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Multi-Agent Based Cooperative Control Framework for Microgrids' Energy Imbalance

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***Abstract*— This paper proposes an cooperative control framework for the coordination of multiple microgrids. The framework is based on the Multi-Agent System (MAS). The control framework aims to encourage the resource sharing among different autonomous microgrids and solve the energy imbalance problems by forming the microgrid coalition self-adaptively. Firstly, the conceptual model of the integrated microgrids and the layered cooperative control framework is presented. Then, an advanced dynamic coalition formation scheme and corresponding negotiation algorithm are introduced to model the coordination behaviors of the microgrids. The proposed control framework is implemented by the Java Agent Development Framework (JADE). A loop distribution system with multiple interconnected microgrids is simulated, and the case studies are conducted to prove the efficiency of the proposed framework.**

***Index Terms*— [1] microgrid, multi-agent system, distributed control, agent coalition, smart grid**

I. Introduction

MODERN power systems have been undergoing profound changes and re-constructions, driven by the factors such as environmental pressure, improved grid operation efficiency, energy conservation, etc. [1]. In this context, the microgrid has developed a lot in the last few years [2]. A typical microgrid often comprises a cluster of Distributed Energy Sources (DERs), Energy Storage Systems (ESSs), critical loads, elastic controllable loads, etc. Microgrid brings a transition of centralized generation fashion to the distributed generation fashion. Currently there have been many microgrid research projects lunched around the world, such as the CERTS in the U.S [3], MICROGRIDS in Europe [4], and NEDO in Japan [5]. In the latest years, the conception of 'energy Internet' also has been proposed [6], [7]. A key feature of the energy Internet is that the different parties can share the energy flexibly, just as the information sharing on the Internet. As an important component of the energy Internet, the energy sharing among different microgrids should be encouraged.

In the literature, the management and control of microgrids have been well studied. Many works focused on the centralized resource scheduling and energy management of microgrids/Virtual Power Plants (VPPs) [8-11]. For example, [8] proposed a stochastic scheduling model for microgrid resources, with the objective to minimize the expected system operational cost and power losses; in our previous work [9], we proposed a two-stage operational planning framework for the VPP in the power markets. The decomposed and distributed control techniques of microgrids are also studied in many research works. [12] identified a hierarchical control structure for microgrids, consisting of primary, secondary, and tertiary control levels. Then, the authors gave comprehensive reviews on the control approaches applied in each level. [13] gave conceptual discussions on the potential applications of MAS on the microgrid control; [14] proposed a decentralized, MAS-based control architecture for the microgrid power management; [15] proposed a distributed secondary/primary controller for converters of a dc microgrid. Voltage regulator and current regulator are designed in their controller, and a graph based communication structure of the converters is established. The same authors also proposed a distributed networked method for load sharing of parallel converters of a microgrid based on the consensus-voting protocols [16]; in [17], the authors proposed reinforcement learning techniques for the control of autonomous microgrids. Their proposed control strategy was based on a dynamic model of islanded microgrids and made use of an internal oscillator for frequency control; [18] proposed a neural network based distributed secondary control to regulate the voltage and frequency of a smart autonomous microgrid. [19] proposed a MAS based control model for the real-time energy imbalance of a microgrid, where the model incorporated a distributed bargaining algorithm for the generation units and the consumption units; [20] proposed a MAS based framework for coordinately scheduling the resources of multiple microgrids; [21] employed an agent coalition formation scheme to optimize the configuration of a VPP; [22] proposed an agent coalition scheme to make DERs in a VPP work together to participant in the power market; in our previ-

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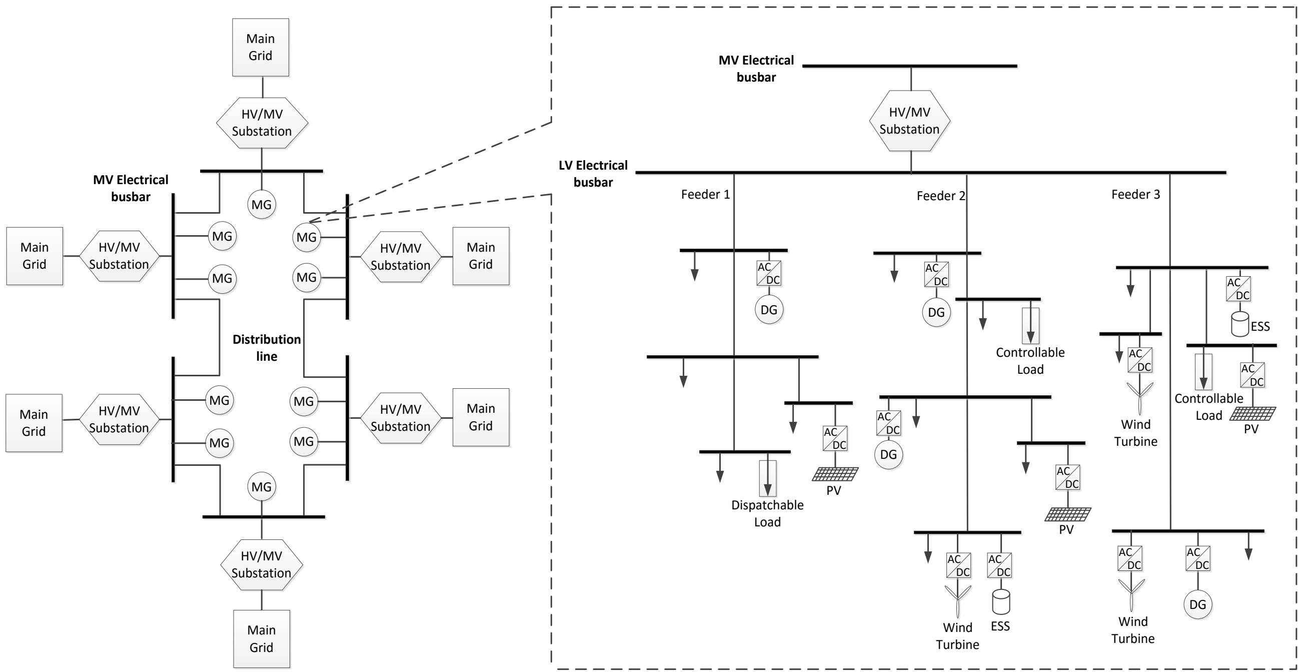

Fig. 1. Conceptual model of the integrated microgrids

ous work [23], a distributed optimal resource scheduling algorithm was applied on VPPs to achieve the optimal power sharing among the VPP resources. More discussions about microgrid control strategies can be found in [24].

By reviewing the literature, it can be found that almost all the existing works focus on the power management and control of the resources within a single microgrid. In the context of the smart grid and energy Internet, multiple autonomous microgrids with different scales can be formed in the low voltage (LV) network. Therefore, it would be more beneficial for different microgrids to communicate and share resources with each other to achieve some specific objectives. In this paper, we propose a MAS based cooperative control framework to solve the power imbalance problems of multiple microgrids. In the proposed framework, when the energy imbalance event of any microgrid is detected, multiple microgrids are allowed to autonomously form coalitions and negotiate the energy trading among each other to solve the energy imbalance problem. To the best of our knowledge, this paper is among the first to study the cooperation of multiple microgrids. In this paper, we employ the agent coalition technology to coordinate the power management of different microgrids, and our major contributions are 2-fold:

a) A MAS-based cooperative control framework is proposed for the multiple autonomous microgrids to coordinately solve the real-time energy imbalance problem;

b) A modified dynamic agent coalition formation scheme is employed to stimulate the energy sharing among microgrids.

Literature [20] also studied the coordination of multiple microgrids. However, [20] focused on the unit commitment problem, which was significant different from the application in this paper. Literatures [21] and [22] employed the agent coalition formation techniques in the VPP control. However, they focused on the coordination of the inner resources of a single VPP, while this work studies the cooperation of multiple microgrids.

This paper will be organized as follows. In Section II, the architecture of the proposed control framework is presented; in Section III, the agent coalition formation scheme is described; Section IV gives the simulation analysis. Finally, the conclusions and future directions are drawn in Section V.

II. Distributed Control Framework for Microgrids

Fig. 1 shows the conceptual model of integrated microgrids in a typical distribution network, where each microgrid autonomously manages the resources located in a certain area.

A. *Agent System for a Single Microgrid*

For each microgrid, the agent-based control system is shown in Fig. 2. The agent roles are explained as follows.

The operations of physical resources are delegated by the Resource Agents (RAs), including the Energy Storage System Agent (ESSA), Distributed Energy Resource Agent (DERA), Load Agent (LA), and Controllable Load Agent (CLA). The agents are located in the lowest level to monitor the states of physical resources (e.g., the state-of-charge (SOC) of battery, power set points of renewable energy sources, dispatchable capacity of the interruptible loads, etc.), and perform control actions to the resources (e.g., adjust the setpoints of DERs, charge/discharge the battery, etc.).

The Microgrid Operation Agent (MOA) controls the operation of the whole microgrid by performing the optimal generation dispatch of the resources. The Microgrid Market Agent (MMA) is responsible for the market operations of the microgrid. It negotiates with the MMAs of other microgrids to purchase/sell energy from/to them, and it also contacts the Dis-

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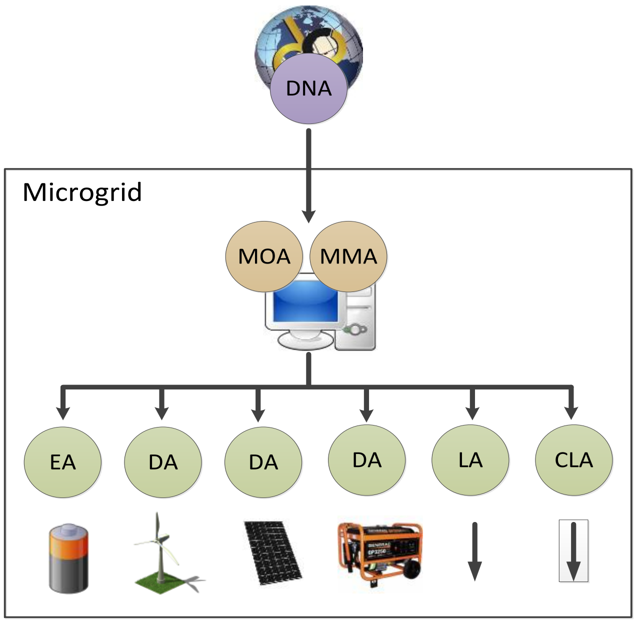

Fig. 2. Agent-based control model of a single microgrid

-tribution Network Agent (DNA) to purchase/sell energy from/to the grid.

B. *MAS-Based Cooperative Control Framework*

The architecture of proposed control framework is shown in Fig. 3. It is with a layered structure. The physical resources of microgrids are located in the *physical layer*. Upon it is the *resource agent layer*, where the agents of physical resources are located. RAs work on this layer to monitor the resource states and perform control actions.

The microgrid operation conditions are assumed to follow [19]. Denoting the autonomous control horizon of the microgrid i as T_c^i, then the LA announces forecasted load demand over the next T_c^i minutes periodically to the MOA. This is a very short-term load forecasting. DNA announces the forecasted prices of buying and selling power from/to the microgrids to MMAs, denoted as p_{buy} and p_{sell}. In some market structures, these two prices are also referred as 'downward regulation price' and 'upward regulation price' [33], [34]. Normally there is $p_{sell} > p_{buy}$ [19], [33].

In the *reaction layer*, when MOA receives the forecasted load demand and detects the power deficit events, it actives RAs to do the optimal scheduling to try to balance the load demand locally. Based on the scheduling results, the MOA sends control signals to the RAs. After receiving the signals, RAs perform control action to the physical resources. If the energy imbalance cannot be solved locally, then the *coordination layer* will be activated. The MMA contacts the MMAs of its neighbored microgrids to launch a coalition request, where the initiated MMA acts as the *coalition leader*. The initiated MMA performs a negotiation process with other MMAs about purchasing energy from those microgrids. The negotiation process is in a self-adaptive and autonomous manner, and the coalition size is dynamical adjusted according to the complexity of the problem. In the extreme case, all the microgrids will be involved to solve the energy imbalance problem.

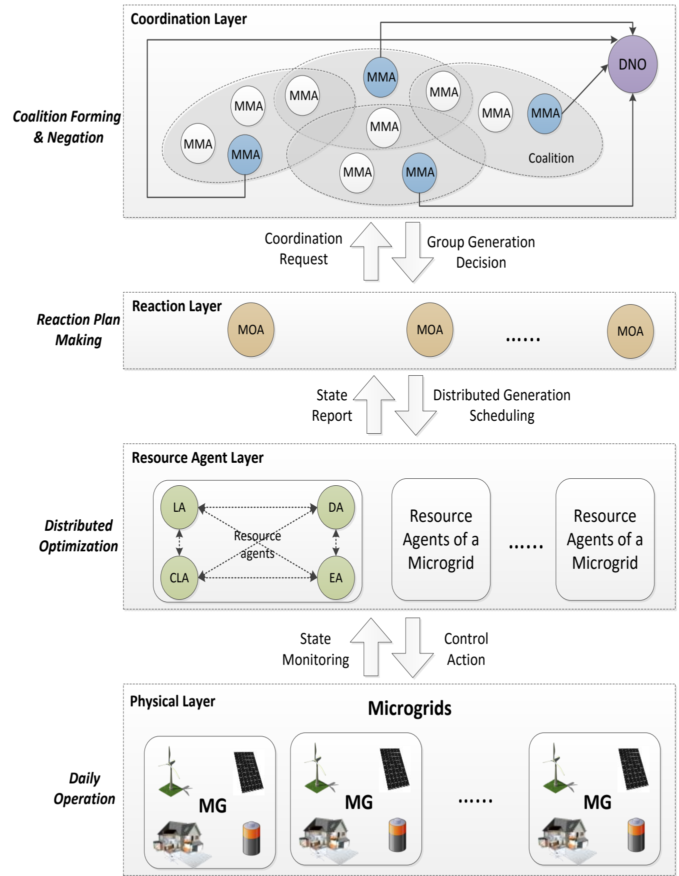

Fig. 3. Cooperative control framework for the microgrids

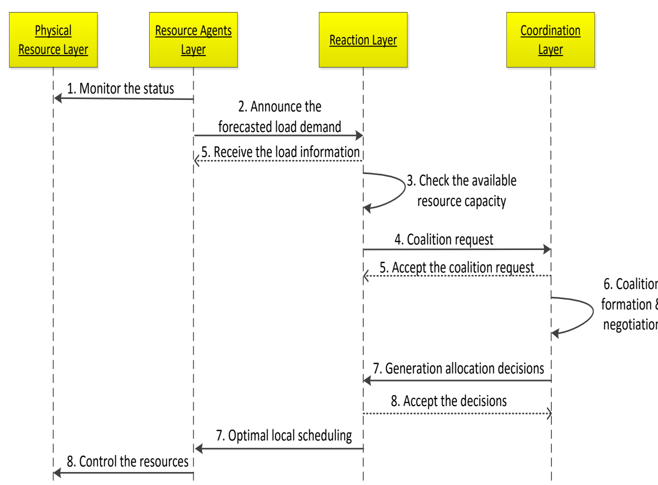

Fig. 4. Coordination diagram of the layered control framework

After the negotiation process, all the coalition members reach agreement about the energy trading. Then the decisions will be forwarded to the *reaction layer*, and the MOA sends control commands to the *resource agent layer*, where RAs are activated to perform control actions to the resources. Finally, if the energy imbalance problems are still not be completely solved after the negotiation, the initiated MMA contacts the DNA to buy the energy from the grid with the price of p_{sell}.

The coordination of different layers is illustrated in Fig. 4.

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III. Self-Adaptive Coalition Formation Scheme for Microgrids

In the MAS paradigm, the agent coalition means groups of agents joint together to complete a task, where none of them can complete it independently. In this paper, we employ a recent proposed coalition formation mechanism [25] to do the multiple microgrid coordination. This coalition formation scheme is notable for 2 features: 1) It considers the topology of underlying agent communication network, and uses limited communications to form the coalition; 2) it designs a self-adaptive mechanism to enable agents to have autonomy when agents execute tasks. In this paper, to make it fit the proposed application, the mechanism in [25] is modified to integrate the proposed concept of sub-task. The self-adaptive coalition formation scheme is presented as follows.

A. Basic Conceptions

In the coordination layer, the MMAs of microgrids form an agent network. Several notations and definitions are given as follows. Firstly, we define the relation of MMAs in the agent network.

Definition 1. An agent network of the microgrids includes a set of interdependent MMAs, namely $A=\{a_1,...,a_n\}$, and a *compatible relation* R, $R\subseteq A\times A$. The meaning of R is "a neighbour of" or 'directly connected', which means there is an ordered pair $\langle a_i,a_j\rangle\in R$ if and only if a_j is a neighbor of a_i. R is *reflexive* and *symmetric*, so that $\forall a_i : a_i\in A\Rightarrow\langle a_i,a_i\rangle\in R$ and $\forall a_i,a_j\in A:\langle a_i,a_j\rangle\in R\Rightarrow\langle a_j,a_i\rangle\in R$.

The definition of the reflexive and symmetric relation R is to ensure the connection between two agents is bidirectional. This definition is necessary, because as what will be discussed later, when an MMA wants another MMA to join in the former's coalition, there is a negotiation between them.

In the coordination layer, a MMA can act as one of 3 roles: *Initiator*, *Participant*, and *Mediator*. A MMA can be *Participant* and *Mediator* simultaneously. These 3 roles are defined as below.

Definition 2. *Initiator* is the MMA which initializes an energy imbalance task; *Participant* is the MMA which accepts the task; *Mediator* is the MMA which receives another agent's commitments for assistance to find participants.

Each MMA $a\in A$ records the information of three tuples $\langle r_a, Neig(a), State(a)\rangle$. r_a represents the available generation capacity of a microgrid; $Neig(a)$ is the set of the neighbors of a; $State(a)$ is the state of a. a can be in one of the two states defined as follows.

Definition 3. There are two states of a MMA: $MMA\_States=\{IDLE, BUSY\}$. An MMA can be only in one of them at any time. When an MMA is an *Initiator*, *Participant* or *Mediator*, its state is *BUSY*. The *IDLE* state indicates the MMA has not been assigned or committed to any task.

It is assumed that only an *IDLE* agent can be assigned to a new task as an *Initiator*; both *IDLE* and *BUSY* agents can join partially fulfilled tasks as *Participants* or be committed to partially fulfilled tasks as *Mediators*.

The set of energy imbalance tasks are defined as follows.

TABLE I
Example of the Task Information

θ	$AT(\theta)$	$DL(\theta)$	$ST\_List(\theta)$
	13:00	13:05	$S\theta_1$, $S\theta_2$
$S\theta_1$	$ST(S\theta)$	$DT(S\theta)$	$E(S\theta)$
	13:07	1 minute	0.8kWh
$S\theta_2$	13:09	1 minute	0.2kWh

Definition 4. The set of the energy imbalance tasks occurred in the microgrids is denoted as $\Theta=\{\theta_1,...,\theta_m\}$. Each task $\theta\in\Theta$ includes 3 tuples: $\langle AT(\theta), DL(\theta), ST\_List(\theta)\rangle$. $AT(\theta)$ is the arriving time of θ; $DL(\theta)$ is the deadline of θ, which is equal to the starting time of next control horizon T_c^i; $ST\_List(\theta)$ is the sub task list of θ. θ consists of one or more sub tasks stored in $ST\_List(\theta)$. That is, $ST\_List(\theta)=\{S\theta_1,...,S\theta_n\}$.

We use the notation $S\theta$ to denote a sub task. The concept of sub task is defined as below.

Definition 5. Each sub task of θ, $S\theta\in ST\_List(\theta)$, represents the energy imbalance event of a time interval within T_c^i. It consists of 3 tuples, $\langle ST(S\theta), DT(S\theta), E(S\theta)\rangle$. $ST(S\theta)$ is the starting time of $S\theta$; $DT(S\theta)$ is the time duration of $S\theta$; $E(S\theta)$ is the amount of the energy needed by $S\theta$.

Definitions 4 and 5 contain the information of the energy imbalance events detected in a microgrid. The task θ actually represents the power deficit events of future multiple time intervals, and each sub task $S\theta$ represents a power deficit event of a specific future time interval. For example, assuming the autonomous control horizon of the microgrid T_c^i is 5 minutes and the duration of each control time interval is 1 minute, and assuming at time 13: 00 the microgrid performs the very short-term forecasting and detects two power deficit events which will happen in the next control horizon which is from 13:05 to 13:10 (with totally 5 control time intervals). In other 3 control time intervals, the microgrid can serve the loads locally. Then, the generated task and sub tasks by the *Initiator* of that microgrid are shown in Table I.

For each θ, the *Initiator* needs to find appropriate microgrids which have available power resources to form a coalition to solve the energy imbalance problem. The *Initiator* must balance all the sub tasks of θ before $DL(\theta)$. As what will be discussed in the next section, firstly the initiator sends the coalition formation request to its neighbored MMAs. If the *Initiator* and its neighbors could not solve the problem, then the neighbors of the *Initiator* will act as the *Mediator* and forward the request to their neighbors to expand the coalition. A coalition of MMAs is defined as below.

Definition 6. A MMA coalition c is a set of MMAs ($c\subseteq A$) which cooperate to complete an energy imbalance task θ.

An *Initiator* a_i and a *Participant* a_j may reach an agreement on the energy trading by signing a *contract*, denoted as CON_{ij}^{θ}. The contract, which is defined as follows, is similar with the energy trading contract in the conventional power markets.

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Definition 7. A *contract* between an *Initiator* a_i and a *Participant* a_j for a task θ, represents the energy trading agreement between a_i and a_j. It consists of 2 tuples: $\langle TE(\theta), PAY(\theta)\rangle$. $TE(\theta)$ is the contracted energy for each sub task: $TE(\theta)=\{TE(S\theta_1),...,TE(S\theta_n)\}$; $PAY(\theta)$ is the total payment ($) of a_j to a_i.

A contract is with one of following two states:

Definition 8. There are two states of a *contract*: $Contract\_States=\{TEMPORY, FINAL\}$. A contract, CON_{ij}^{θ}, can be only in one of two states at any time step. In our application, CON_{ij}^{θ} is in *TEMPORY* state before the arrival of $DL(\theta)$; afterwards, the state of CON_{ij}^{θ} is changed to $FINAL$.

The *Initiator* and *Participant* have different objectives. An *Initiator* tends to minimize the payment of purchasing power. Therefore, the *Initiator* can negotiate with multiple *Participant*s simultaneously. A *Participant*'s objective is to maximize its profit. Thus the *Participant* is allowed to join in multiple coalitions and adjust the $TE(\theta)$ of any *contract* by paying some penalty, if the state of the *contract* is $TEMPORY$. A *contract* is not allowed to be adjusted when its state is changed to $FINAL$. The detailed coalition formation and negotiation algorithms are presented as follows.

B. Coalition Formation Mechanism

Firstly, the *partition* of *Compatible Relation R* is defined as $P=\{P_1,...,P_n\}$. Pseudo codes of creating a partition *P* on *R* are shown in Table II. *P* is essentially the set of agent pairs. In Algorithm 1, the *partition P* is initialized to contain the neighbors of *a*. However, unlike $Neig(a)$, *P* can be expanded to not only include the neighbors of agent *a*, but also the other agents which have indirect connections with *a*.

Let $AE_j^{S\theta}$ denotes the available energy of the *j*th microgrid over the duration of $S\theta$, and $CP_{i\_grid}^{\theta}$ denotes the *contract* formed between a_i and DNA. And the term $\sum_{k\in P_i} CON_{ik}^{\theta}{:}TE(S\theta)$ represents the sum of contracted energy capacities of all the existing contracts of a_i. Then based on Algorithm 1, the coalition formation algorithm is shown in Table III.

TABLE II
ALGORITHM 1: ALGORITHM OF CREATING *P* ON *R*

begin:
(1) for each $a_i \in A$, in sequential order
(2) **if** $\exists a_j \in A: \langle a_i, a_j\rangle \in R$ **then**
(3) $\quad P_i \leftarrow P_i \cup \{\langle a_i, a_j\rangle\}$
end

TABLE III
ALGORITHM 2: ALGORITHM OF COALITION FORMATION

begin:
(1) **Perform Algorithm 1** to generate *P*;
(2) **for each** $\theta \in \Theta$, in sequential order
(3) set the MMA a_i which submit the task θ as *Initiator*;
(4) set $State(a_i)$ as *BUSY*;
(5) **while** $t < DL(\theta)$ /**t* is the real time*/
(6) **for** each $a_j \in A: \langle a_i, a_j\rangle \in P_i$
(7) **if** $\exists S\theta \in ST\_List(\theta)$, $AE_j^{S\theta} > 0$ and $\sum_{k\in P_i} CON_{ik}^{\theta}{:}TE(S\theta) < E(S\theta)$
(8) set CON_{ij}^{θ} =**Negotiate** (a_i, a_j);
(9) **end if**
(10) **end for**
(11) **if** $\forall S\theta \in ST\_List(\theta)$, $\sum_{k\in P_i} CON_{ik}^{\theta}{:}TE(S\theta) == E(S\theta)$ **then**
(12) **break**;
(13) **else**
(14) **if** $\exists a_l \in A: \langle a_i, a_l\rangle \notin P_i$
(15) select a_k as *Mediator* where $\langle a_i, a_k\rangle \in P_i$;
(16) set $State(a_k)$ as *BUSY*;
(17) $P_i = P_i \circ P_k$;
(18) **else**
(19) **break**;
(20) **end if**
(21) **end if**
(22) **end while**
(23) **for each** $S\theta$ in $ST\_List(\theta)$, in sequential order
(24) **if** $\sum_{k\in P_i} CON_{ik}^{\theta}{:}TE(S\theta) < E(\theta)$
(25) set $CP_{i\_grid}^{\theta}{:}TE(S\theta)=E(\theta)-\sum_{k\in P_i} CON_{ik}^{S\theta}{:}TE(S\theta)$;
(26) set $CP_{i\_grid}^{\theta}{:}PAY(\theta) \mathrel{+}= p_{sell}\cdot E(S\theta)$;
(27) **end if**
(28) **end for**
(29) **end for**
end

In Algorithm 2, firstly Algorithm 1 is executed to generate the partition for each MMA (Line 1). Then for each task θ, the corresponding MMA a_i is set as the *Initiator* for θ (Lines 2-4). Then, a_i lunches the coalition formation request for θ. If there is at least one sub task which has not been solved, a_i communicates with the MMAs which have connection with it to negotiate, before the arrival of deadline (Lines 5-10). The conditions of launching a successful negotiation include: (1) the *Participant* has available energy to trade at the time point of the sub task, and (2) the sum of contracted energy already signed by a_i and other participants is still less than the required energy of the sub task (Line 7). After the negotiations, if θ is still not be solved, then a_i asks its neighbors to act as *Mediators* to contact more MMAs to negotiate (Lines 14-17). The notation of "$\circ$" in Line 17 represents the relational composition operation. That is, $\forall\langle x_i, y_j\rangle \in X, \langle y_j, z_k\rangle \in Y \Rightarrow \langle x_i, z_k\rangle \in Z$. The relational composition operation expands the partition of compatible relation to include not only the directly connected neighbors, but also the indirectly connected agents. If θ is still not be solved when one of the 2 conditions occurs: (1) the deadline arrives; (2) all the MMAs has already been negotiated with the *Initiator*, then the *Initiator* contacts the DNA to purchase energy from the grid (Lines 23-28).

C. MMA Negotiation Protocol

The core step of the coalition formation is the negotiation protocol among MMAs. The *Initiator* a_i negotiates with the participants about the energy trading. In the negotiation, basically a_i provides an offer to the *Participant* a_j, and the *Participant* evaluates its local generation cost, and chooses to accept the offer or generate an counter offer to the *Initiator*. De-

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noting $CON\_Set(a_i)$ as the set of the signed contracts of a_i and maximum allowable negotiation duration time as TN, then the overall procedures of the negotiation protocol are shown in Table IV.

TABLE IV
ALGORITHM 3: NEGOTIATION PROTOCOL OF TWO MMAS

begin:
(1) **while** t < *TN* **do**
(2) for task θ, a_i generates an offer o to a_j;
(3) **if** a_j accepts o **then**
(4) generate *contract* CON_{ij}^{θ} based on o;
(5) $CON\_Set(a_i) \leftarrow CON\_Set(a_i) \cup \{CON_{ij}^{\theta}\}$;
(6) $CON\_Set(a_j) \leftarrow CON\_Set(a_j) \cup \{CON_{ij}^{\theta}\}$;
(7) set $State(a_j)$ as *BUSY*;
(8) **return**;
(9) **else**
(10) a_j generates an counter-offer o' to a_i;
(11) **if** a_i accepts o' **then**
(12) generate *contract* CON_{ij}^{θ} based on o';
(13) $CON\_Set(a_i) \leftarrow CON\_Set(a_i) \cup \{CON_{ij}^{\theta}\}$;
(14) $CON\_Set(a_j) \leftarrow CON\_Set(a_j) \cup \{CON_{ij}^{\theta}\}$;
(15) set $State(a_j)$ as *BUSY*;
(16) **return**;
(17) **else**
(18) **continue;**
(19) **end if**
(20) **end if**
(21) **end while**
end

a_i and a_j iteratively negotiate the trading energy and the price within TN (Line 1). Firstly, a_i sends a_j an offer o (Line 2), where $o=\langle TE(\theta), PAY(\theta), PE(\theta), DT(\theta)\rangle$.

$TE(\theta)=\{TE(S\theta_1),...,TE(S\theta_n)\}$ is the intended purchasing energy of each sub task made by a_i to a_j. For a given sub task, the initial value of $TE(S\theta)$ in an offer is,

$$TE(S\theta)^{init}=\min(E(S\theta)-\sum_{k\in P_i} CON_{ik}^{S\theta}:TE(S\theta), AE_j^{S\theta}) \tag{1}$$

pr is the intended price made by a_i to a_j, which is linearly increased with the approaching of $DL(\theta)$,

$$pr=p_{buy}+(p_{sell}\text{-}p_{buy})\frac{t-AT(\theta)}{DL(\theta)-AT(\theta)} \tag{2}$$

where t is the current time. $PAY(\theta)=\{PAY(S\theta_1),...,PAY(S\theta_n)\}$, where $PAY(S\theta)$ represents the payment made by a_i to a_j for the subtask $S\theta$,

$$PAY(S\theta)=pr\cdot CON_{ij}^{\theta}:TE(S\theta) \tag{3}$$

$PE(\theta)=\{PE(S\theta_1),...,PE(S\theta_n)\}$, where $PE(S\theta)$ is the penalty if a_j wants to reduce the $CON_{ij}^{\theta}:TE(S\theta)$ in a_i's coalition, calculated as Eq. (4),

$$PE(S\theta)=\alpha\cdot pr \tag{4}$$

where α is the penalty coefficient. The exact penalty a_j should pay to a_i (denoted as $PE(S\theta)_{j\rightarrow i}$) is calculated as,

$$PE(S\theta)_{j\rightarrow i}=\frac{PE(S\theta)}{AE_j^{S\theta}\text{-}CON_{ij}^{\theta,\min}(S\theta)}\cdot(CON_{ij}^{\theta}:TE(S\theta)\text{-}CON_{ij}^{'\theta}:TE(S\theta)) \tag{5}$$

As introduced before, $CON_{ij}^{\theta}:TE(S\theta)$ is the current contracted trading energy of $S\theta$ between a_i and a_j; $CON_{ij}^{'\theta}:TE(S\theta)$ is the intended selling energy to which a_j wants to adjust. a_j is not allowed to adjust the contracted energy lower than a predefined threshold $CON_{ij}^{\theta,\min}(S\theta)$ for a sub task $S\theta$. In this paper, $CON_{ij}^{\theta,\min}(S\theta)$ is set as $CON_{ij}^{\theta,\min}(S\theta)=TE(S\theta)^{init}/5$.

After receiving the offer, a_j evaluates whether the offer is acceptable. a_j contacts mda_j to solve the optimal dispatch model. Then, a_j calculates the revenue by Eq. (6), where the notation $PE(\theta)_{j\text{-}*}$ means the penalty that a_j has to pay other *Initiators* if a_j wants to reduce its contracted selling energy in their coalitions; $COST(\theta)$ represents the cost of executing the task θ; $RV(\theta)$ is the final revenue by executing $S\theta$.

$$RV(\theta)=\begin{cases} PAY(\theta)-COST(\theta) & \text{if } CON\_Set(a_j)=\varnothing \\ PAY(\theta)-COST(\theta)\text{ -}PE(\theta)_{j\text{-}*} & \text{otherwise} \end{cases} \tag{6}$$

If $RV(\theta)>0$, then a_j will accept the offer and a temporary agreement is achieved (Lines 3-8); if not, a_j contacts mda_j to solve the optimal dispatch model to calculate $CON_{ij}^{'\theta}$ to meet a predefined revenue threshold δ. a_j then sends a_i the counter-offer o' with the newly calculated $CON_{ij}^{'\theta}$. Then, a_i compare $CON_{ij}^{'\theta}$ and $CON_{ij}^{\min}(\theta)$. If $CON_{ij}^{'\theta}:TE(S\theta)>CON_{ij}^{\min}(S\theta)\ \forall S\theta\in STL(\theta)$, then a_i accepts o'; otherwise, a_i continues to start the next round negotiation until TN is reached. In this paper, δ is defined as,

$$\delta=(p_{buy}\cdot CON_{ij}^{\theta}\cdot DT(\theta)\text{-}COST(\theta)) \tag{7}$$

D. Temporary Contract Adjustment Strategy

Since a microgrid is an autonomous entity, and a participant could joint different coalitions at different time points, it would be necessary for a *Participant* to have the flexibility to adjust its contracted trading energy in current coalitions when it joins a new coalition. Supposing a *Participant*, a_j, has joined n coalitions at time interval t and temporarily agreed to sell all its available power at t to the n coalitions. Now a_j is interested in another offer from another coalition ($CON_{(n+1)j}^{\theta}$), and there is a sub task $S\theta_{(n+1)j}$ in $CON_{(n+1)j}^{\theta}$ where $ST(S\theta_{(n+1)j})=t$. a_j then needs to calculate the intended energy reduction in ith coalition for the sub task $S\theta_{ij}$ (denoted as $\Delta CON_{ij}^{\theta}(S\theta_{ij})$, where $0\le\Delta CON_{ij}^{\theta}(S\theta_{ij})\le CON_{ij}^{\theta}:TE(S\theta_{ij})\text{-}CON_{ij}^{\theta,\min}(S\theta_{ij})$) where $ST(S\theta_{ij})=t$ to minimize $\sum_{1\le i\le n}\frac{CON_{ij}^{\theta}:PE(S\theta)}{AE_{ij}^{S\theta}\text{-}CON_{ij}^{\theta,\min}(S\theta)}\Delta CON_{ij}^{\theta}(S\theta_{ij})$, given $\sum_{1\le i\le n}(CON_{ij}^{\theta}:TE(S\theta)\text{-}\Delta CON_{ij}^{\theta}(S\theta_{ij}))+\Delta CON_{(n+1)j}^{\theta}(S\theta_{(n+1)j})=1$. Denoting $peRate(S\theta_{ij})=\frac{CON_{ij}^{S\theta}:PE(S\theta)}{AE_{ij}^{S\theta}\text{-}CON_{ij}^{\theta,\min}(S\theta)}$ and $\sum_{1\le i\le n}\Delta CON_{ij}^{\theta}(S\theta_{ij})=C$, then the *contract* adjustment algorithm for a given sub task $S\theta$ is shown in Table V.

TABLE V
ALGORITHM 4: STRATEGY FOR ADJUSTING TEMPORARILY CONTRACT

begin:
if $\sum_{1\le i\le n}(CON_{ij}^{\theta}{:}TE(S\theta_{ij})\text{-}CON_{ij}^{\theta,\min}(S\theta_{ij}))<C$ **then**
  break;
else if $\sum_{1\le i\le n}(CON_{ij}^{S\theta}{:}TE(S\theta_{ij})\text{-}CON_{ij}^{\min}(S\theta_{ij}))=C$ **then**
  for each CON_{ij} /* $1\le i\le n$ */
    $\Delta CON_{ij}^{\theta}(S\theta_{ij})=CON_{ij}^{\theta}{:}TE(S\theta_{ij})\text{-}CON_{ij}^{\theta,\min}(S\theta_{ij})$;
    end for
else
  ranking $peRate(S\theta_{ij})$, such that $peRate(S\theta_{1j})\le\ldots\le peRate(S\theta_{nj})$
  find an integer *k*, $1\le k<n$, such that
    $\sum_{1\le i<k}(CON_{ij}^{\theta}{:}TE(S\theta_{ij})\text{-}CON_{ij}^{\theta,\min}(S\theta_{ij}))<C$ and
    $\sum_{1\le i\le k}(CON_{ij}^{\theta}{:}TE(S\theta_{ij})\text{-}CON_{ij}^{\theta,\min}(S\theta_{ij}))\ge C$;
  for $1\le i<k$
    $\Delta CON_{ij}^{\theta}(S\theta_{ij})=CON_{ij}^{\theta}{:}TE(S\theta_{ij})\text{-}CON_{ij}^{\theta,\min}(S\theta_{ij})$;
  end for
  for $i=k$
    $\Delta CON_{ij}^{\theta}(S\theta_{ij})=C\text{-}\sum_{1\le i<k}CON_{ij}^{\theta}{:}TE(S\theta_{ij})\text{-}CON_{ij}^{\theta,\min}(S\theta_{ij})$;
  end for
  for $k<i<n$
    $\Delta CON_{ij}^{\theta}(S\theta_{ij})==0$
  end for
end if
end

E. Lower Level Optimal Dispatch Model

Given a certain amount of contracts, a *Participant j* solves an optimal dispatch model to dispatch the power among different microgrid resources, aiming to minimize the total operation cost over T_c^j. In this study, 3 kinds of controllable resources are considered: wind turbines, BESS, and interruptible loads. We assume that operational cost of the wind turbines is zero, then the optimal dispatch model can be formulated as,

$$F=\min\sum_{t=1}^{T_c^j}\left(cost\_BESS(P_{BES}^t)+cost\_IL(P_{IL}^t)\right) \tag{8}$$

where t is the control time interval index; $cost\_BESS(P_{BES}^t)$ is the operational cost of the BESS; $cost\_IL(P_{IL}^t)$ is the cost of shedding the interruptible loads; P_{BES}^t is the power output of the BESS at time t; P_{IL}^t is the shed power of the interruptible loads at time t.

In this paper, the maximum amount of the interruptible loads at t is set as $P_{IL}^t\le\lambda\cdot P_{load}^t$, where P_{load}^t is the forecasted load at t and λ is the coefficient within (0,1). $cost\_BES(P_{BES}^t)$ and $cost\_IL(P_{IL}^t)$ are then with the following forms,

$$cost\_BES(P_{BES}^t)=\beta\cdot P_{BESS}^t\cdot\Delta t+\beta\cdot P_{BESS}^t\cdot\eta_l\cdot\Delta t \tag{9}$$

$$cost\_IL(P_{IL}^t)=p_{IL}\cdot P_{IL}^t \tag{10}$$

where β is the cost coefficient of the BESS lifetime depression; η_l is the leakage loss of the BESS; p_{IL} is the load shedding cost coefficient. The energy changing of BESS can be described as,

$$E_{BESS}^{t+1}=E_{BESS}^t+\Delta t\cdot P_{BESS}^t-|P_{BESS}^t|\cdot\eta_c\cdot\Delta t-E_{BESS}^t\cdot\eta_l\cdot\Delta t \tag{11}$$

where E_{BESS}^t is the energy stored in the BESS at time *t*. The SOC of BESS at time *t* is then calculated as follows,

$$SOC^t=E_{BESS}^t\big/E_{BESS}^r \tag{12}$$

where E_{BESS}^r is the rated energy capacity of the BESS (KWh).

Model (8) is subjected to following constraints:

b) BESS power limits constraint, where $P_{BESS}^{Dis,Max}$ and $P_{BESS}^{Chr,Max}$ represent the rated discharging and charging power of the BESS,

$$P_{BESS}^{Dis,Max}\le P_{BESS}^t\le P_{BESS}^{Chr,Max} \tag{13}$$

c) Interruptible load capacity constraint,

$$P_{IL}^t\le\lambda\cdot P_{load}^t\qquad\lambda\in(0,1) \tag{14}$$

d) Load balance constraint,

$$P_{wind}^t+P_{BESS}^t=P_{load}^t\text{-}P_{IL}^t+\sum_{i}^{NC}CON_{ij}^{\theta}{:}TE(\theta) \tag{15}$$

Based on the generation source and interruptible load models used in this paper, the lower level optimization model (8) is a linear programming problem, which can be handled by the linear programming technique.

It is worthy to mention that the lower-level scheduling can be considered as an independent module in the proposed control framework, which is decoupled from the coalition formation procedures of MMAs. Since it is not the major focus of this paper, in this section we just consider some typical resources (e.g, wind turbine and BESS) and use relatively simple interruptible load model. In future, more sophisticated resources models can be easily integrated into the lower-level dispatch model.

IV. SIMULATION STUDY

A. Experiments Setup

The proposed control framework is implemented on the Java Agent Development Framework (JADE) [26]. The detailed programming guides of JADE can be found in [27]. We simulate 10 microgrids in a looped LV network, where each one is configured with a certain capacities of resources. Basic configuration of the microgrids is shown in Table VI. Note that Table VI shows the asynchronous coordination of microgrids is simulated, where the microgrids have different autonomous control intervals. Topology of the LV network is shown in Fig. 6. It is assumed that the communication topology of the MMAs is consistence with the power physical network topology, as shown in the circle of Fig. 6.

The Vestas V27-225 KW wind turbine [32] is used for simulation, where the rated, cut-in, and cut-out wind speeds are 14.0m/s, 3.5m/s, and 25.0m/s, respectively. The interruptible load coefficient λ is set to be 0.9. The wind power generation model follows [28]. Advanced wind and load forecasting tools developed by our research group, *OptiWind* and *OptiLoad* [29], are utilized to generate the different forecasted wind and load profiles for the 10 microgrids in a minutely basis. The initial SOC of all the BESS of the microgrids are assumed to be their

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TABLE VI
BASIC CONFIGURATION OF THE 10 MICROGRIDS

MicroGrid	WP Capacity	Peak Load Capacity	BES Configuration			Control Interval
			Capacity	MinSOC	MaxSOC	
MG1	500kW	500kW	50kW, 100kWh	20%	80%	180s
MG2	750kW	750kW	50kW, 100kWh	20%	80%	120s
MG3	200kW	200kW	20kW, 40kWh	20%	80%	180s
MG4	300kW	300kW	20kW, 40kWh	20%	80%	120s
MG5	750kW	500kW	50kW, 100kWh	20%	80%	300s
MG6	500kW	750kW	50kW, 100kWh	20%	80%	180s
MG7	300kW	200kW	20kW, 40kWh	20%	80%	180s
MG8	200kW	300kW	20kW, 40kWh	20%	80%	120s
MG9	550kW	550kW	20kW, 40kWh	20%	80%	180s
MG10	550kW	550kW	20kW, 40kWh	20%	80%	120s

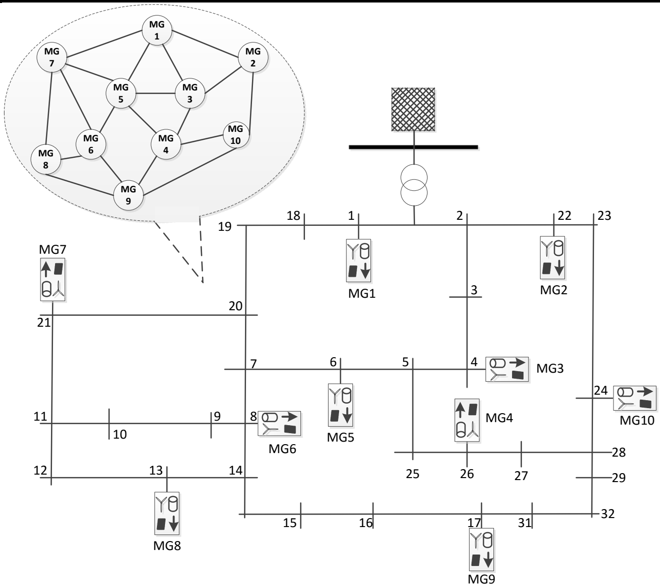

Fig. 6. Loop distribution network with multiple microgrids

TABLE VII
COALITION INFORMATION OF THE SHORT-TERM OPERATION

Task	Sub Task	ST	NCT	Initiator	Participants	Penalty
T1	ST1_1	03:00	03:45	MG2	MG1, MG10	-
	ST1_2		03:43			
T2	ST2_1	07:00	07:44	MG7	MG5, MG6, MG9, Grid	-
	ST2_2		07:46			
	ST2_3		07:54			
T3	ST3_1	9:00	9:21	MG8	MG5, MG9	MG9 $\xrightarrow{ST2\_1}$ MG7
	ST3_2		9:50			
T5	ST4_1	16:00	16:25	MG5	MG3, MG4, MG6, MG7, MG8, Grid	-
	ST4_2		16:52			
	ST4_3		16:34			
	ST4_4		16:34			

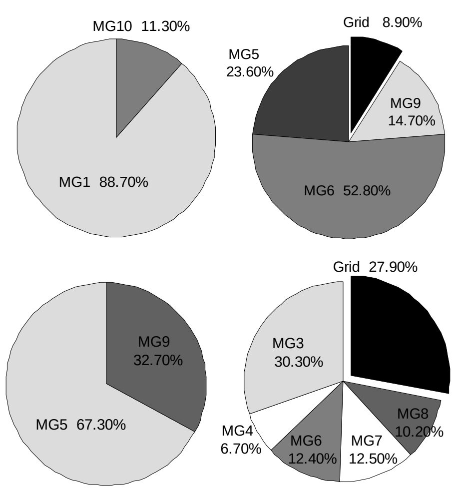

Fig. 7. Trading power of the 4 tasks of Case 1 (T1: upper-left; T2: upper-right; T3: lower-left; T4: lower-right)

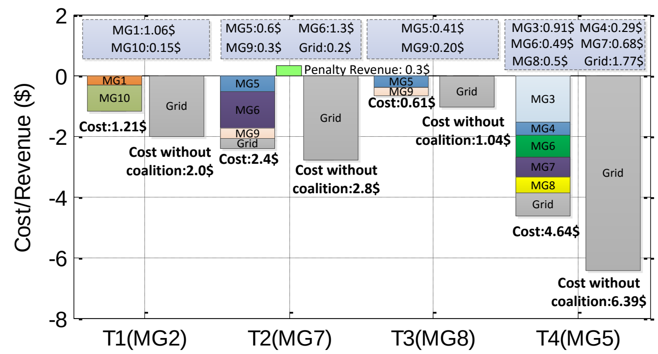

Fig. 8. Cost & Revenue of the initiators of the 4 tasks of Case 1

SOC lower limit. p_{buy} and p_{sell} are set to be 0.1$/kWh and 0.3$/kWh, respectively.

All the input data of the microgrids are stored in the text files, and are loaded by the Java classes when the simulation starts. The commercial optimization software called AMPL/IPORT [30] is employed to solve the lower-layer dispatch model represented by (8)-(15). The Java program invokes the AMPL/IPORT optimizer by using the external execution command, and then retrieve the optimize results.

B. Case1: Short-Term Operation

Firstly, we simulate a 30-minute operation horizon of the 10 microgrids. During the simulation, there are totally 4 power deficit events detected, and corresponding 4 tasks are formed. The 4 tasks consist of totally 15 sub tasks. The corresponding coalitions are then formed to solve the tasks. The main coalition information is recorded in Table VII. For each task, the proportions of the traded energy between the initiator and participants are shown in Fig. 7.

From Table VII and Fig. 7, it can be seen that task 1 and task 3 are relatively easy to solve. Task 1 is launched by MG2, and is solved with the help of two of its directly connected neighbors MG1 and MG10, where MG10 undertakes most of the deficit energy (88.7%). Task 3 is launched by MG8, and the coalition members include its neighbor MG9 and its indirectly connected agent MG5. MG8 purchases majority of its deficit energy from MG5. For task 2 and task 3, more coalition members are involved, and the initiator cannot solve all the subtasks completely by forming the coalitions. Therefore, the initiators have to buy power from the grid. For example, for task 4, as much as 27.9% of deficit energy are still need to be purchased from the grid after the negotiation among microgrids.

The cost of the initiator of each task is investigated, comparing with the scenario without the proposed framework. In the

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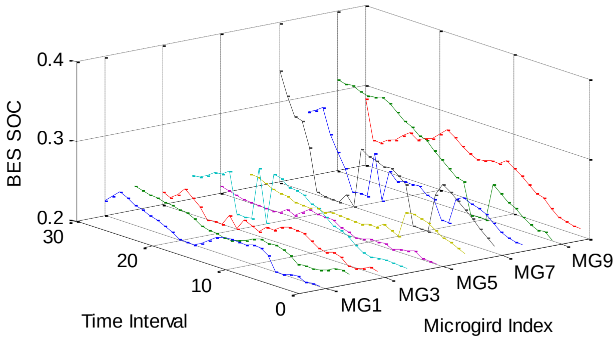

Fig. 9. BES SOC profiles of the 10 microgrids of Case 1

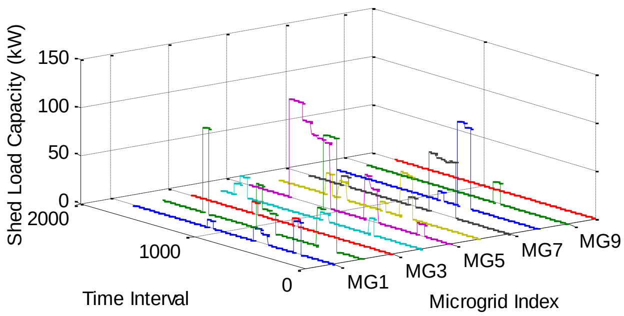

Fig. 10. Profiles of shed load capacities of the microgrids of Case 1

TABLE VIII
COALITION INFORMATION OF CASE2

Initiator	Task Count	Sub Task Count	Total Trade Energy (kWh)
MG1	893	1,342	7,984.9
MG2	1,014	1,873	18,012.0
MG3	612	1,044	2,992.8
MG4	1,066	1,233	5,301.9
MG5	918	2,290	16,526.1
MG6	1,322	1,541	17,644.5
MG7	593	919	2,634.4
MG8	858	1,243	5,510.6
MG9	1,122	1,937	15,754.3
MG10	1,046	1,860	14,415.0
Total	9,444	15,282	106,776.5

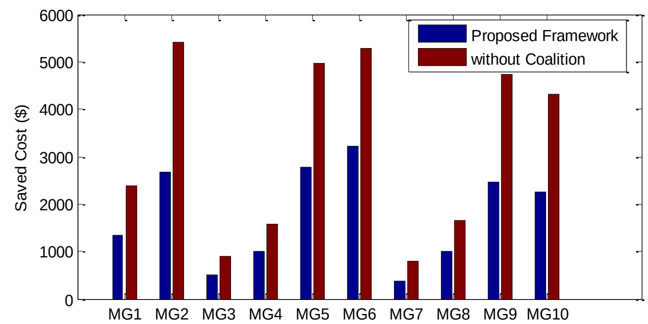

Fig. 11. Cost reduction of 10 microgrids under two scenarios

latter scenario, when the microgrids detect the energy imbalance events, it can only choose to buy the energy from the grid; and the microgrids can also only sell the energy to the grid. The final result is shown in Fig. 8. It can be clearly seen that the costs of the initiators are significantly reduced by introducing the proposed coalition formation scheme. And generally the initiators pay more to the microgrid with which it trades more energy. The comparison results in Fig. 8 clearly prove the effectiveness of the proposed control framework.

As a demonstration, Figs. 9 and 10 show the profiles of the BESS SOC and the interrupted load capacity of each microgrid by performing the low-level scheduling. It can be seen that for each battery, the BESS SOC is well controlled between its operational lower and upper limits. And MG5 sheds most load capacities among the 10 microgrids.

C. Case2: Long-Term Evaluation

Based on the same benchmark system, we simulate 1-year operation of the microgrids to evaluate the long-term efficiency of the proposed framework. During the operation, totally 9,444 tasks are formed, including 15,282 subtasks. The summarized information of the coalitions is shown in Table VIII. MG6 generated maximum number of coalition requests among the microgrids (1,322). MG5 only generated totally 918 coalition requests, but has maximum number of the subtasks (2,290). This is because the control interval of MG5 is the longest among the 10 microgrids (5 minutes). MG2 purchases more energy than other microgrids, reaching 18,012.0 kWh. Also, the scenario without the proposed framework is compared, and Fig. 11 shows the total cost reduction of the 10 microgrids under both scenarios. The results clearly show that all the 10 microgrids can significant save the energy purchase costs under the proposed framework than that under the scenario without the proposed framework.

V. CONCLUSIONS AND FUTURE WORK

This paper proposes a distributed control framework for microgrids operation, based on the multi-agent system. A layered agent framework is presented for microgrids modeling firstly. Then, an advanced self-adaptive coalition formation scheme and negotiation algorithm are introduced to model the coordination behaviors of microgrids. The proposed control framework is implemented by JADE, and the case studies prove the efficiency of the proposed method.

For simplicity, in this paper the communication structure of the MAS system is assumed to be fixed and identical with the physical network structure. However, this constraint can be relaxed where the communication network topology can be self-adapted according to the real-time network performance. The authors are currently working on developing a self-adaptive MAS system for the microgrids control. Also, in this work, we use the same microgrid operation conditions with [19], where the pricing schemes are relatively simple and lack of specific power market rule considerations. In future, the agent coalition scheme of multiple microgrids under specific market structures can be investigated. Another potential direction is to apply the agent coalition technology on other applications in the low voltage networks. For example, the authors are also working on developing an agent coalition based control scheme to coordinate different battery energy storage systems (BESSs) on different nodes to do the real-time voltage regulation in the distribution system.

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