Optimal operation of multimicrogrids via cooperative energy and reserve scheduling

Li, Yuanzheng; Zhao, Tianyang; Wang, Ping; Gooi, Hoay Beng; Wu, Lei; Liu, Yun; Ye, Jian

2018

Li, Y., Zhao, T., Wang, P., Gooi, H. B., Wu, L., Liu, Y., & Ye, J. (2018). Optimal operation of multimicrogrids via cooperative energy and reserve scheduling. *IEEE Transactions on Industrial Informatics*, 14(8), 3459-3468. doi:10.1109/TII.2018.2792441

<https://hdl.handle.net/10356/90253>

<https://doi.org/10.1109/TII.2018.2792441>

© 2018 IEEE. Personal use of this material is permitted. Permission from IEEE must be obtained for all other uses, in any current or future media, including reprinting/republishing this material for advertising or promotional purposes, creating new collective works, for resale or redistribution to servers or lists, or reuse of any copyrighted component of this work in other works. The published version is available at:
<https://doi.org/10.1109/TII.2018.2792441>

Downloaded on 26 Apr 2023 20:15:55 SGT

Optimal Operation of Multi-Microgrids via Cooperative Energy and Reserve Scheduling

Y.Z. Li, T.Y. Zhao, P. Wang, *Senior Member IEEE*, H.B. Gooi, *Senior Member IEEE*,

L. Wu, *Senior Member IEEE*, Y. Liu, *Member IEEE* and J. Ye

Abstract—Microgrid (MG) represents one of major drives of adopting Internet of Things for smart cities, as it effectively integrates various distributed energy resources. Indeed, MGs can be connected with each other and presented as a system of multi-microgrid (MMG). This paper proposes the optimal operation of MMGs by a cooperative energy and reserve scheduling model, in which energy and reserve can be cooperatively utilized among MMGs. In addition, values of Shapely are introduced to allocate economic benefits of the cooperative operation. Finally, a case study based on a system of MMGs is conducted, and simulation results verify the effectiveness of the proposed cooperative scheduling model.

Index Terms—Multi-microgrids, uncertainty, cooperative scheduling model, energy and reserve.

I. INTRODUCTION

With the development of smart cities, microgrids (MGs) are being increasingly deployed in communities, e.g., the MG capacity will exceed 1.8 GW by 2018 in the U.S. [1]. As we know, MGs can effectively integrate various distributed energy resources (DERs), such as wind turbines (WTs), photovoltaic cells (PVs), diesel generators (DGs), energy storage systems (ESSs), etc [2]–[5]. By aggregating these DERs, MGs are regarded as a powerful supplement to the centralized transmission and distribution power systems [6]. Usually, an MG has two operational states, i.e., the isolated and grid-connected modes. It is operated in isolated mode for supplying local loads when external grid is in fault. On the contrary, the MG

is connected to a distribution power network (DPN) for the grid-connected mode [7].

For the isolated operation, an MG dispatcher aims to schedule DGs and ESSs for minimizing the operational cost, while considering uncertain outputs of DERs. For instance, Su *et al.* [8] develop a stochastic MG scheduling model, and it minimizes the expected operational cost and accommodate intermittent wind and solar power. Ding *et al.* [9] present a stochastic operational strategy for scheduling generation and demand resources, for improving efficiency of an MG. Alipour *et al.* [10] propose a stochastic day-ahead scheduling model for combined heat and power in an MG, with the consideration of uncertainties of wind power. In [11], an optimal MG scheduling solution is obtained by optimizing the worst-case scenario, which is robust against realizations of various uncertainties. Furthermore, Hu *et al.* [12] propose a two-stage robust optimization approach, which is targeted to minimize the averaged economic cost while satisfying operational constraints.

On the other hand, for the grid-connected operation, an MG can be connected with a DPN and other MGs to form a multi-microgrid (MMG) [13]. In this way, each MG coordinates its local resources [14]–[17], the DPN [18]–[21], and other MGs [22]–[26]. For managing local resources of an MG, Nguyen *et al.* [14] consider uncertain power outputs of PV, and minimize the operational cost by optimizing charging/discharging schedule of ESSs. Jiang *et al.* [15] maximize the economic profit of an MG by adjusting power outputs of DGs and ESSs. Furthermore, Zhang *et al.* [16] propose a scheduling model in which the operational cost of an MG comprises penalty cost caused by renewable energy.

For the coordinative operation between an MG and a DPN, Marvasti *et al.* [18] propose a hierarchical optimization approach for addressing interactions between the DPN and MGs. In [19], a bi-level optimization model of an MG is presented. This model reduces the loss and improves the voltage quality by optimizing the power transaction between the MG and DPN. Bahramara *et al.* [20] adopt a decision making framework for assisting in operating a DPN in which distribution company and MGs cooperate with each other. Furthermore, Lv *et al.* [21] indicate that it is of great importance for the cooperation between an MG and a DPN.

In terms of the coordinative operation of MMGs, Erol *et al.* [22] introduce an idea for sharing resource among MMGs, which can effectively reduce the amount of purchased electricity from the utility grid. Wang *et al.* [23] presents a novel solution for the coordinative operation of MMGs, which

Y.Z. Li is with Huazhong University of Science and Technology, Wuhan 430074, China, and also with State Key Laboratory of Alternate Electrical Power System with Renewable Energy Sources, North China Electric Power University, Beijing 102206, China (Email: Yuanzheng_Li@hust.edu.cn).

T.Y. Zhao (Corresponding author) is with Energy Research Institute, Nanyang Technological University, Singapore 639798, Singapore (Email: zhaoty@ntu.edu.sg).

P. Wang is with School of Computer Engineering, Nanyang Technological University, Singapore 639798, Singapore (Email: WANGPING@ntu.edu.sg).

H.B. Gooi and J. Ye are with School of Electrical and Electronic Engineering, Nanyang Technological University, Singapore 639798, Singapore. (Email: EHBGOOI, JYE007@ntu.edu.sg).

L. Wu is with Department of Electrical and Computer Engineering, Clarkson University, Potsdam, NY 13699, USA. (Email: lwu@clarkson.edu).

Y. Liu is with the College of Mechatronics and Control Engineering, Shenzhen University, Shenzhen 518060, China (e-mail: liyun19881026@gmail.com).

The work is supported in part by the National Natural Science Foundation of China under Grant 51707069, in part by the Ministry of Education Key Laboratory of Image Processing and Intelligence Control, Wuhan, China under Grant IPIC2015-01, in part by the StateKey Laboratory of Alternate Electrical Power System with Renewable Energy Sources (Grant No.LAPS16004), North China Electric Power University, and in part by the Energy Innovation Programme Office through the National Research Foundation and Singapore Economic Development Board. The work of L. Wu is supported by the U.S. National Science Foundation grants PFI: BIC-1534035 and CNS 1647135.

is obtained by a stochastic bi-level model. Wu *et al.* [24] use the coordinated information and strategies among MMGs, for reducing the operational cost of an MG. Nikmehr *et al.* [25] propose a probabilistic model for both small-scale energy resources and load demand of each MG, in order to realize economic operation of MMGs while considering the power exchange between MGs. Similarly, an energy cooperation strategy among MMGs is proposed in [26], which enables their energy exchange and realizing the economic operation.

From existing literature we notice that: (i) Prior work on MMGs mainly focuses on energy cooperation, while reserve cooperation is not considered for coping with uncertain power output of DERs. Indeed, one MG could provide reserve support to other MGs in a MMG system; and (ii) If the cooperative energy and reserve operation of MMGs is considered, proper allocation of economic benefits to individual MG needs to be studied, as an MG should obtain compensation when it provides energy or reserve to other MGs.

For addressing these issues, this paper proposes a cooperative energy and reserve scheduling model for the optimal operation of MMGs. The main contributions of the paper are threefold.

(1) A cooperative energy and reserve scheduling model based on game theory is proposed, which can facilitate the optimal operation of MMGs;

(2) In the cooperative operation of MMGs, values of Shapely are used for allocating economic benefits for individual MGs;

(3) Numerical case studies are conducted for verifying the effectiveness of the proposed scheduling model for cooperative operation of MMGs, compared with the isolated operation.

The rest of this paper is organized as follows. The cooperative energy and reserve scheduling model of MMGs are presented in Section II. Section III shows the economic benefit allocation scheme between MMGs. In Section IV, numerical case studies verify the effectiveness of the proposed cooperative energy and reserve scheduling model of MMGs. Finally, conclusions are drawn in Section V.

II. COOPERATIVE ENERGY AND RESERVE SCHEDULING OF MULTI-MICROGRIDS

A. System structure

Fig. 1 shows a typical structure of an MMG system, in which each MG comprises DGs, WTs, PVs, ESSs, and local loads. MMGs are interconnected by a common low-voltage bus. As for the day-ahead energy scheduling of MMGs, each MG reports forecast information on power outputs of WTs, PVs, the local load demand, as well as physical information of DGs and ESSs to the interconnection control center of MMGs. Meanwhile, the distribution power network control center sends information of forecast electricity price to the control center of MMGs. In this way, the control center of MMGs can determine the optimal energy scheduling solution for individual MGs in a centralized manner, including power outputs of DGs and charging/discharging of ESSs, as well as purchasing/selling plan with the DPN.

However, the reserve scheduling is critical for real-time operations of power systems [27]. Therefore, it should be

Fig. 1. A typical structure of multi-microgrids system

considered for MMGs operations, due to real-time uncertain power outputs of WTs and PVs. Indeed, the interconnection control center of MMGs can coordinate the energy and reserve transactions among MMGs. For instance, an MG could offer its excessive energy and reserve to others, and the control center of MMGs will make an economic compensation to that MG. On the other hand, when an MG is in shortage of energy and/or reserve, this center arranges other MGs to provide energy and/or reserve to this MG. In this way, energy and reserve can be shared and exchanged within the MMGs.

Consequently, we propose a cooperative energy and reserve scheduling model for supporting the optimal operation of MMGs. Formulations of energy and reserve scheduling for a single MG are first presented in Section II.B, followed by the cooperative energy and reserve scheduling model based on game theory for MMGs in Section II.C.

B. Energy and Reserve Scheduling Model for a Single MG

An MG usually comprises DGs, ESSs, WTs, PVs, etc. Its optimal scheduling of an MG is to minimize the total economic cost (EC), which includes the operational cost of DGs and ESSs as well as the transaction cost between the MG and DPN. The EC of a DG with a diesel engine is formulated as follows:

$$C_{m,DG}^{n,t}(p_{m,DG}^{n,t}) = a_{m,DG}^n p_{m,DG}^{n,t} + b_{m,DG}^n \quad (1)$$

where $C_{m,DG}^{n,t}(p_{m,DG}^{n,t})$ and $p_{m,DG}^{n,t}$ are the EC and the active power output of the m th DG in the n th MG during the t th time interval. $n = 1, 2, \dots, N_{MG}$, and N_{MG} is the number of MGs; $m = 1, 2, \dots, N_{DG}^n$, and N_{DG}^n is the number of DGs in the n th MG; $a_{m,DG}^n$ and $b_{m,DG}^n$ are EC coefficients of the m th DG in the n th MG.

EC of an ESS is presented as follows:

$$C_{r,ESS}^{n,t}(p_{r,ESS}^{n,t}) = c_{r,ESS}^n |p_{r,ESS}^{n,t}| \quad (2)$$

where $C_{r,ESS}^{n,t}(p_{r,ESS}^{n,t})$ and $p_{r,ESS}^{n,t}$ are the EC and the charging or discharging power of the r th ESS in the n th MG during the t th time interval. Note that $|p_{r,ESS}^{n,t}|$ in Eq. (2) is the absolute value of $p_{r,ESS}^{n,t}$. $r = 1, 2, \dots, N_{ESS}^n$, and N_{ESS}^n is the number of ESSs. $c_{r,ESS}^n$ stands for the EC coefficient of the r th ESS in the n th MG.

The transaction cost between an MG and the DPN is shown as follows:

$$C_{DN}^{n,t}(p_{DN}^{n,t}) = e_{DN}^{n,t} p_{DN}^{n,t} \quad (3)$$

where $C_{DN}^{n,t}(p_{DN}^{n,t})$ is the purchasing or selling cost of electricity from or to a DPN for the n th MG during the t th time interval. $p_{DN}^{n,t}$ and $e_{DN}^{n,t}$ stand for the transaction power and the corresponding electricity price, respectively.

Therefore, the total EC for the n th MG is shown as follows.

$$C^n = \sum_{t=1}^T \left\{ \sum_{m=1}^{N_{DG}^n} C_{m,DG}^n(p_{m,DG}^{n,t}) + \sum_{r=1}^{N_{ESS}^n} C_{r,ESS}^n(p_{r,ESS}^{n,t}) + C_{DN}^n(p_{DN}^{n,t}) \right\} \quad (4)$$

where T is the total number of scheduling time intervals.

The objective of an MG scheduling is the minimization of the total EC, while satisfying prevailing constraints. The constraints with respect to DGs and ESSs are presented as follows:

$$p_{m,DG}^{n,min} \leq p_{m,DG}^{n,t} \leq p_{m,DG}^{n,max} \quad (5)$$

$$-R_{m,down}^n \leq p_{m,DG}^{n,t} - p_{m,DG}^{n,t-1} \leq R_{m,up}^n \quad (6)$$

$$0 \leq p_{r,ESSdc}^{n,t} \leq p_{r,ESSdc}^{n,max} \quad (7)$$

$$0 \leq p_{r,ESSc}^{n,t} \leq p_{r,ESSc}^{n,max} \quad (8)$$

$$E_{r,ESS}^{n,t} = E_{r,ESS}^{n,t-1} + p_{r,ESSc}^{n,t} \eta_{r,c}^n - \frac{p_{r,ESSdc}^{n,t}}{\eta_{r,dc}^n} \quad (9)$$

$$E_{r,ESS}^{n,min} \leq E_{r,ESS}^{n,t} \leq E_{r,ESS}^{n,max} \quad (10)$$

$$E_{r,ESS}^{n,t} = E_{r,ESS}^{n,t+T} \quad (11)$$

where $p_{m,DG}^{n,min}$ and $p_{m,DG}^{n,max}$ are minimum and maximum power outputs of the m th DG in the n th MG, respectively. $R_{m,down}^n$ and $R_{m,up}^n$ are ramp up and down rate limits. $p_{r,ESSdc}^{n,max}$ and $p_{r,ESSc}^{n,max}$ are maximum discharging and charging powers of the r th ESS, and $E_{r,ESS}^{n,t}$ is its energy at the end of t th time interval. $\eta_{r,c}^n$ and $\eta_{r,dc}^n$ are charging and discharging efficiencies of the r th ESS, and $E_{r,ESS}^{n,min}$ and $E_{r,ESS}^{n,max}$ are its minimum and maximum energy capacities, respectively.

For power outputs of WTs and PVs, it is difficult to obtain their accurate values, which means that forecast errors always exist. Therefore, actual power outputs of WTs and PVs can be described by the sum of forecast values and errors:

$$p_{q,WT}^{n,t} \in [p_{q,WT}^{n,t,f} - p_{q,WT}^{n,t,e}, p_{q,WT}^{n,t,f} + p_{q,WT}^{n,t,e}] \quad (12)$$

$$p_{s,PV}^{n,t} \in [p_{s,PV}^{n,t,f} - p_{s,PV}^{n,t,e}, p_{s,PV}^{n,t,f} + p_{s,PV}^{n,t,e}] \quad (13)$$

where $p_{q,WT}^{n,t}$, $p_{q,WT}^{n,t,f}$ and $p_{q,WT}^{n,t,e}$ are the actual, forecast, and forecast error of the q th WT ($q = 1, 2, \dots, N_{WT}^n$), and N_{WT}^n is

Fig. 2. The energy and reserve scheduling of an MG

the number of WTs in the n th MG. $p_{s,PV}^{n,t}$, $p_{s,PV}^{n,t,f}$ and $p_{s,PV}^{n,t,e}$ are the actual, forecast, and forecast error of the s th PV ($s = 1, 2, \dots, N_{PV}^n$), and N_{PV}^n is the number of PVs in the n th MG.

Similarly, the actual electricity price $e_{DN}^{n,t}$ and load demand $P_L^{n,t}$ are formulated as follows:

$$e_{DN}^{n,t} \in [e_{DN}^{n,t,f} - e_{DN}^{n,t,e}, e_{DN}^{n,t,f} + e_{DN}^{n,t,e}] \quad (14)$$

$$P_L^{n,t} \in [P_L^{n,t,f} - P_L^{n,t,e}, P_L^{n,t,f} + P_L^{n,t,e}] \quad (15)$$

where $e_{DN}^{n,t,f}$ and $e_{DN}^{n,t,e}$ are the forecast electricity price and its error. $P_L^{n,t,f}$ and $P_L^{n,t,e}$ are the forecast load demand and its error during the t th time interval, respectively.

For the n th MG, power outputs of DGs, WTs, and PVs, charging/discharging electricity of ESSs, the transaction power from/to the DPN, and the total load should be balanced.

$$\sum_{m=1}^{N_{DG}^n} p_{m,DG}^{n,t} + \sum_{r=1}^{N_{ESS}^n} p_{r,ESS}^{n,t} + \sum_{q=1}^{N_{WT}^n} p_{q,WT}^{n,t} + \sum_{s=1}^{N_{PV}^n} p_{s,PV}^{n,t} + p_{DN}^{n,t} = P_L^{n,t} \quad (16)$$

It is known that forecast errors of power outputs of WTs and PVs, and the load demand exists, which bring significant challenges to balance power generation with load demand, i.e., satisfying Eq. (15). In this paper, we introduce the method of participation factor [28], [29] to solve this issue by two steps. The first step is to conduct energy scheduling based on day-ahead forecast information, which is shown in Fig. 2. The energy scheduling aims to determine the power output of DGs, charging/discharging power of ESSs, and the transaction power between the MG and the DPN, which consist of the base-point scheduling solution. The reason why we call “base-point” is that the obtained energy scheduling solution is based on the day-ahead forecasting information of power outputs of WTs and PVs, electricity price of DPN, and load demand, while it satisfies:

$$\sum_{m=1}^{N_{DG}^n} p_{m,DG}^{n,t,f} + \sum_{r=1}^{N_{ESS}^n} p_{r,ESS}^{n,t,f} + \sum_{q=1}^{N_{WT}^n} p_{q,WT}^{n,t,f} + \sum_{s=1}^{N_{PV}^n} p_{s,PV}^{n,t,f} + p_{DN}^{n,t,f} = P_L^{n,t,f} \quad (17)$$

where $p_{m,DG}^{n,t,f}$, $p_{r,ESS}^{n,t,f}$ are base-point scheduling power outputs of the m th DG and the scheduling charging/discharging of the r th ESS. $p_{DN}^{n,t,f}$ stands for the base-point transaction power.

The second step is the reserve scheduling, i.e., conducting reserve regulation of DGs, ESSs, and DPN, which is also shown in Fig. 2. In other words, we adjust power outputs of controllable units and transaction power, in order to compensate forecast errors of power outputs of WTs and PVs, and load demand. The time window is usually 5 minutes [30], [31]. These forecast errors lead to the mismatched power $\varepsilon^{n,t}$ of the n th MG, which can be presented as follows.

$$\varepsilon^{n,t} = P_L^{n,t} - \sum_{m=1}^{N_{DG}^n} p_{m,DG}^{n,t,f} - \sum_{r=1}^{N_{ESS}^n} p_{r,ESS}^{n,t,f} - \sum_{q=1}^{N_{WT}^n} p_{q,WT}^{n,t} - \sum_{s=1}^{N_{PV}^n} p_{s,PV}^{n,t} - p_{DN}^{n,t,f} \quad (18)$$

and

$$P_L^{n,t,\max} = P_L^{n,t,f} + P_L^{n,t,e} \quad (19)$$

$$p_{q,WT}^{n,t,\max} = p_{q,WT}^{n,t,f} + p_{q,WT}^{n,t,e} \quad (20)$$

$$p_{s,PV}^{n,t,\max} = p_{s,PV}^{n,t,f} + p_{s,PV}^{n,t,e} \quad (21)$$

$$P_L^{n,t,\min} = P_L^{n,t,f} - P_L^{n,t,e} \quad (22)$$

$$p_{q,WT}^{n,t,\min} = p_{q,WT}^{n,t,f} - p_{q,WT}^{n,t,e} \quad (23)$$

$$p_{s,PV}^{n,t,\min} = p_{s,PV}^{n,t,f} - p_{s,PV}^{n,t,e} \quad (24)$$

where $P_L^{n,t,\max}$, $p_{q,WT}^{n,t,\max}$, and $p_{s,PV}^{n,t,\max}$ are the maximum values of $P_L^{n,t}$, $p_{q,WT}^{n,t}$, and $p_{s,PV}^{n,t}$, respectively. $P_L^{n,t,\min}$, $p_{q,WT}^{n,t,\min}$, and $p_{s,PV}^{n,t,\min}$ are the corresponding minimum values.

From Eqs. (18-24), it can be seen that $\varepsilon^{n,t}$ is an interval number, and its maximum and minimum values are obtained and shown as follows.

$$\varepsilon_{\max}^{n,t} = \sum_{q=1}^{N_{WT}^n} p_{q,WT}^{n,t,e} + \sum_{s=1}^{N_{PV}^n} p_{s,PV}^{n,t,e} + P_L^{n,t,e} \quad (25)$$

$$\varepsilon_{\min}^{n,t} = - \sum_{q=1}^{N_{WT}^n} p_{q,WT}^{n,t,e} - \sum_{s=1}^{N_{PV}^n} p_{s,PV}^{n,t,e} - P_L^{n,t,e} \quad (26)$$

The forecast errors of wind power, solar power, and load demand, rather than electricity price, can affect the mismatched power shown in Eq. (18). Therefore, the maximum of such mismatched power is the sum of forecasting errors of wind power, solar power and load demand, as shown in Eq. (25).

It is noted that DGs, ESSs and the DPN are the sources of reserve to eliminate this imbalance power $\varepsilon^{n,t}$. That is, the power outputs of DGs, the charging/discharging power of ESSs, and the transaction power between the MG and the DPN should be adjusted based on solutions obtained by the first step of energy scheduling, i.e., $p_{m,DG}^{n,t,f}$, $p_{r,ESS}^{n,t,f}$, and $p_{DN}^{n,t,f}$. The sum of these adjusted power should be equal to the mismatched power $\varepsilon^{n,t}$. Therefore, we let $\beta_{m,DG}^n$, $\beta_{r,ESS}^n$ and β_{DN}^n denote the contribution ratios of the m th DG, the r th ESS and the DPN, for the reserve scheduling. Such ratios are called participation factors, and their sum is equal to 1, shown in Eq. (31). In this way, the adjusted power of DGs,

ESSs, and the DPN are $\beta_{m,DG}^n \varepsilon^{n,t}$, $\beta_{r,ESS}^n \varepsilon^{n,t}$, and $\beta_{DN}^n \varepsilon^{n,t}$, respectively. Then actual power outputs of DGs and ESSs, and the transaction power can be determined by the following formulations.

$$p_{m,DG}^{n,t} = p_{m,DG}^{n,t,f} + \beta_{m,DG}^n \varepsilon^{n,t} \quad (27)$$

$$p_{r,ESS}^{n,t} = p_{r,ESS}^{n,t,f} + \beta_{r,ESS}^n \varepsilon^{n,t} \quad (28)$$

$$p_{DN}^{n,t} = p_{DN}^{n,t,f} + \beta_{DN}^n \varepsilon^{n,t} \quad (29)$$

Then the power balance can be guaranteed:

$$P_L^{n,t} = \sum_{m=1}^{N_{DG}^n} p_{m,DG}^{n,t} + \sum_{r=1}^{N_{ESS}^n} p_{r,ESS}^{n,t} + \sum_{q=1}^{N_{WT}^n} p_{q,WT}^{n,t} + \sum_{s=1}^{N_{PV}^n} p_{s,PV}^{n,t} \quad (30)$$

when the following formulations hold.

$$\sum_{m=1}^{N_{DG}^n} \beta_{m,DG}^n + \sum_{r=1}^{N_{ESS}^n} \beta_{r,ESS}^n + \beta_{DN}^n = 1 \quad (31)$$

$$0 \leq \beta_{m,DG}^n \leq 1 \quad (32)$$

$$0 \leq \beta_{r,ESS}^n \leq 1 \quad (33)$$

$$0 \leq \beta_{DN}^n \leq 1 \quad (34)$$

It can be observed that the total EC of an MG comprises various parts, i.e., the day-ahead operational cost corresponding to base-point scheduling solutions, and the reserve cost of DGs, ESSs and the DPN. Then Eq. (4) is reformulated as follows.

$$C^n = \sum_{t=1}^T \left\{ \sum_{m=1}^{N_{DG}^n} C_{m,DG}^n(p_{m,DG}^{n,t,f}) + \sum_{r=1}^{N_{ESS}^n} C_{r,ESS}^n(p_{r,ESS}^{n,t,f}) + C_{DN}^n(p_{DN}^{n,t,f}) + \sum_{m=1}^{N_{DG}^n} C_{m,DG}^n(\beta_{m,DG}^n \varepsilon^{n,t}) + \sum_{r=1}^{N_{ESS}^n} C_{r,ESS}^n(\beta_{r,ESS}^n \varepsilon^{n,t}) + C_{DN}^n(\beta_{DN}^n \varepsilon^{n,t}) \right\} \quad (35)$$

Consequently, the energy and reserve scheduling of the n th MG aims to obtain the optimal solution for decision variables $p_{m,DG}^{n,t,f}$, $p_{r,ESS}^{n,t,f}$, $p_{DN}^{n,t,f}$, $\beta_{m,DG}^n$, $\beta_{r,ESS}^n$ and β_{DN}^n , which would minimize C^n while meeting equality and inequality constraints as in (5)-(34).

C. Cooperative Energy and Reserve Scheduling Model Based on Game Theory for MMGs

A cooperative game is the one which has groups of players or coalitions with possible external enforcement of cooperative behavior, such as through the contract law. This game is focused on joint actions of multiple groups of players and the resulting collective payoffs. Because of its well-recognized advantage on enhancing the whole benefit of all players, cooperative game has been widely used in profit allocation of power producers [33], power system economic dispatch [36], demand side management [37], etc. In this paper, we attempt to propose the cooperative energy and reserve scheduling model

based on such a game, in order to support optimal operations of MMGs.

The cooperative game for the energy and reserve scheduling model is denoted as $\{\mathcal{N}, v, \phi\}$. $\mathcal{N}$ represents the whole MMG system, and the number of MGs is N . In other words, N MGs participate in the cooperative game, with 2^N possible coalitions. For instance, a 3-MG game includes 8 possible coalitions, including the empty coalition $\{\emptyset\}$ and the grand coalition $\{\mathcal{N}\}$. v stands for the characteristic function, with respect to an arbitrary coalition $\mathcal{S} \subset 2^N$, and ϕ is the vector of benefits to be allocated to individual MGs.

To well adopt this game, a cooperative energy and reserve scheduling model of MMGs is established first, which is based on the coalition's characteristic function for quantifying the economic benefit of cooperation operation in MMGs. Then, an allocation mechanism is adopted to distribute the benefit to individual MGs fairly. In detail, when MMGs are operated cooperatively, power transaction between MMGs should be also taken into account for realizing the energy sharing with respect to the whole MMGs system. In addition, an MG can provide reserve to others within the MMGs system, in order to well handle uncertainties in the interconnected MMGs. In this way, the interconnected control center of MMGs can determine the optimal energy and reserve scheduling solutions.

We first define the benefit function $\pi_{\mathcal{S}}$, which is formulated as follows.

$$\pi_{\mathcal{S}} = -C_{\mathcal{S}} = -\sum_{n=1}^S C^n = -\sum_{n=1}^S \sum_{t=1}^T \sum_{m=1}^{N_{\text{DG}}^n} \{C_{m,\text{DG}}^n(p_{m,\text{DG}}^{n,t,f}) + \sum_{n=1}^{N_{\text{ESS}}^n} C_{n,\text{ESS}}^n(p_{n,\text{ESS}}^{n,t,f}) + C_{\text{DN}}^n(p_{n,\text{DN}}^{n,t,f}) + \sum_{m=1}^{N_{\text{DG}}^n} C_{m,\text{DG}}^n(\beta_m^n \varepsilon^t) + \sum_{n=1}^{N_{\text{ESS}}^n} C_{r,\text{ESS}}^n(\beta_r^n \varepsilon^t) + C_{\text{DN}}^n(\beta_{\text{DN}}^n \varepsilon^t)\} \quad (36)$$

where $C_{\mathcal{S}}$ is the total economic cost for coalition $\mathcal{S}$, and S is the number of MGs in this coalition. $\varepsilon^t = \sum_{n=1}^S \varepsilon^{n,t}$, representing the total power imbalance in terms of the whole MMG system.

$$\varepsilon^t = \sum_{n=1}^S \varepsilon^{n,t} = \sum_{n=1}^S \{P_{\text{L}}^{n,t} - \sum_{m=1}^{N_{\text{DG}}^n} p_{m,\text{DG}}^{n,t,f} - \sum_{r=1}^{N_{\text{ESS}}^n} p_{r,\text{ESS}}^{n,t,f} - \sum_{q=1}^{N_{\text{WT}}^n} p_{q,\text{WT}}^{n,t} - \sum_{s=1}^{N_{\text{PV}}^n} p_{s,\text{PV}}^{n,t} - p_{\text{DN}}^{n,t,f}\} \quad (37)$$

According to Eqs. (18-19), we can derive maximum and minimum values of the total power imbalance, which are shown as follows:

$$\varepsilon_{\max}^t = \sum_{n=1}^S \left\{ \sum_{q=1}^{N_{\text{WT}}^n} p_{q,\text{WT}}^{n,t,e} + \sum_{s=1}^{N_{\text{PV}}^n} p_{s,\text{PV}}^{n,t,e} + P_{\text{L}}^{n,t,e} \right\} \quad (38)$$

$$\varepsilon_{\min}^t = -\sum_{n=1}^S \left\{ \sum_{q=1}^{N_{\text{WT}}^n} p_{q,\text{WT}}^{n,t,e} + \sum_{s=1}^{N_{\text{PV}}^n} p_{s,\text{PV}}^{n,t,e} + P_{\text{L}}^{n,t,e} \right\} \quad (39)$$

It is noted that DGs and ESSs of MGs as well as the DPN all could provide reserves for eliminating the uncertainty of

ε^t . That is, power balance of the whole MMGs is achieved, when the following formulations hold via the method of participation:

$$\sum_{n=1}^S \left\{ \sum_{m=1}^{N_{\text{DG}}^n} \beta_{m,\text{DG}}^n + \sum_{r=1}^{N_{\text{ESS}}^n} \beta_{r,\text{ESS}}^n + \beta_{\text{DN}}^n \right\} = 1 \quad (40)$$

$$0 \leq \beta_{m,\text{DG}}^n \leq 1 \quad (n = 1, 2, \dots, S) \quad (41)$$

$$0 \leq \beta_{r,\text{ESS}}^n \leq 1 \quad (n = 1, 2, \dots, S) \quad (42)$$

$$0 \leq \beta_{\text{DN}}^n \leq 1 \quad (n = 1, 2, \dots, S) \quad (43)$$

In this way, actual power outputs of DGs and ESSs, and the actual transaction power between individual MGs and the DPN can be obtained, taking the n th MG as an instance:

$$p_{m,\text{DG}}^{n,t} = p_{m,\text{DG}}^{n,t,f} + \beta_{m,\text{DG}}^n \varepsilon^t \quad (44)$$

$$p_{r,\text{ESS}}^{n,t} = p_{r,\text{ESS}}^{n,t,f} + \beta_{r,\text{ESS}}^n \varepsilon^t \quad (45)$$

$$p_{\text{DN}}^{n,t} = p_{\text{DN}}^{n,t,f} + \beta_{\text{DN}}^n \varepsilon^t \quad (46)$$

Consequently, the compact formulation of the proposed energy and reserve scheduling model for the whole MMGs system can be shown as follows.

$$\max \pi_{\mathcal{S}}(\mathbf{x}, \mathbf{u}) \text{ or } \min C_{\mathcal{S}}(\mathbf{x}, \mathbf{u}) \quad (47)$$

$$\text{s.t. } G(\mathbf{x}, \mathbf{u}) = 0 \quad (48)$$

$$H(\mathbf{x}, \mathbf{u}) \leq 0 \quad (49)$$

where $\mathbf{x}$ is the vector of decision variables, including $p_{m,\text{DG}}^{n,t,f}$, $p_{r,\text{ESS}}^{n,t,f}$, $p_{\text{DN}}^{n,t,f}$, β_m^n , β_r^n and β_{DN}^n , where $n = 1, 2, \dots, N$. $\mathbf{u}$ are uncertain variables of the whole MMGs, comprising $p_{q,\text{WT}}^{n,t}$, $p_{s,\text{PV}}^{n,t}$, $e_{\text{DN}}^{n,t}$ and $P_{\text{L}}^{n,t}$. $G(\mathbf{x}, \mathbf{u})$ are equality constraints, consisting of (9), (11), (16)-(31), (37)-(40) and (44)-(46), while $H(\mathbf{x}, \mathbf{u})$ represent inequality constraints of (5)-(8), (10), (32)-(34) and (41)-(43). Note that “ $\max \pi_{\mathcal{S}}(\mathbf{x}, \mathbf{u})$ ” is equivalent to “ $\min C_{\mathcal{S}}(\mathbf{x}, \mathbf{u})$ ” based on Eq. (35).

Note that (47)-(49) is an uncertain optimization problem, and uncertain variables are represented via interval numbers. Therefore, the popular robust optimization approach [38] can be used for solving it. The details of this approach is not given in this paper, which can be referred to [38].

III. BENEFITS ALLOCATION BETWEEN MMGS

In a cooperative game, each coalition $\mathcal{S}$ aims to obtain a monetary payoff for its players, i.e., the value of characteristic function of alliance, which is denoted as $v(\mathcal{S})$. Therefore, it is necessary to study the characteristic function of MMGs alliance, which indicates the incremental benefit due to the cooperation of MMGs. We set the characteristic function as follows.

$$v(\mathcal{S}) = \pi_{\mathcal{S}} - \sum_{w \in \mathcal{S}} \pi_w \quad (50)$$

where w is a single MG in the allocation $\mathcal{S}$. $\sum_{w \in \mathcal{S}} \pi_w$ means the total benefits obtained by MGs in $\mathcal{S}$ when they are operated without cooperation.

Proposition: The proposed energy and reserve scheduling model of MMGs via cooperative game is superadditive.

Proof: Based on the Eq. (50), for any two disjoint alliances $\mathcal{S}$ and $\mathcal{U}$, the sum of their characteristic functions can be expressed as follows.

$$\begin{aligned} v(\mathcal{S}) + v(\mathcal{U}) &= \pi_{\mathcal{S}} - \sum_{w \in \mathcal{S}} \pi_w + \pi_{\mathcal{U}} - \sum_{w \in \mathcal{U}} \pi_w \\ &= \pi_{\mathcal{S}} + \pi_{\mathcal{U}} - \sum_{w \in \mathcal{S} \cup \mathcal{U}} \pi_w \leq \pi_{\mathcal{S} \cup \mathcal{U}} - \sum_{w \in \mathcal{S} \cup \mathcal{U}} \pi_w \\ &= v(\mathcal{S} \cup \mathcal{U}) \end{aligned} \quad (51)$$

It is shown from (44) that the coalitional game is super-additive [39]. Therefore, the grand coalition of all MGs is a stable and the optimal solution for the cooperative game attains the maximum aggregate benefit. This is also verified from simulation results shown in Section IV.

When the coalitional game is super-additive, the Shapely value can be used to allocate benefits to individual MGs [40]. The concept of Shapely value stems from [41], which is a fair way to allocate total benefits to multiple players in a cooperative game. As a coalition of MMGs cooperates, some MGs may contribute more to the coalition, how to allocate the obtained benefit to each MG is to be solved. Therefore, in this paper, we adopt the Shapely value to deal with the problem of benefits allocation. For the n th MG, its Shapely value can be formulated as follows.

$$\phi_n(v) = \sum_{\mathcal{S} \subseteq \mathcal{N} \setminus \{n\}} \frac{|\mathcal{S}|!(|\mathcal{N}| - |\mathcal{S}| - 1)!}{|\mathcal{N}|!} [v(\mathcal{S} \cup \{n\}) - v(\mathcal{S})] \quad (52)$$

where $|\mathcal{N}|$ is the total number of MGs and the sum extends over all subsets $\mathcal{S}$ of $\mathcal{N}$ excluding the n th MG. $|\mathcal{S}|$ is the number of MGs in $\mathcal{S}$. The formula can be interpreted as follows: considering the coalition being formed one MG at a time, each MG demands its contribution $v(\mathcal{S} \cup \{n\}) - v(\mathcal{S})$ as a fair compensation, then it takes the average of this contribution over possible different permutations in which the coalition can be formed.

It should be mentioned that the interconnection control center of multiple MGs is the authorized entity for conducting the benefit distribution. The reason is that this center functions the coordinating the energy and reserve transactions among MMGs, as mentioned in Section II.A.

IV. CASE STUDY

A. Simulation settings

A test system including 3 MGs is used to conduct the simulation study, as shown in Fig. 1. Each MG comprises 1 DG, 1 ESS, 1 WT and 1 PV. The related parameters are listed in Table I. For DGs of MMGs, parameters include EC coefficients, ramp up and ramp down rates, and minimum and maximum power outputs. In terms of ESSs, they contain maximum charging and discharging rates, initial energy state, minimum and maximum energy storage capacities, and charging and discharging efficiencies. Forecast values of power outputs of WT and PV, electricity price, and load demands are shown in Fig. 3, and their forecast errors are set to be 20% [12], 10% [42], 20% [12], and 10% [43], respectively.

To verify the effectiveness of the proposed game theory based cooperative energy and reserve scheduling model for

TABLE I
THE RELATED PARAMETERS OF MMGS

Resources	Parameters	MG1	MG2	MG3
DG	a_{DG}^n (\$/kW)	0.04335	0.04554	0.05154
	b_{DG}^n (\$)	0	0	0
	R_{up}^n (kW/h)	80	40	40
	R_{down}^n (kW/h)	75	35	35
	P_{min}^n (kW)	40	40	40
	P_{max}^n (kW)	200	100	100
ESS	$p_{ESS}^{n,max}$ (kW/h)	25	25	25
	$p_{ESS}^{n,min}$ (kW/h)	20	20	20
	$E_{ESS}^{n,0}$ (kWh)	6	5	6
	$E_{ESS}^{n,min}$ (kWh)	5	5	5
	$E_{ESS}^{n,max}$ (kWh)	45	45	45
	η_c^n	0.95	0.95	0.95
	η_{dc}^n	0.95	0.95	0.95
	η_{dc}^n	0.95	0.95	0.95
	$c_{r,ESS}^n$	0.05	0.05	0.05

MMGs, simulation results are mainly presented in the following two aspects:

- (1) The benefits of each coalition are comprehensively investigated, and benefit allocations to individual MGs are studied;
- (2) The reason why the benefits are obtained is discussed in terms of the cooperative operation of MMGs, compared with their isolated operation.

Fig. 3. Forecast values of power outputs of WT and PV, electricity prices, and load demands

B. Simulation results and discussion

As the MMGs system includes 3 MGs, 8 coalitions exist in the cooperation game, i.e., $\{\emptyset\}$, $\{MG_1\}$, $\{MG_2\}$, $\{MG_3\}$, $\{MG_1, MG_2\}$, $\{MG_1, MG_3\}$, $\{MG_2, MG_3\}$ and $\{MG_1, MG_2, MG_3\}$. $\{\emptyset\}$ means no MGs in the coalition, which is not studied. Table II shows values of the day-ahead operational cost (DAOC), day-ahead transaction cost (DATC), the reserve cost (RC) in terms of DGs, ESSs, and the DPN, the total EC, and the benefit of remaining 7 coalitions. Specifically, benefits for $\{MG_1, MG_2\}$, $\{MG_1, MG_3\}$, $\{MG_2, MG_3\}$ and $\{MG_1, MG_2, MG_3\}$ respectively are \$7.31, \$14.52, \$4.2, and \$20.66, which are calculated by (43). The largest benefit, i.e., \$20.66 is obtained by the coalition $\{MG_1, MG_2, MG_3\}$, which means that all MGs are encouraged to cooperate with each other for energy and reserve scheduling. It is also observed that the total EC of $\{MG_3\}$ is \$-46.71, showing that

this MG can obtain economic gain, as it sells electricity worthy of \$186.49 to the DPN in the energy scheduling. The reserve cost of DPN are all 0 in all coalition situations, indicating that reserves of DGs and ESSs are sufficient, and there is no need to purchase extra reserve from the DPN.

In terms of $\{MG_1, MG_2, MG_3\}$, the optimal solution of cooperative energy and reserve scheduling consists of day-ahead power outputs of DGs, charging and discharging plan of ESSs, power transactions between MMGs and the DPN, as well as participation factors (PFs) of DGs, ESSs and the DPN. The values are shown in Fig. 4 and Fig. 5, respectively. It can be seen that DGs perform in both energy and reserve scheduling, indicated by the day-ahead power outputs and participation factors of DGs shown by Fig. 4(a) and Fig. 5(a), respectively. However, in Fig. 4(b), it is noted that ESSs in MG_1 and MG_2 does not participate in the energy scheduling, while they are focused on the reserve scheduling as shown in Fig. 5(b). Indeed, their participation factors exceed 0.2 for all time intervals and even as high as 0.47 for the 1st hour.

It is also observed from Fig. 4(b) that the ESS in MG_3 is scheduled to charge and discharge during the 1st~4th and the 24th time intervals, respectively, while ESSs in other MGs do not take part in the energy scheduling. As a result, participation factors of ESS in MG_3 for the reserve scheduling are less than those of ESSs in MG_1 and MG_2 during these time intervals, as shown in Fig. 5(b). In addition, Fig. 4(c) shows the day-ahead transaction power between MMGs and the DPN. Note that the values are below zero for most time intervals, which means that MMGs sell electricity to the DPN for pursuing economic benefit. However, as for the 19th-22nd hours, MMGs have to purchase electricity from the DPN, as the load demand is high and outputs of WT and PV are relatively low during these periods, as shown in Fig. 3. The reason is that the DPN does not provide reserve for MMGs, and the reserve cost of DPN is 0 for $\{MG_1, MG_2, MG_3\}$. This means that the reserves are sufficient for MMGs to deal with the uncertainties by their own. In this way, participation factors of the DPN are all 0 for the time intervals, therefore, they are not shown in Fig. 5.

Furthermore, the transaction power between each MG and the DPN as well as the ones between individual MGs are presented in Fig. 6 and Fig. 7, respectively. It can be observed from Fig. 6 that MG_3 always sells electricity to the DPN, for the pursuit of economic benefit. It also transmits power to MG_1 during most time intervals, as shown in Fig. 7. This is because the load demand of MG_3 is low, and it has sufficient electricity to provide for others. On the contrary, as the load requirement of MG_1 is the highest in MMGs, it purchases electricity from the DPN for some time intervals, while MG_2 and MG_3 also provide power for it to meet load demand of MG_1 .

Using the obtained optimal energy and reserve scheduling solution for $\{MG_1, MG_2, MG_3\}$, we obtain the values of day-ahead operational cost for DGs, ESSs, day-ahead transaction cost between MMGs and DPN, and reserve cost for DGs, ESSs, and the DPN when MMGs are in the cooperative operation. The above values are shown in Table III. Compared with the corresponding values for $\{MG_1\}$, $\{MG_2\}$, and $\{MG_3\}$ presented in Table II, the differences indicate

Fig. 4. Optimal energy scheduling of DGs, ESSs, and the transactive power between MMGs and the DPN

Fig. 5. Optimal reserve scheduling of DGs, ESSs, and the transactive power between MMGs and the DPN using PFs

Fig. 6. The transaction power between each MG and the DPN

TABLE II
THE OPERATIONAL COST AND THE RESERVE COST IN TERMS OF DGs, ESSs, AND THE DPN FOR COALITIONS OF MMGs

Coalition	{MG ₁ }	{MG ₂ }	{MG ₃ }	{MG ₁ , MG ₂ }	{MG ₁ , MG ₃ }	{MG ₂ , MG ₃ }	{MG ₁ , MG ₂ , MG ₃ }
DAOC of DGs (\$)	185.63	108.45	123.68	297.45	317.44	232.94	427.19
RC of DGs (\$)	22.44	0.84	0.01	19.92	14.32	0.04	13.87
DAOC of ESSs (\$)	2.11	1.36	1.31	1.10	1.17	1.92	1.43
RC of ESSs (\$)	22.47	21.27	14.78	47.77	47.22	36.93	70.02
DATC (\$)	73.78	-30.93	-186.49	33.85	-135.09	-221.78	-172.48
RC of DPN	0	0	0	0	0	0	0
Total EC (\$)	306.43	100.98	-46.71	400.10	245.07	50.07	340.04
Benefit (\$)	—	—	—	7.31	14.52	4.2	20.66

TABLE III
THE OPERATIONAL COST AND THE RESERVE COST IN TERMS OF DGs, ESSs, AND THE DPN FOR EACH MG IN {MG₁, MG₂, MG₃}

MG	DAOC of DGs (\$)	RC of DGs (\$)	DAOC of ESSs (\$)	RC of ESSs (\$)	DATC (\$)	RC of DPN (\$)	Allocation (\$)
MG ₁	199.60	8.47	0	23.96	29.38	0	9.125
MG ₂	106.86	2.42	0	23.96	-25.99	0	3.965
MG ₃	120.71	2.98	1.42	22.08	-175.87	0	7.57

Fig. 7. The transaction power between each MG

Fig. 8. The benefits of cooperative operations of MMGs

economic benefits of the cooperative cooperation of MMGs. The benefits of day-ahead operational and transaction cost for DGs, ESSs, and the DPN, combined with their reserve cost, are shown in Fig. 8. Evidently, the major benefit is for the day-ahead transaction cost between {MG₁} and DPN, as the value has been decreased from \$73.78 (isolated operation) to \$29.38 (cooperative operation), value of such benefit is \$73.78-\$29.38=\$42.4. The reason is that the DG in MG₁ provides less reserve in cooperative operations of MMGs, as shown in Fig. 9. Then the DG takes more responsibility for energy scheduling, and its power outputs are higher than those of

Fig. 9. The outputs of DG, transaction power, and reserve of DG for MG₁

isolated operation. Therefore, MG₁ sells more electricity to the DPN during the 1st~7th time intervals, while purchasing less from the DPN during other hours. In this way, the day-ahead transaction cost between DPN and MG₁ has been significantly decreased, which leads to less total economic cost. Therefore, it has been verified that the proposed cooperative energy and reserve scheduling are beneficial for the economic operations of MMGs.

V. CONCLUSION

This paper has proposed a cooperative energy and reserve scheduling model for operations of MMGs. This model is formulated via cooperative game, and the benefits allocation for each MG is determined by values of Shapely. Case study has been conducted based on a system of MMGs, and simulation results have been investigated in terms of the benefits of each coalition in MMGs. Furthermore, we verify the effectiveness of the proposed cooperative energy and reserve scheduling model for economic operation of

MMGs, compared with their isolated operations. It is noted the robust optimization method is used for solving the cooperative energy and reserve scheduling model of MMGs. However, this method is conservative though it is currently an popular optimization approach. Therefore, our future research direction is how to reduce the conservativeness of robust optimization, for dealing with the cooperative energy and reserve scheduling model of MMGs.

REFERENCES

- [1] M. Munsell, "US microgrid capacity will exceed 1.8 GW by 2018," <https://www.greentechmedia.com/articles/read/US-Microgrid-Capacity-Will-Exceed-1.8-GW-by-2018>.
- [2] A. Hamidi, D. Nazarpour, and S. Golshannavaz, "Multi-objective scheduling of microgrids to harvest higher photovoltaic energy," *IEEE Transactions on Industrial Informatics*, vol. in press, 2017.
- [3] L. Ma, N. Liu, J. Zhang, W. Tushar, and C. Yuen, "Energy management for joint operation of chp and pv prosumers inside a grid-connected microgrid: A game theoretic approach," *IEEE Transactions on Industrial Informatics*, vol. 12, no. 5, pp. 1930–1942, 2016.
- [4] H. Farzin, M. Fotuhi-Firuzabad, and M. Moeini-Aghaie, "Stochastic energy management of microgrids during unscheduled islanding period," *IEEE Transactions on Industrial Informatics*, vol. 13, no. 3, pp. 1079–1087, 2017.
- [5] W. Zhang, Y. Xu, Z. Dong, and K. P. Wong, "Robust security-constrained optimal power flow using multiple microgrids for corrective control under uncertainty," *IEEE Transactions on Industrial Informatics*, vol. in press, 2017.
- [6] L. Wu, T. Ortmeyer, and J. Li, "The community microgrid distribution system of the future," *The Electricity Journal*, vol. 29, no. 10, pp. 16–21, 2016.
- [7] J. Li and L. Wu, "Optimal operation for community based multi-party microgrid in grid-connected and islanded modes," *IEEE Transactions on Smart Grid*, vol. in press, 2017.
- [8] W. Su, J. Wang, and J. Roh, "Stochastic energy scheduling in microgrids with intermittent renewable energy resources," *IEEE Transactions on Smart Grid*, vol. 5, no. 4, pp. 1876–1883, 2014.
- [9] Z. Ding, W.-J. Lee, and J. Wang, "Stochastic resource planning strategy to improve the efficiency of microgrid operation," *IEEE Transactions on Industry Applications*, vol. 51, no. 3, pp. 1978–1986, 2015.
- [10] M. Alipour, B. Mohammadi-Ivatloo, and K. Zare, "Stochastic scheduling of renewable and CHP-based microgrids," *IEEE Transactions on Industrial Informatics*, vol. 11, no. 5, pp. 1049–1058, 2015.
- [11] Y. Xiang, J. Liu, and Y. Liu, "Robust energy management of microgrid with uncertain renewable generation and load," *IEEE Transactions on Smart Grid*, vol. 7, no. 2, pp. 1034–1043, 2016.
- [12] W. Hu, P. Wang, and H. Gooi, "Towards optimal energy management of microgrids via robust two-stage optimization," *IEEE Transactions on Smart Grid*, vol. in press, 2016.
- [13] G. E. Asimakopoulou, A. L. Dimeas, and N. D. Hatziaargyriou, "Leader-follower strategies for energy management of multi-microgrids," *IEEE Transactions on Smart Grid*, vol. 4, no. 4, pp. 1909–1916, 2013.
- [14] T. A. Nguyen and M. Crow, "Stochastic optimization of renewable-based microgrid operation incorporating battery operating cost," *IEEE Transactions on Power Systems*, vol. 31, no. 3, pp. 2289–2296, 2016.
- [15] Q. Jiang, M. Xue, and G. Geng, "Energy management of microgrid in grid-connected and stand-alone modes," *IEEE Transactions on Power Systems*, vol. 28, no. 3, pp. 3380–3389, 2013.
- [16] Y. Zhang, N. Gatsis, and G. B. Giannakis, "Robust energy management for microgrids with high-penetration renewables," *IEEE Transactions on Sustainable Energy*, vol. 4, no. 4, pp. 944–953, 2013.
- [17] G. Liu, Y. Xu, and K. Tomovic, "Bidding strategy for microgrid in day-ahead market based on hybrid stochastic/robust optimization," *IEEE Transactions on Smart Grid*, vol. 7, no. 1, pp. 227–237, 2016.
- [18] A. K. Marvasti, Y. Fu, S. DorMohammadi, and M. Rais-Rohani, "Optimal operation of active distribution grids: A system of systems framework," *IEEE Transactions on Smart Grid*, vol. 5, no. 3, pp. 1228–1237, 2014.
- [19] T. Lv, Q. Ai, and Y. Zhao, "A bi-level multi-objective optimal operation of grid-connected microgrids," *Electric Power Systems Research*, vol. 131, pp. 60–70, 2016.
- [20] S. Bahramara, M. P. Moghaddam, and M. R. Haghifam, "Modelling hierarchical decision making framework for operation of active distribution grids," *IET Generation, Transmission & Distribution*, vol. 9, no. 16, pp. 2555–2564, 2015.
- [21] T. Lv and Q. Ai, "Interactive energy management of networked microgrids-based active distribution system considering large-scale integration of renewable energy resources," *Applied Energy*, vol. 163, pp. 408–422, 2016.
- [22] M. Erol-Kantarci, B. Kantarci, and H. T. Mouftah, "Reliable overlay topology design for the smart microgrid network," *IEEE Network*, vol. 25, no. 5, pp. 38–43, 2011.
- [23] Z. Wang, B. Chen, J. Wang, M. M. Begovic, and C. Chen, "Coordinated energy management of networked microgrids in distribution systems," *IEEE Transactions on Smart Grid*, vol. 6, no. 1, pp. 45–53, 2015.
- [24] J. Wu and X. Guan, "Coordinated multi-microgrids optimal control algorithm for smart distribution management system," *IEEE Transactions on Smart Grid*, vol. 4, no. 4, pp. 2174–2181, 2013.
- [25] N. Nikmehr and S. N. Ravadanegh, "Optimal power dispatch of multi-microgrids at future smart distribution grids," *IEEE Transactions on Smart Grid*, vol. 6, no. 4, pp. 1648–1657, 2015.
- [26] K. Rahbar, C. C. Chai, and R. Zhang, "Energy cooperation optimization in microgrids with renewable energy integration," *IEEE Transactions on Smart Grid*, vol. in press, 2016.
- [27] Y. Ding, M. Xie, Q. Wu, and J. Østergaard, "Development of energy and reserve pre-dispatch and re-dispatch models for real-time price risk and reliability assessment," *IET Generation, Transmission & Distribution*, vol. 8, no. 7, pp. 1338–1345, 2014.
- [28] T. Dragicevic, J. C. Vasquez, J. M. Guerrero, and D. Skrlec, "Advanced LVDC electrical power architectures and microgrids: A step toward a new generation of power distribution networks," *IEEE Electrification Magazine*, vol. 2, no. 1, pp. 54–65, 2014.
- [29] R.-E. L. M. and P. G. C. B., "Scheduling and control framework for distribution-level systems containing multiple energy carrier systems: Theoretical approach and illustrative example," *International Journal of Electrical Power & Energy Systems*, vol. 66, pp. 194–215, 2015.
- [30] N. Y. I. S. Operator, "Day-ahead scheduling manual," http://www.nyiso.com/public/webdocs/markets_operations/documents/Manuals_and_Guides/Manuals/Operations/dayahd_schd_mnl.pdf, June 2017.
- [31] C. I. S. Operator, "Market processes and products," <https://www.caiso.com/market/Pages/MarketProcesses.aspx>.
- [32] R. Ferrero, S. Shahidehpour, and V. Ramesh, "Transaction analysis in deregulated power systems using game theory," *IEEE transactions on power systems*, vol. 12, no. 3, pp. 1340–1347, 1997.
- [33] S. R. Dabbagh and M. K. Sheikh-El-Eslami, "Risk-based profit allocation to ders integrated with a virtual power plant using cooperative game theory," *Electric Power Systems Research*, vol. 121, pp. 368–378, 2015.
- [34] P. H. Nguyen, W. L. Kling, and P. F. Ribeiro, "A game theory strategy to integrate distributed agent-based functions in smart grids," *IEEE Transactions on Smart Grid*, vol. 4, no. 1, pp. 568–576, 2013.
- [35] R. Roson and F. Hubert, "Bargaining power and value sharing in distribution networks: a cooperative game theory approach," *Networks and Spatial Economics*, vol. 15, no. 1, pp. 71–87, 2015.
- [36] B. Zhou, K. Chan, T. Yu, and C. Chung, "Equilibrium-inspired multiple group search optimization with synergistic learning for multiobjective electric power dispatch," *IEEE Transactions on Power Systems*, vol. 28, no. 4, pp. 3534–3545, 2013.
- [37] A. Sheikhi, M. Rayati, S. Bahrami, A. M. Ranjbar, and S. Sattari, "A cloud computing framework on demand side management game in smart energy hubs," *International Journal of Electrical Power & Energy Systems*, vol. 64, pp. 1007–1016, 2015.
- [38] Z. Chen, L. Wu, and Y. Fu, "Real-time price-based demand response management for residential appliances via stochastic optimization and robust optimization," *IEEE Transactions on Smart Grid*, vol. 3, no. 4, pp. 1822–1831, 2012.
- [39] D. M. Topkis, *Supermodularity and complementarity*. Princeton university press, 1998.
- [40] J. Ni and Q. Ai, "Economic power transaction using coalitional game strategy in micro-grids," *IET Generation, Transmission & Distribution*, vol. 10, no. 1, pp. 10–18, 2016.
- [41] L. S. Shapley, "A value for n-person games," *Contributions to the Theory of Games*, vol. 2, no. 28, pp. 307–317, 1953.
- [42] S. Chen, H. Gooi, and M. Wang, "Solar radiation forecast based on fuzzy logic and neural networks," *Renewable energy*, vol. 60, pp. 195–201, 2013.

- [43] C. Wan, Z. Xu, Y. Wang, Z. Y. Dong, and K. P. Wong, "A hybrid approach for probabilistic forecasting of electricity price," *IEEE Transactions on Smart Grid*, vol. 5, no. 1, pp. 463–470, 2014.

Yuanzheng Li received the M.S. degree and Ph.D. degree in Electrical Engineering from Huazhong University of Science and Technology (HUST), Wuhan, China, and South China University of Technology (SCUT), Guangzhou, China, in 2011 and 2015, respectively. He has published several peer-reviewed papers in international journals. His current research interests include optimal power system/microgrid scheduling and decision making, stochastic optimization considering large-scale integration of renewable energy into the power system

and multi-objective optimization.

Tianyang Zhao received the B.Sc. and M.Sc. degree in automation of electric power systems from North China Electric Power University, Beijing, China in 2011 and 2013, respectively. Currently, he is pursuing his Ph.D. degree in automation of electric power systems in North China Electric Power University, Beijing, China. His research interests include power system operation optimization and game theory.

Ping Wang (SM'15) received the PhD degree in electrical engineering from University of Waterloo, Canada, in 2008. Currently she is an Associate Professor in the School of Computer Science and Engineering, Nanyang Technological University, Singapore. Her current research interests include microgrid scheduling, wireless communications, cloud computing, and smart grid. She was a corecipient of the Best Paper Award from IEEE Wireless Communications and Networking Conference (WCNC) 2012 and IEEE International Conference on Com-

munications (ICC) 2007.

Hoay Beng Gooi (SM'95) received his PhD degree from Ohio State University in 1983. From 1983 to 1985 he was an Assistant Professor in the Electrical Engineering Department at Lafayette College, Easton, Pennsylvania, USA. From 1985 to 1991, he was a Senior Engineer with Empros (now Siemens), Minneapolis, Minnesota, USA.

In 1991, Dr. Gooi joined the School of Electrical and Electronic Engineering, Nanyang Technological University (NTU), Singapore as a Senior Lecturer. He has been an Associate Professor since 1999. He

has served as an Editor for IEEE Transactions on Power Systems.

Lei Wu (SM'13) is an Associate Professor in the Department of Electrical and Computer Engineering at Clarkson University. He received the B.S. degree in Electrical Engineering and the M.S. degree in Systems Engineering from Xian Jiaotong University, Xian, China, in 2001 and 2004, respectively, and the Ph.D. degree in Electrical Engineering from the Illinois Institute of Technology (IIT), Chicago, IL, USA, in 2008. His primary research and teaching areas are focused on power and energy system optimization and control, with specific interests in the modeling of large-scale power systems with a high penetration of demand response and renewable energy, and community resilience microgrid.

Yun Liu obtained the B.Eng. degree (with First Class Honors) and Ph.D. degree from the College of Electrical Engineering, Zhejiang University, Hangzhou, China, in June 2011 and June 2016, respectively. He is currently a Research Fellow of the Energy Research Institute at Nanyang Technological University, Singapore. He was a visiting student in the Department of Electrical Engineering and Computer Science, University of Central Florida, Orlando, from August 2014 to September 2015. His research interests include power system stability

analysis and distributed control of renewable energy.

Jian Ye received the B.Eng. degree in electrical engineering from Wuhan University, Wuhan, China, in 2012, and the M.Sc. degree from Nanyang Technological University, Singapore, in 2013, where he is currently working towards the Ph.D. degree at the School of Electrical and Electronic Engineering.