of total demand; $\overline{P}_i^L$ and $\Delta \overline{P}_i^L$ are the corresponding maximum active power of total demand and energy dispatch of controllable loads, respectively.

2) Energy Storage System: The storage system (such as batteries) is key for all microgrids since it allows to smooth intermittent RES power flow and provides peak power load shaving. For a microgrid i, we let $E_i(k), E_i^{ch}(k)$, and $E_i^{dch}(k)$ denote the amount of electricity stored, charged, and discharged at time k, respectively. Furthermore, the energy charging and discharging amounts are bounded, and satisfy the following constraints:

$$0 \le E_i^{ch}(k) \le \overline{E}_i^{ch}, \forall i \in M \tag{4}$$

$$\underline{E}_i^{dch} \le E_i^{dch}(k) \le 0, \forall i \in M \tag{5}$$

where $\overline{E}_i^{ch} > 0$ and $\underline{E}_i^{dch} < 0$ denote the maximum charging and minimum discharging limits, respectively.

The battery's life time event is heavily affected by repeated charging and discharging events, which cause degradation of energy storage devices over time. The depth-of-discharge (DoD) is introduced as the maximum discharge to the capacity. We denote DoD_i as the DoD requirement for battery operation in microgrid i, and have the following constraint for the energy level:

$$(1 - DoD_i)\overline{E}_i \le E_i(k) \le \overline{E}_i, \forall i \in M \tag{6}$$

where $(1 - DoD_i)\overline{E}_i$ and $\overline{E}_i$ are lower and upper bounds for the level of battery in microgrid i, respectively.

Finally, to account for charging/discharging losses, we denote $\eta_i^{ch} \in (0, 1]$ and $\eta_i^{dch} \in (0, 1]$ as the charging and discharging conversion efficiencies, respectively. Therefore, we obtain the energy storage dynamics of microgrid i at time k as

$$\begin{aligned} E_i(k+1) =& E_i(k) + (1 - \alpha_i(k))\eta_i^{ch} E_i^{ch}(k) \\ &+ \alpha_i(k) E_i^{dch}(k)/\eta_i^{dch} \end{aligned} \tag{7}$$

where

$$\alpha_i(k) = \begin{cases} 1, & \text{discharging mode} \\ 0, & \text{charging mode} \end{cases}$$

3) Renewable Supply: There are various types of renewable energy technologies, such as a PV generator or a WT that are not controllable and their output power is dependent on the utilization of the nature sources (i.e., sun irradiance or wind). Hence, their future profiles over a certain finite time horizon interval can be obtained using forecasting methods. The output of RESs is assumed to be not controllable but predictable with noises and enough to cover all the power usage in this paper. Assume that microgrid i has renewable energy with total generation capacity $P_i^{RES}(k)$ and then the following constraint for the RES supply holds:

$$\underline{P}_i^{RES} \le P_i^{RES}(k) \le \overline{P}_i^{RES}, \forall i \in M \tag{8}$$

where $\underline{P}_i^{RES}$ and $\overline{P}_i^{RES}$ are the minimum and maximum output power produced by the renewable source, respectively.

B. AMGs Prediction Model

Suppose there are a total of M microgrids in the investigated system. At each time interval, the dynamic balance of each microgrid under energy mismatch can be formulated as (7) and

$$\begin{aligned} P_i^{UL}(k) - P_i^{RES}(k) =& P_i^B(k) - P_i^S(k) - E_i^{dch}(k) \\ & - E_i^{ch}(k) - \Delta P_i^L(k), i = 1, 2, \ldots, M \end{aligned} \tag{9}$$

where $P_i^B(k)$ and $P_i^S(k)$ are the energy purchased from DNO and the energy sold back to DNO, respectively. Then the state space model from (7) and (9) is expressed as

$$\begin{aligned} x_i(k+1|k) &= a_i x_i(k|k) + b_i u_i(k|k) \\ y_i(k|k) &= c_i u_i(k|k) \end{aligned} \tag{10}$$

where

$$\begin{aligned} x_i(k|k) &= [E_i(k|k)], \\ u_i(k|k) &= [E_i^{dch}(k|k) \quad E_i^{ch}(k|k) \quad P_i^B(k|k) \\ &\qquad P_i^S(k|k) \quad \Delta P_i^L(k|k)]^T, \\ y_i(k|k) &= [P_i^L(k|k) - P_i^{RES}(k|k)], \\ a_i &= [1], \\ b_i &= [\alpha_i(k)/\eta_i^{dch} \quad (1 - \alpha_i(k))\eta_i^{ch} \quad 0 \quad 0 \quad 0], \\ c_i &= [-1 \quad -1 \quad 1 \quad -1 \quad 0]. \end{aligned}$$

Here the matrices a_i, b_i, c_i are the state, input and output matrices, respectively. Note that the energy mismatch between supply and demand, $P_i^L(k|k) - P_i^{RES}(k|k)$, is the system output $y_i(k|k)$. The dispatchable sources $E_i^{dch}(k), E_i^{ch}(k), P_i^B(k), P_i^S(k)$ and $\Delta P_i^L(k)$ are the control inputs. For any subsystem $i = 1, 2, \ldots, M$, let the predicted

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state and input at time instant $k+l, l \geq 0$, based on data at time k, be denoted by $x_i(k+l|k) \in \Theta^{n_i}$ and $u_i(k+l|k) \in \Omega_i \subset \Theta^{m_i}$, respectively, where Ω_i is the set of admissible controls for subsystem i. Let N denote the control horizon. Define $\Upsilon_i = \Omega_i \times \Omega_i \times \ldots \times \Omega_i \subset \Theta^{m_i N}$. The finite horizon predicted state and input trajectory vectors in distributed MPC framework are given by:

$$\mathbf{x}_i(k) = [x_i(k+1|k), x_i(k+2|k), \ldots, x_i(k+N|k)]^T$$
$$\mathbf{u}_i(k) = [u_i(k|k), u_i(k+1|k), \ldots, u_i(k+N-1|k)]^T$$

The proposed energy management scheme is discussed in Section IV, which is designed based on the above predictive model.

C. Dynamic Modelling of Energy Trading

1) Power Price Mechanism: All MGs need to be connected to the DNO, and can send or receive power from the DNO. This means that buyer MGs may trade among sellers MGs through the DNO in the electricity markets [29]. Depending on the real pricing, it is expected that trading among AMGs may obtain higher benefits for sellers through the DNO. The average price of AMGs determined by the DNO over the optimization horizon is defined as

$$\overline{\lambda}(k) = \frac{\sum_{i=1}^{M} \lambda_i(k)}{M} \tag{11}$$

where $\lambda_i(k)$ is the trading price of MG i at time k. Also, we denote λ_i^E as the cost of charging/discharging of the storage battery.

2) Conditional Probability Distribution Model: In our setting, energy trading between any two microgrids has to be achieved through DNO. By doing so, we can fully use the existing distribution lines interacted with a common bus for electric power. When the produced renewable power in microgrid i is unable to meet their own demand at time k, microgrid i will buy energy from DNO or using its own battery. In this sense, we have four operation modes Ω: event R (battery charging), event $\overline{R}$ (battery discharging), event W (buying electricity from DNO) and event $\overline{W}$ (selling electricity to DNO).

Each operation mode is adopted according to state conditions. For example, when microgrid i has a surplus of energy, we may charge the local battery or sell electricity to DNO, depends on the average trading price and charging cost. Similarly, when there is lack of electricity in the microgrid i, the local battery can be sold or electricity can be bought from DNO depending on average trading price, discharging cost and surplus energy in the whole system. Hence, let $\{D, Pr\}$ be a probability space where D represents the event set of state condition with size of 16 and Pr is the corresponding conditional probability. The probability set is shown in Table I, where each condition is explained in Table II.

Remark 1. *$D_{u.}$ are energy-related modes, which evaluate the algebraic sum of the overall system outputs and the output of the local microgrid i, namely, energy required/provided by all AMGs and energy required/provided by MG i. For example, $D_{1.}$, means DNO has surplus energy from the overall system outputs to dispatch, and microgrid i has also surplus energy. So does the others in $D_{u.}$.*

TABLE I
CONDITIONAL PROBABILITY DISTRIBUTION MODELLING.

$Pr_i(\Omega\|D_{uv})$ \ $D_{.v}$; $D_{u.}$	$D_{.1}$	$D_{.2}$	$D_{.3}$	$D_{.4}$
$D_{1.}$	π_i^{11}	π_i^{12}	π_i^{13}	π_i^{14}
$D_{2.}$	π_i^{21}	π_i^{22}	π_i^{23}	π_i^{24}
$D_{3.}$	π_i^{31}	π_i^{32}	π_i^{33}	π_i^{34}
$D_{4.}$	0	π_i^{42}	0	π_i^{44}

TABLE II
DESCRIPTION OF SUBSETS D_{uv}.

Events	Mathematical Description
$D_{1.}$	$\sum_{j=1}^{M} y_j(k) < 0, y_i(k) < 0$
$D_{2.}$	$\sum_{j=1}^{M} y_j(k) < 0, y_i(k) > 0$
$D_{3.}$	$\sum_{j=1}^{M} y_j(k) > 0, y_i(k) < 0$
$D_{4.}$	$\sum_{j=1}^{M} y_j(k) > 0, y_i(k) > 0$
$D_{.1}$	$\lambda_i^E > \overline{\lambda}(k), \alpha_i(k) = 0$
$D_{.2}$	$\lambda_i^E > \overline{\lambda}(k), \alpha_i(k) = 1$
$D_{.3}$	$\lambda_i^E < \overline{\lambda}(k), \alpha_i(k) = 0$
$D_{.4}$	$\lambda_i^E < \overline{\lambda}(k), \alpha_i(k) = 1$

Remark 2. *$D_{.v}$ are battery-related modes, which compare average trading price, charging/discharging cost, and state of storage battery $\alpha_i(k)$. For example, $D_{.1}$, indicates that the battery is charging and charging price is higher than average trading price. So does the others in $D_{.v}$.*

Note that the conditional probability in Table I is subject to physical constraints. To better demonstrate the probability set, Table III shows decision-making for randomness of conditional probability distribution. For example, the event D_{12} corresponding to π_i^{12}, means that microgrid i has surplus energy and has the option to sell it to DNO or charge the local battery. But currently the price of charging is higher than average trading price and the battery is in discharge mode. Therefore, the microgrid i can only sell electricity to the DNO, which means it belongs to $\overline{W}$. Especially, given the event D_{41} corresponded to π_i^{41}, it means microgrid i needs more power for its load but no surplus energy can be provided by DNO and the storage battery is operated in a charging mode. Therefore, the case won't exist, namely, $\pi_i^{41} = 0$. So does other cases.

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TABLE III
DECISION-MAKING FOR CONDITIONAL PROBABILITY DISTRIBUTION.

Operation mode	Conditional Probability
R (battery charging)	π_i^{11}, π_i^{31}
$\overline{R}$ (battery discharging)	$\pi_i^{24}, \pi_i^{42}, \pi_i^{44}$
W (buying electricity)	$\pi_i^{21}, \pi_i^{22}, \pi_i^{23}$
$\overline{W}$ (selling electricity)	$\pi_i^{12}, \pi_i^{13}, \pi_i^{14}, \pi_i^{32}, \pi_i^{33}, \pi_i^{34}$

Furthermore, we have the following definition:

Definition 1. *Events $D_{11}, D_{12}, \ldots, D_{uv}$ are jointly independent if, for any $1 \le u \le 4, 1 \le v \le 4$, the following properties hold true:*

$$0 < \pi_i^{uv} < 1, \quad \sum_{u=1}^{4}\sum_{v=1}^{4} Pr_i(D_{uv}) = 1. \tag{12}$$

D. Main Assumptions

In the AMGs control structure, developed in this work, two assumptions are needed, whose requirements involve microgrid configuration.

1) AMG cannot simultaneously purchase and sell power from/to other MGs. Moreover, local critical loads have higher priority and their demand can always be met.
2) At any time instant, the battery can only be either charged or discharged. This means $\alpha_i(k) = 0$ or 1 at time k.

IV. COORDINATED ENERGY DISPATCH SCHEME

In this section, the two-layer coordinated optimization problems are formulized.

A. Optimization Problem for DNO

As discussed in the previous sections, a MG can be either a seller (surplus energy), a buyer (energy mismatch), or not participating (balance equals to zero) at each time step. The aim of upper level coordinated controller is to generate optimal set points for each MG so that economically optimized power dispatch is performed. The following *Problem 1* is formulated to guarantee global coordination of the energy between DNO and AMGs with the conditional probability distribution.

Problem 1:

$$\begin{aligned}\min_{\substack{E_i^{ch}(k+l|k),\\ E_i^{dch}(k+l|k),\\ P_i^B(k+l|k),\\ P_i^S(k+l|k)}} \quad & \sum_{l=1}^{N}\sum_{i=1}^{M} Pr_i(W|D_{uv})\overline{\lambda}(k)P_i^B(k+l|k)\\ & - Pr_i(R|D_{uv})\lambda_i^E E_i^{ch}(k+l|k)\\ & - (Pr_i(\overline{R}|D_{uv})\lambda_i^E E_i^{dch}(k+l|k)\\ & - Pr_i(\overline{W}|D_{uv})\overline{\lambda}(k)P_i^S(k+l|k)) \end{aligned} \tag{13}$$

$$s.t. (2)-(5), (12)$$

$$P_i^B(k+l|k) \ge 0, P_i^S(k+l|k) \ge 0, \tag{14}$$

$$\sum_{i=1}^{M} P_i^B(k+l|k) = \sum_{i=1}^{M} P_i^S(k+l|k) \tag{15}$$

In the objective function (13), the DNO controller is aimed at minimizing the costs, while satisfying power balance, ESs and energy exchange constraints. The first two terms in the objective function are related to the cost of the power purchased from the DNO and the storage battery, while the second two terms are related to the cost of the power sold to the DNO and local storage. Constraints (2)-(5) and (12), discussed in the previous section, include autonomous loads constraints, RESs and batteries power limits. Inequality constraints (14) guarantee that the amount of purchased and sold energy is nonnegative. Equality constraints (15) guarantees that the algebraic sum of the purchased energy is equal to the sold energy between DNO and AMGs.

The optimal $z_{i,ref}(k+l|k)$ is determined as $E_i^{ch}(k+l|k), E_i^{dch}(k+l|k), P_i^B(k+l|k), P_i^S(k+l|k)$, as follows,

$$\begin{aligned} z_{i,ref}(k+l|k) = & P_i^L(k+l|k) - P_i^{RES}(k+l|k)\\ & + E_i^{dch}(k+l|k) + E_i^{ch}(k+l|k)\\ & - P_i^B(k+l|k) + P_i^S(k+l|k) \end{aligned} \tag{16}$$

Here $z_{i,ref}(k+l|k) < 0$ means that the local microgrid has a surplus of energy to supply, while $z_{i,ref}(k+l|k) > 0$ means there is no sufficient energy in local system. So we should optimize at the lower layer, which is described in Section IV-B. The detail of coordinated energy dispatch strategy is given in Section IV-C.

B. Optimization Problem for AMGs

The objectives of local microgrid include tracking $z_{i,ref}(k+l|k)$ by adjusting local controllable load and battery, as well as minimizing its own cost of charging and discharging. Thus, the optimization index $J_i(u_i(k))$ should include two parts as follows:

$$\begin{aligned} J_i(u_i(k)) = & \sum_{l=1}^{N}(\gamma_1\left(\Delta P_i^L(k+l|k) - z_{i,ref}(k+l|k)\right)^2\\ & + \gamma_2\lambda_i^E\left(E_i^{ch}(k+l|k) - E_i^{dch}(k+l|k)\right)^2) \end{aligned} \tag{17}$$

where γ_1 and γ_2 are weighting coefficients. Note that at each time instant, there is only one nonzero value between $E_i^{ch}(k+l|k)$ and $E_i^{dch}(k+l|k)$.

For ease of notation, the time dependence in the state and input vectors in the distributed MPC framework is dropped, i.e. $J_i(u_i) \leftarrow J_i(u_i(k))$ and $\mathbf{u}_i \leftarrow \mathbf{u}_i(k), \forall i = 1, 2, \ldots, M$. Let $p(k)$ represent the number of allowable iterations for the sampling interval at time k, which guarantees the terminate the cooperation-based algorithm when system sampling interval are in sufficient to derive the convergence of an iteration. Also, the optimization of the local controller is affected by control actions from other subsystems. Hence, denote the cooperation-based cost function $J(\cdot)$ after p iterations as follows, which measures the system wide impact of local control actions,

$$J(\mathbf{u}_1^p, \mathbf{u}_2^p, \ldots, \mathbf{u}_M^p) = \sum_{i=1}^{M} w_i J_i(\mathbf{u}_1^p, \mathbf{u}_2^p, \ldots, \mathbf{u}_M^p) \tag{18}$$

Then we have the system wide objectives as follows, which is a strict convex combination of each local controller objectives, *Problem 2:*

$$\begin{aligned}\Re_i \triangleq \min_{\mathbf{u}_i} & \sum_{i=1}^{M} w_i J_i(\mathbf{u}_1^{p-1},\ldots,\mathbf{u}_{i-1}^{p-1},\mathbf{u}_i,\mathbf{u}_{i+1}^{p-1},\ldots,\mathbf{u}_M^{p-1}) \\ s.t.\quad & (2)-(6),(8),(10), \\ & w_i > 0, \quad \sum\nolimits_i w_i = 1, \\ & u_i(k+l|k) \in \Omega_i, \quad 0 \le l \le N-1 \\ & u_i(k+l|k) = 0, \quad N \le l.\end{aligned} \tag{19}$$

The solution to *Problem 2* is denoted by $\mathbf{u}_i^{*(p)}$. By definition $\mathbf{u}_i^{*(p)} = [u_i^{*(p)}(k|k), u_i^{*(p)}(k+1|k), \ldots, u_i^{*(p)}(k+N-1|k)]^T$

Remark 3. *To achieve these local and global objectives, this section presents two-layer coordinated dispatch scheme. At the upper layer, a DNO controller is designed as global objectives to determine an optimal trajectory. At the lower layer, to develop a reliable distributed MPC framework, namely, feasibility of the DMPC, we need to ensure that the AMGs cooperate with each other in achieving system wide objectives.*

C. DMPC Strategy for Coordinated Control

So far, both the DNO controller and the microgrid local controllers have been designed. As discussed above, the upper layer DNO solves its own optimization problem, and provides references for the local microgrid. In this way, at the beginning of each scheduling cycle, the DNO computes the scheduling command by solving the *Problem 1*. The specific implementation of coordinated energy dispatch strategy is implemented by the Algorithm 1 as follows

Algorithm 1 Coordinated Energy Dispatch

1: **Initialization** $E_i(0)$, $P_i^{RES}(0)$, $P_i^L(0)$, $E_i^{ch}(0)$, $E_i^{dch}(0)$, $P_i^B(0)$ and $P_i^S(0)$, $\forall i = 1,\ldots,M$
2: **for** $k = 1$ **do**
3: Get measure $P_i^{RES}(k)$, $P_i^L(k)$, $E_i(k)$, $E_i^{ch}(k)$ and $E_i^{dch}(k)$ at local MGCC; estimate $P_i^{RES}(k+l|k)$, $P_i^L(k+l|k)$, $E_i(k+l|k)$, $E_i^{ch}(k+l|k)$, $E_i^{dch}(k+l|k)$, $P_i^B(k+l|k)$ and $P_i^S(k+l|k)$.
4: Exchange the information of $y_i(k+l|k)$, and broadcast its sequence to DNO.
5: Solve the upper layer optimization *Problem 1*.
6: **until** convergence
7: Send the reference control sequence $z_{i,ref}(k+l|k)$ to local MGCC.
8: $k \leftarrow k+1$ and go to step 3.
9: **end for**

In the following scheduling cycle, the computed $z_{i,ref}(k+l|k)$ is sent to the lower layer microgrid controllers for execution. Instances of *Problem 2* are solved in a parallel and iterative manner. Using this DMPC strategy, not only does the local controller focus on their own local objectives, but also cooperate with each other to achieve a system-level optimization. The proposed DMPC strategy is illustrated in Algorithm 2.

Algorithm 2 Proposed DMPC Algorithm

Initialization $\Delta P_i^L(0), \rho_i, p = 1, \forall i = 1,\ldots,M$
Given $p_{max}(k) \ge 0$ and $\epsilon > 0$
Get measure of current loads; get the estimation of $E_i^{ch}(k+l|k), E_i^{dch}(k+l|k), P_i^L(k+l|k)$ and $\Delta P_i^L(k+l|k)$; receive the reference control sequence $z_{i,ref}(k+l|k)$ from DNO.
if $z_{i,ref}(k+l|k) > 0$ **then**
  if $SOC > 20\%$ **then**
    Discharge the battery.
    if $z_{i,ref}(k+l|k) + E_i^{dch}(k+l|k) > 0$ **then**
      Set $z_{i,ref}(k+l|k) = z_{i,ref}(k+l|k) + E_i^{dch}(k+l|k)$ and broadcast it to local controllers.
    end if
  else
    Broadcast $z_{i,ref}(k+l|k)$ to local controllers.
  end if
  while $\rho_i > \epsilon$ for some $i = 1,2,\ldots,M$ and $p \le p_{max}$ **do**
    $\mathbf{u}_i^{*(p)} = arg(\Re_i), \forall i = 1,2,\ldots,M$, (*Problem 2*).
    for each $i = 1,2,\ldots,M$ **do**
      $\mathbf{u}_i^p \leftarrow w_i \mathbf{u}_i^{*(p)} + (1-w_i)\mathbf{u}_i^{p-1}$
      $\rho_i \leftarrow \|\mathbf{u}_i^p - \mathbf{u}_i^{p-1}\|$.
    end for
    $p \leftarrow p+1$
  end while
  Implement the first step of the optimal control sequence, $\Delta P_i^L(k+l|k)$, shift the corresponding loads.
else if $SOC < 80\%$ **then**
  Charge the battery.
end if

D. Convergence of DMPC Algorithm

Theorem 1. *If $J_i(u_i)$ satisfies the form in (17), then $J_i(u_i)$ is convex over the set Ω_i .*

Proof: From (17), we have $J_i(u_i) \ge 0$. Rewriting the objective function in (17) based on the distributed discrete-time system model (10), we have

$$\begin{aligned}J_i(u_i) = \sum_{l=1}^{N} & (u_i(k+l|k)^T S_1 u_i(k+l|k) \\ & - 2S_2 u_i(k+l|k) + S_3) \ge 0\end{aligned} \tag{20}$$

where

$$S_1 = \begin{bmatrix} \gamma_2\lambda_i^E & & & & \\ & \gamma_2\lambda_i^E & & & \\ & & 0 & & \\ & & & 0 & \\ & & & & \gamma_1 \end{bmatrix} \ge 0,$$
$$S_2 = \begin{bmatrix} 0 & 0 & 0 & 0 & \gamma_1 z_{i,ref}(k+l|k) \end{bmatrix},$$
$$S_3 = \gamma_1 z_{i,ref}(k+l|k)^2 \ge 0.$$

If we take the second derivative to the equation (20), then

$$J_i''(u_i) = 2N(2\gamma_2\lambda_i^E + \gamma_1) \ge 0$$

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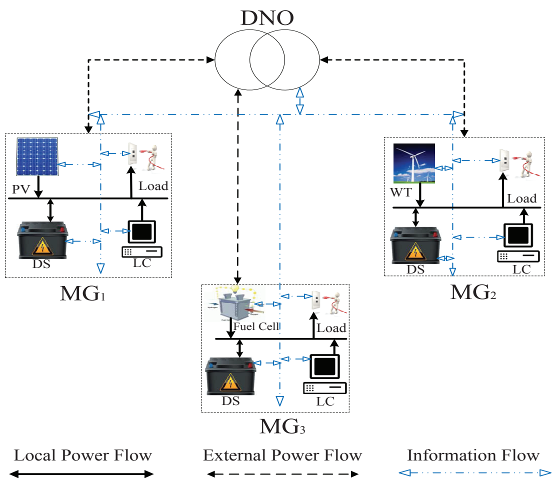

Fig. 3. Schematic of the studied microgrids.

Thus, $J_i(u_i)$ is convex, the proof is completed. ■

Theorem 2. *Given the distributed MPC formulation* $\Re_i$ *defined in (19),* $\forall i = 1, 2, \ldots, M$*, the sequence of cost functions* $J(\boldsymbol{u}_1^p, \boldsymbol{u}_2^p, \ldots, \boldsymbol{u}_M^p)$ *generated by Algorithm 2 is non-increasing with iteration number* p*.*

The detailed proof is similar to Lemma 1 in [30]. For simplicity, the proof is omitted.

From Theorem 1, we know that $J_i(u(i))$ is convex and bounded below. Using Theorem 2 assures non-increasing with with iteration number p. Hence, the distributed MPC formulation $\Re_i$ defined in (19) is convergent.

V. CASE STUDY

The microgrid systems considered in the simulations are shown in Fig. 3; they are in an autonomous mode and comprise of three microgrids with PV, WT, battery and local loads. To simplify the expression, the power and energy were converted to power unit (p.u.). We used an MPC optimization period $N_p = 4$, and control horizon $N_u = 1$. This corresponds to one hour intervals over a 24 hour period and consisting of typical horizon and time step for scheduling updates. Other detailed parameters and settings of AMGs are discussed in the following subsections.

A. Simulation Setup

Set the minimum active power of total demand $\underline{P}_i^L$ to be 10 p.u., and $\overline{P}_i^L = 120$ p.u., $\Delta\overline{P}_i^L = 80$ p.u., $\forall i = 1, 2, 3$. The minimum and maximum power of RESs are 5 p.u. and 120 p.u., respectively. The initial value of the battery is set to $E_i(0) = 40$ p.u., $\overline{E}_i^{ch}$, $\overline{E}_i^{dch}$, $\overline{E}_i$ are chosen to be 30 p.u., 30 p.u., 60 p.u., respectively, and $\eta_i^{ch} = 0.7, \eta_i^{dch} = 0.65, DoD_i = 0.92$, $\forall i = 1, 2, 3$. Let the cost weight coefficients be $\gamma_1 = 1, \gamma_2 = 0.5$.

In China, the "different duration with a different price" strategy is adopted. It is specified in Fig. 4, where yellow lines represent the average price among AMGs. In addition, the cost of charging or discharging of the storage battery λ_i^E is set to be 0.82 Yuan for each microgrid.

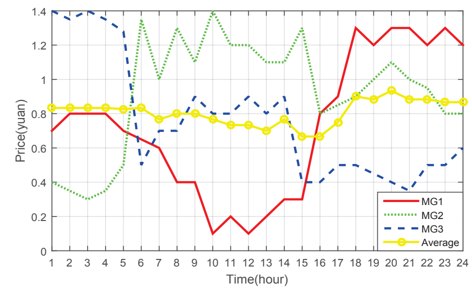

Fig. 4. Trading price of each microgrid.

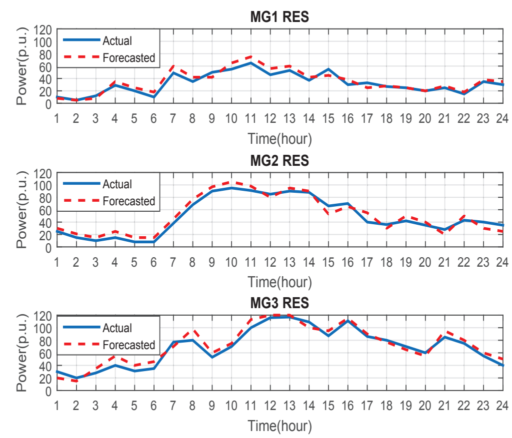

Fig. 5. Forecasted and actual RES.

B. Forecasts

To implement DMPC and provide reference signal for the optimization problem, renewable power and demand forecasts are required to be computed at each time step over the finite time horizon. The renewable power and demand data series generally exhibit high-frequency fluctuations and peak shifting as well as uncertainties. Therefore, we apply least-square Support Vector Machines (SVMs) [31] for regression with a moving time window to forecast the renewable power generation and the demand for day ahead [32]–[34]. Note that the day ahead forecast is based on the historical data and the current real RES output has the uncertainties. Besides, we use the conditional probability distribution to characterize the randomness of decision-making which was affected by the RES output with uncertainties. Examples of renewable power production profiles and daily demand employed in the optimization routine are shown in Fig. 5 and 6, respectively. Although there is a small forecasting error due to the uncertainties in demand and renewable generation amounts, it can be seen that the predicted RESs and load demand at each time step can track the actual value very well.

C. Results and Discussion

With the above initial conditions, operation mode dynamics among AMGs during the whole time period are shown in Fig. 7. The values $1, 2, 3, 4$ in the y-axis indicate battery charging, battery discharging, buying energy and selling energy,

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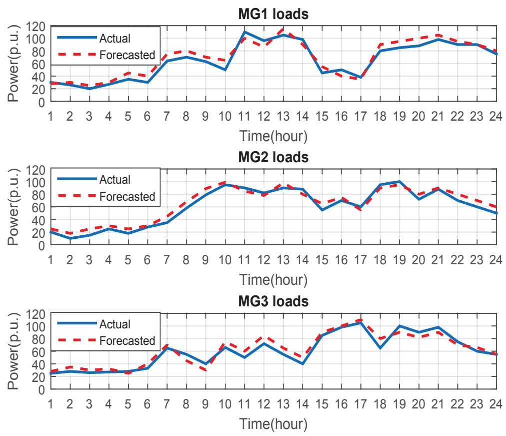

Fig. 6. Forecasted and actual demand.

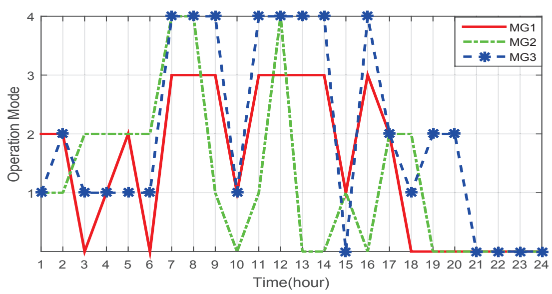

Fig. 7. Operation mode transition.

respectively. It can be observed that MG1 purchases the energy while MG3 sells the energy to the DNO from 11am to 2pm. The energy exchange between DNO and each microgrid is reported in Fig. 8, where positive values represent the energy purchased from the DNO, and negative values represent the energy sold to the DNO. It should be noted that, in Fig. 8, MG1 tends to trade energy when MG3 supplies the DNO with the majority of their surplus energy from 11am to 2pm. The battery working mode can be seen in Fig. 9, which illustrates the power charge/discharge of the battery in each MG. As a convention, positive values correspond to battery charging while negative ones represent battery discharging. We can see that there is no charging or discharging among MGs from 11am to 2pm. That is because the cost of charging/discharging is higher than the average trading price during that time for MG2 and MG3, while MG1 requires surplus energy, which can be seen clearly in Fig. 4 and Fig. 8. Secondly, we evaluate the proposed scheme in terms of reference trajectory tracking. Figs. 10-11 show the results of this test. The optimal states of different batteries are shown in Fig. 10. It is reported that local storage systems show different behaviours. Their operation is strongly affected by the capacity of each battery, the cost of charging or discharging, and the optimal control strategies of the lower layer in local MG. The energy of storage can compensate partly the mismatch between RESs and loads. Fig. 11 shows the scheduling of shiftable loads by the aggregator with proposed method. In order to follow the desired trajectory,

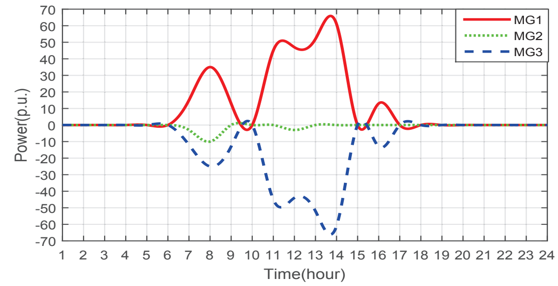

Fig. 8. Buy/sell electricity between DNO and each microgrid.

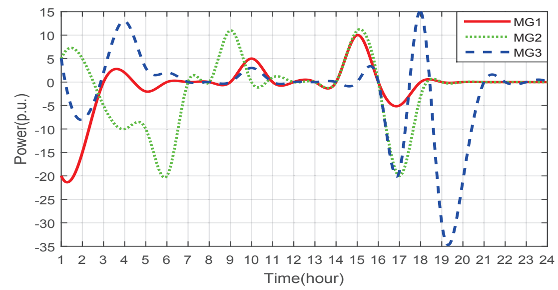

Fig. 9. Battery charging/discharging.

it is clear that an amount of loads needed to be curtailed because renewable generation during night was much smaller, which is shown in Fig. 5.

From an economic perspective, when coordinated DMPC is employed, the average daily operating cost is reduced from 173.4 Yuan to 156.62 Yuan, compared with those achieved by the no-cooperation scheme.

VI. Conclusion

In this paper, we exploited the potential benefits of the cooperative framework for AMGs with RESs and energy storage units through a coordinated DMPC strategy. With the proposed scheme, the energy exchange between DNO and AMGs is brought to an optimal trajectory, thereby making local controller optimized actions based on the trajectory. Meanwhile, by considering the uncertainties in RESs and loads, a better trade-off between supply-demand balance and economic performance is achieved in the whole system. Numerical results confirm that the proposed coordinated control approach can effectively deal with the uncertainties of microgrids operation.

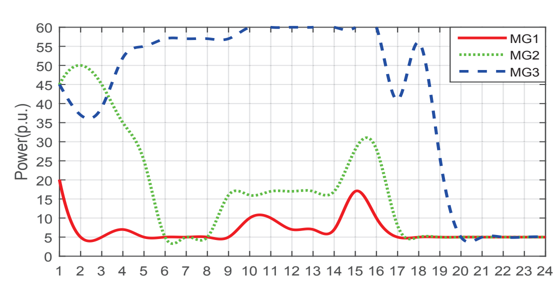

Fig. 10. State of battery in each microgrid.

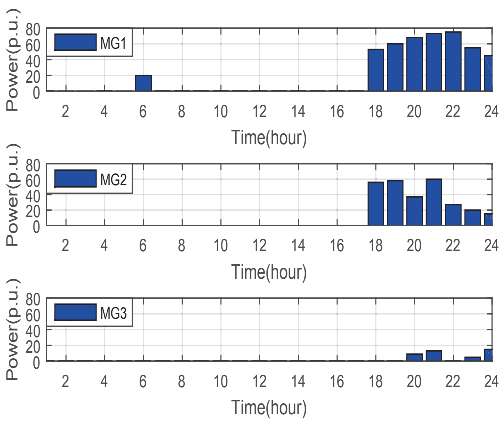

Fig. 11. Optimized scheduling of controllable loads.

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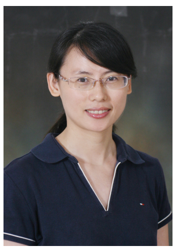

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