IET Generation, Transmission & Distribution

Research Article

Economic power transaction using coalitional game strategy in micro-grids

ISSN 1751-8687
Received on 13th November 2014
Revised on 25th August 2015
Accepted on 4th September 2015
doi: 10.1049/iet-gtd.2014.1084
www.ietdl.org

Jianmo Ni ✉, *Qian Ai*

Department of Electrical Engineering, Shanghai Jiao Tong University, Shanghai 200240, People's Republic of China
✉ *E-mail: nijianmo@gmail.com*

Abstract: Due to the uncontrollability of renewable energy resources, micro-grids (MGs) often have to exchange excessive or insufficient power with the utility grid in traditional non-cooperative mode. In contrast, power transaction considering direct energy trading between MGs has been considered as a promising method to improve economic efficiency. Specifically, MGs with complementary power surplus or shortage have an incentive to cooperate with each other and perform direct trading due to lower costs and power losses. In this study, the authors focus on comprehensive economic power transaction of the multiple MGs network with multi-agent system. A three-stage algorithm based on coalitional game strategy is proposed consisting of request exchange stage, merge-and-split stage and cooperative transaction stage. The developed algorithm enables MGs to form coalitions, where each MG can exchange power directly by paying a transmission fee. With local power transaction, MGs can minimise their expenditures comprising the generation costs, transmission costs, power losses and load shedding compensation; hence, ensure the cost efficiency of the whole MGs network. Moreover, the implementation of load shedding is discussed and its benefit is demonstrated. Simulation results show that the proposed cooperative scheme significantly reduces the total cost of MGs compared with the non-cooperative method.

1 Introduction

In recent year, smart micro-grids (MGs) have emerged as key components in smart grid, which can supply electricity to end users (EUs) with integrated renewable energy resources [e.g. wind, solar, water and plug-in hybrid electric vehicle (PHEV)]. Indeed, MGs help balance loads with generation locally and assure high self-adaptive characteristics. Meanwhile, intelligent real-time operation of MGs requires exact foresight of generation outputs and load demands to meet the variable demand. However, accurate generation scheduling remains a big challenge due to the uncontrollability of the renewable resources.

In conventional mode, MG works individually and only performs energy trading towards a macro station (MS), which is the primary substation connected to the utility grid. When MG's electricity generation is insufficient or excessive, it needs to export extra power to or import additional power from MS. With the advent of the multi-agent system (MAS), MGs can form networks and exchange information with each other. By taking advantage of the MAS, it is possible for the MGs to autonomously perform energy management and make decisions on cooperative transaction. In this context, there has been a rising trend to study the cooperative mode of MGs.

MS, which works as a typical wholesaler in the power market [1], takes in charge of a group of MGs and performs central control of the coordination of MGs. Utility grid usually has different purchase price and retail price [2] when trading with MS. For instance, when MGs have power surplus and transfer to MS, utility grid will purchase the extra electricity from MS at the price p_{pur}. On the other hand, when MGs meet with power shortage, MS will sell electricity to MGs with the price p_{rt}, which is the retail price of utility grid. In most cases, $p_{\mathrm{rt}} > p_{\mathrm{pur}}$ which ensures the profit of the utility grid. There exist drawbacks in the conventional mode that it will increase the cost of MGs as well as keep MS with a high level of power load. Furthermore, MGs are usually located near the groups of EUs in different areas. The distributive deployment will give rise to a long distance between MGs and MS, which makes the power losses more noticeable. Therefore, the MGs have an incentive to work in a cooperative way so as to decrease the unnecessary power transmission between each MG and MS. To improve the economic efficiency of the cooperative mode, there is a need to study on the power transaction scheme comprising a variety of information, such as electricity generation of various energy resources, user demand, topological structure of the MGs network and different kinds of expenses. As different cooperative pairs of MGs lead to different costs, how to decide the criteria for MGs to collaborate remains to be solved.

In this paper, we focus on the problem of how to make MGs cooperate with each other to obtain an optimal cost including various kinds of expenditures. To this end, an economic transaction scheme (ET-scheme) is proposed based on the coalitional game theory. MGs first send their power surplus and needs to MS. Subsequently, the MS performs merge-and-split operations to decide an optimal formation structure on behalf of the MGs. After receiving formation direction from MS, MGs in the same coalition then start power exchange with each other, which directly decrease their power transmission with MS. This inner power transfer will bring monetary benefit to MGs by saving the cost of purchasing extra electricity and alleviating power losses. Moreover, load shedding is one of the traditional methods to deal with electricity insufficiency. Hence, the willingness of load shedding is considered here so as to further improve the economic efficiency. MGs can apply load shedding to interruptible loads when the achieved profit is larger than the monetary penalty.

The rest of the paper is organised as follows. Section 2 introduces the background and related works. The system model and problem definition are demonstrated in Section 3. In Section 4, the proposed coalitional game-based algorithm is presented in detail. The simulation results are summarised in Section 5. Finally, Section 6 concludes the paper.

2 Background and related works

The economic efficiency of smart grid has been considered as an important issue and gained a lot of attention in recent years. With an increasing number of distributed generators emerging in the electricity market, direct trading has been a promising method to bring benefits to both users and retailers. Vasirani and Ossowski [3] put forward a new model of smart consumer load balancing, where small-scale electricity suppliers (SESs) and EUs can actively participate in trading indirectly through the retailers. Lee *et al.* [4] presented an electricity pricing scheme to achieve a fair distribution of the profits between SESs and EUs, while improving the benefits of both parties. In this context, the power transaction considering direct trading within MGs has recently aroused considerable attention [5–10] in multiple MGs networks.

In [9], a smart MG network design is proposed to satisfy the demand of each MG with an optimised purchase cost. The main idea is to form virtual clusters based on an integer linear programming (ILP) formulation, where those MGs in the same cluster can share stored power. However, the high computational complexity of ILP makes it difficult to meet with the real-time character of the smart grid. At present, coalition game theory is applied to cooperation-based problems in smart grid, which shows a great performance in scalability and flexibility [1, 11–14]. Saad *et al.* [11] presented a novel cooperative strategy based on coalitional game theory that MGs can form coalitions and coordinate power transactions within the coalitions so as to reduce the power losses over distribution lines. Wei *et al.* [12] proposed a greedy coalition formation algorithm to minimise the power loss of MGs with the consideration of energy storage.

While the afore-mentioned works mainly focus on the optimisation of one individual aspect (e.g. purchase cost or power loss), our paper aims to provide a comprehensive economic power transaction to optimise the economic efficiency of the whole MGs network. In this regard, there are many other factors that should be combined and analysed. For instance, transmission cost is often required in the real electricity market to control the transmission congestion. Besides, load shedding, accompanying with compensation costs, has shown to be an efficient method to cope with energy shortages of MGs. It is of no surprise that it can be applied to multiple MGs scenarios and therefore enhances the flexibility and capability of the MGs network. Nevertheless, few of the existing works have combined these factors into their energy trading framework. Whilst in this work, our ET-scheme comprises the generation costs, transmission costs, power losses and load shedding compensation.

3 System model and problem definition

In this section, we describe the economic power transaction among MGs and MS in detail. The corresponding system model is shown in Fig. 1.

Consider a multiple MG network consists of a set of N MGs and a MS which is connected to the utility grid. Integrated with renewable resources (e.g. solar panels, wind farms, PHEVs etc.), MG can provide power supply for a group of EUs. For simplicity, MG and its connected users are taken as a whole. When MG generates excessive or insufficient power, it can sell or buy power towards the MS or with other MGs. Fig. 1 shows a system model of multiple MGs which is considered for simulation studies in our work. The solid line represents the distribution network and the red dotted line represents the communication network. All MGs are linked to the MS by common distribution lines (medium voltage) in a radial pattern, through which they can perform power transfer with MS and other MGs when there are power surplus or shortage. Due to the higher expenses (e.g. purchase cost and power loss) of the power transfer between the MGs and the MS, MGs are expected to exchange complementary energies with each other. In [1, 12], every two MGs are assumed to be connected by a power line which enables the local power transfer. However, such a topological structure requires extremely high construction expenditure and is difficult to be applied in the real network. A more practical way is to allow the MGs transfer energy on the common power distribution lines connected to the MS. This leads to the consideration of transmission cost, which will be explained later in this section.

According to Fig. 1, each MG is associated with an agent, which can perform sole energy management. Each agent can perform information exchange with other agents and the MS through the multi-agent communication network. Besides, the agent can receive formation instruction from MS and autonomously perform power transfer with other MGs. Taking $\{MG_1, MG_2, MG_3\}$ as example, each agent of these three MGs can send their information (e.g. power surplus or demand, location) to the MS. Conversely, they can receive coalition formation information from the MS. As Fig. 1 depicts, MG_2 has power surplus to sell while MG_1 and MG_3 have power demands to satisfy. After MS receives this information, it will decide to which MG MG2 will sell power surplus, and how much MG2 will sell. Subsequently, MGs receive the coalition formation instruction and the agents start to establish power transfer connection. Finally, local transfer starts and MG_2 sells excessive electricity to MG_1 and MG_3 by forming a coalition.

Let $\mathcal{N}$ denotes the set of all MGs. Assume that one day is divided into 24 periods, each representing 1 h. In each period, the power generation of MG_i is G_i and the total demand of its EUs is D_i, where G_i and D_i are both active power. It is to be noted that reactive power for loads is assumed to be sufficient during all time periods in our model. Taking MG and its users as a whole, the real

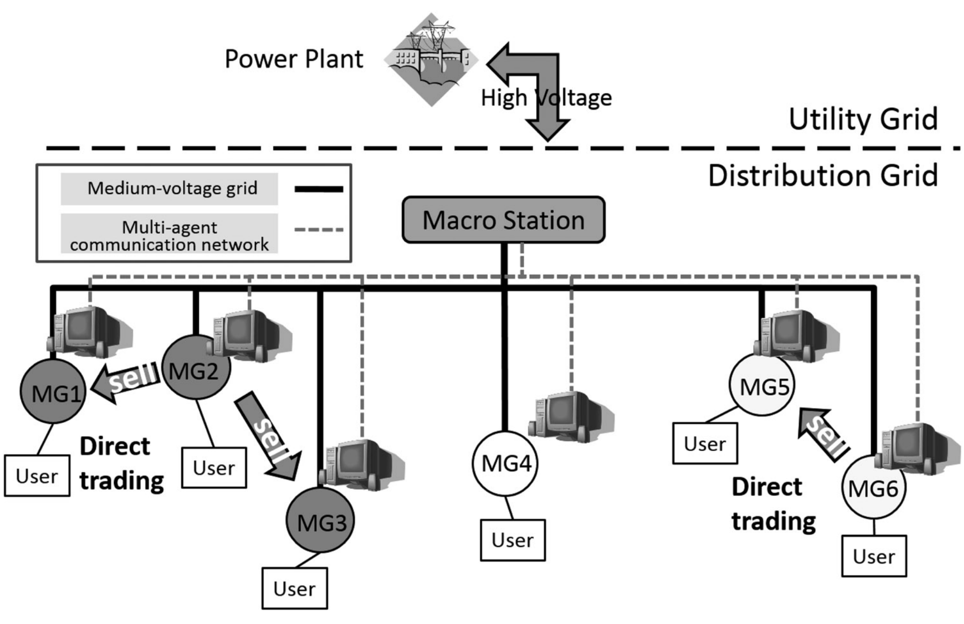


Fig. 1 *System model for multiple MGs network with coalitions*

Table 1 Notification of expenditures

Symbol	Description
C_g	generation cost of all MGs
C_b	retail price for MGs to buy electricity from MS
C_l	transmission cost per unit distance of MGs to transmit electricity on distribution lines
$C_\mathrm{l}^{\mathrm{com}}$	communication cost per unit distance for MGs to exchange information via the communication network
C_{shed}	load shedding compensation price for MGs
C_{ij}	electricity price for MG_i to purchase power from MG_j
$\mathrm{Cost}_i^{\mathrm{pur}}$	total purchase cost for MG_i to buy electricity
$\mathrm{Cost}_i^{\mathrm{loss}}$	total cost of power losses for MG_i
$\mathrm{Cost}_i^{\mathrm{shed}}$	total compensation cost of load shedding for MG_i
$\mathrm{Cost}_i^{\mathrm{com}}$	total communication cost for MG_i

quantity $\mathrm{Req}_i = G_i - D_i$ is defined as the total surplus or demand of MG_i. Additionally, $\theta_{\max}$ is supposed to be the maximum capacity percentage of the allowable loads that can be cut off. Therefore, the real function is $\mathrm{Req}_i = G_i - (1-\theta_{\max})D_i$ when considering load shedding. For each MG_i, $\mathrm{Req}_i > 0$ means that it generates excessive electricity and can sell it to others; $\mathrm{Req}_i < 0$ implies that its demand cannot be satisfied and wants to buy electricity from others; $\mathrm{Req}_i = 0$ represents that its production balances its demand. The MGs with $\mathrm{Req}_i > 0$ constitute the set of sellers S_s while the MGs with $\mathrm{Req}_i < 0$ make up the set of buyers S_b. According to [15], the generation G_i and demand D_i are usually considered as random numbers. To achieve a more cost-efficient power transaction, the MGs are willing to directly trading energies between sellers and buyers when it gains benefits than trading with the MS.

As Table 1 illustrates, our ET-scheme considers a variety of expenditures. For each MG_i, C_g represents the electricity generation cost which depends on the dominant renewable source type. For simplicity, C_g is assumed to be same for all MGs. C_b is the retail price for the MGs to buy electricity from the MS. It fluctuates with different time periods and it will be higher in peak time. C_l is the transmission cost per unit distance. As mentioned before, the MGs are supposed to transfer energy on the common distribution line. Intuitively, the longer the power line between two trading MGs is, the more influence (e.g. the higher risk of congestion) they will bring to the distribution network. Naturally, the transmission cost is assumed to be with respect to distance. $C_\mathrm{l}^{\mathrm{com}}$ denotes the communication cost per unit distance. MGs exchange information through the communication network which requires certain expenditure. Similar to transmission cost, the communication cost is considered as a function of connection distance. C_{shed} denotes the compensation cost paid to the cut off loads after perform load shedding. In real case, C_{shed} will be different according to the importance of the interruptible loads.

In [1, 11], coalitional game theory have been applied in smart grids to minimise power losses by forming cooperative groups. Basically, a coalitional game is defined as a three tuple $(\mathcal{N}, v, \boldsymbol{\phi})$ [16], where $\mathcal{N} = \{1, 2, \dots, N\}$ is a set of players, $v{:}2^{\mathcal{N}} \to \mathcal{R}$ is a utility function corresponding to each coalition $\mathcal{S} \subseteq \mathcal{N}$ that defines the total payoff achieved by $\mathcal{S}$ and $\boldsymbol{\phi}$ is a vector which represents the obtained payoffs of each members.

In this paper, each MG is taken as a player which finds other MGs to form a coalition to achieve economic savings for itself and the whole coalition. Each coalition is divided into two subsets: the sellers' set S_s and the buyers' set S_b. In each coalition, the 'seller' MG will directly trade electricity with 'buyer' MG. After the local power transfer is done, the coalition will perform transaction with MS if there is still power surplus or demand. Obviously, there should be at least one seller and one buyer in any coalition S.

As the basis of analysing cooperative behaviours of the players, the payoff function is first defined here. In this problem, our goal is to minimise the total power transaction cost of MGs. For each coalition S, the total cost in a given time period t consists of four parts:

- The power purchase cost for each 'buyer' MG to purchase electricity from other MGs or the MS.
- The cost spent on the power losses.
- The communication cost for each MG to exchange information with other MGs.
- The compensation cost to make up for the load shedding.

In our scheme, the 'seller' MGs are supposed to sell electricity to others at the price of generation cost. It is to be noted that 'seller' MGs achieve profit from the distribution of the total cost reduction. As a result, the profit of selling is not considered here. Hence, the total payoff function of a coalition S can be formulated as

$$\mu(S, \Omega) = -\left(\sum_{i\in S_\mathrm{b}} \mathrm{Cost}_i^{\mathrm{pur}} + \sum_{i\in S} \mathrm{Cost}_i^{\mathrm{loss}} + \sum_{i\in S} \mathrm{Cost}_i^{\mathrm{com}} + \sum_{i\in S} \mathrm{Cost}_i^{\mathrm{shed}}\right) \tag{1}$$

where Ω is the joining order of the buyers in the coalition S. Besides, the minus here is to change the minimisation problem into the maximisation problem. For each buyer MG_i, $\mathrm{Cost}_i^{\mathrm{pur}}$ represents the cost to purchase electricity from MGs and MS. When purchasing from any other MG_j, the cost C_{ij} comprises two parts: the generation cost C_g and the transmission cost C_l, which can be denoted as

$$C_{ij} = C_\mathrm{g} + l_{ij}C_\mathrm{l} \tag{2}$$

where l_{ij} means the distance from the buyer MG_i to the seller MG_j. On the other hand, MG needs to pay C_b to buy electricity from the MS. Therefore, the purchase cost can be calculated as

$$\mathrm{Cost}_i^{\mathrm{pur}} = \sum_{j\in S_\mathrm{s}} C_{ij} f_{ij} + C_\mathrm{b} f_{i0} \tag{3}$$

here f_{ij} is the power transmitted between these two MGs and f_{i0} is the power transaction with MG_i and MS if there still remains power surplus or demand in MG_i after the local power transfer.

$\mathrm{Cost}_i^{\mathrm{loss}}$ is the expenditure with corresponding to power losses for each MG_i in the coalition. The power transactions between MG_i and other MGs or MS are accompanied with power losses and need to be considered differently. If the buyer MG_i wants to exchange f_{i0} power with the MS, the incurred power loss can be expressed as [11]

$$P_{i0}^{\mathrm{loss}} = \frac{R_{i0} f_{i0}^2}{U_0^2} + \alpha f_{i0} \tag{4}$$

where R_{i0} means the resistance of the distribution line between MG_i and MS, U_0 is the voltage of the common distribution line and α is the fraction of power loss due to transformer in the MS. On the other hand, when the buyer MG_i wants to exchange f_{ij} power with the seller MG_j, the accompanied power loss can be expressed as

$$P_{ij}^{\mathrm{loss}} = \frac{R_{ij} f_{ij}^2}{U_0^2} \tag{5}$$

where R_{ij} is the resistance of the distribution line between MG_i and MG_j. Both R_{i0} and R_{ij} are with respect to distance. Adding up these two parts, the expenditure $\mathrm{Cost}_i^{\mathrm{loss}}$ can be calculated as

$$\mathrm{Cost}_i^{\mathrm{loss}} = C_\mathrm{b} P_{i0}^{\mathrm{loss}} + \sum_{j\in S} C_{ij} P_{ij}^{\mathrm{loss}} \tag{6}$$

$\mathrm{Cost}_i^{\mathrm{com}}$ is the communication cost for MG_i to exchange information with other MGs in the same coalition via the communication network. As the communication cost per unit distance is represented as $C_\mathrm{l}^\mathrm{com}$, $\mathrm{Cost}_i^\mathrm{com}$ is calculated as

$$\mathrm{Cost}_i^\mathrm{com} = \sum_{j \in S \backslash \{i\}} l_{ij} C_\mathrm{l}^\mathrm{com} \tag{7}$$

$\mathrm{Cost}_i^\mathrm{shed}$ is the expenditure for MG_i to compensate for the loads that are cut off. As the total capacity of interruptible loads is $\theta_\mathrm{max} D_i$, $\mathrm{Cost}_i^\mathrm{shed}$ can be denoted as

$$\mathrm{Cost}_i^\mathrm{shed} = C_\mathrm{shed} \theta_\mathrm{max} D_i \tag{8}$$

By using (1), the value function for any coalition $S \subseteq \mathcal{N}$ of the MGs coalitional game is defined as

$$v(S) = \max_{\Omega \in \Omega_S} \mu(S, \Omega) \tag{9}$$

where Ω_S is the set of all joining orders over the buyers in S. Since the total utility for any coalition S depends on the joining sequence of the MGs, (9) is used to find out the maximum total utility that can be obtained.

4 Economic transaction based on coalitional game strategy

On the basis of the definition in Section 3, our problem to minimise the total expenditure of the MGs is transferred into the coalitional game $(\mathcal{N}, v, \boldsymbol{\phi})$, which aims at finding out an optimal coalition structure that maximises the payoffs of each MG. Particularly, there are three subproblems need to be solved:

(i) Maximise payoff of the coalitions.
(ii) Distribute obtained profit by forming coalitions to all the players.
(iii) Find optimal coalition structure.

4.1 Maximise payoff of the coalitions

Fundamentally, the goal of the first subproblem is to determine the maximum total payoff of a coalition as (9) shows. Note that, the total payoff depends on the power transaction between MGs and MS. In other words, the matching pairs of seller MGs and buyer MGs make a difference in the total payoff. According to (2), the purchase cost C_{ij} within each two MGs is comprised of generation cost C_g and transmission cost C_l. In our scheme, we assume the retail price C_b is much larger than the generation cost C_g. Moreover, the transmission cost is assumed to be proportional with the distance between MGs. For those MGs which are close to each other, the transmission cost C_l is relatively small. Therefore, if those MGs near each other form coalitions and perform local power transfer within the coalition, the total purchase cost tends to be smaller than purchasing from MS. To minimise the purchase cost, MGs with a close distance are expected to form pairs to transfer power. Similarly from (5), if there exists MG_j which is closer to MG_i than MS, then the power loss P_{ij} is smaller than P_{i0} when transmitting from MG_i to MG_j rather than MS. Therefore, the more cooperative transactions performed within MGs which are close to each other, the less the expenditure of power loss will be. Moreover, the short distance power transaction within MGs is preferred than the long distance case. Moreover, communication cost also increases with respect to distance, as shown in (7). Meanwhile, based on (8), the compensation cost is determined by the demand of each MG. Compared with the other three terms, the compensation for load shedding is not a dominant factor because the θ_max is usually not large. In this respect, distance is taken as the primal criteria when matching the seller MGs to the buyer MGs.

Similar to [11], a simple scheme is subsequently applied to match the seller MGs to the buyer MGs. For a given coalition S, assume that its buyer subset $S_\mathrm{b} \subset S$ has k buyers and the buyers join the coalition in the order $\Omega \in \Omega_S$, which can be denoted as $S_\mathrm{b} = \{b_1, \ldots, b_k\}$. As shown in Algorithm 1 (Fig. 2), each buyer b_i is considered sequentially according to the given order. For each b_i, the sellers $S_j \in S_\mathrm{s}$ are sorted according to their distance with b_i. Then buyer b_i tries to purchase from the first s_j in S_s. If the residual power surplus of s_j can satisfy the need of b_i including the power losses as (10)

$$Q_{s_j} \geq -Q_{b_i} + \frac{R_{ij}(-Q_{b_i})^2}{U_0^2} \tag{10}$$

then the buyer b_i does not require further transaction and the next buyer starts acting. Otherwise, b_i buys all the possible power s_j can provide, and then requires power transaction with the next closest seller s_{j+1}.

The process is repeated until all the buyers in S_b have no power demand, or none of the sellers in S_s have energy to trade. Then, the coalition S will transmit power with MS if there remains power surplus or demand. By performing this matching process, the maximum utility function satisfying (9) of coalition S can be obtained.

4.2 Profit distribution in coalition

After the maximum total utility of a coalition S is determined, there comes the problem of how to appropriately distribute the produced profit in the coalition. The concept of 'shapley value' has been widely used in the fair distribution of coalitional games [1, 16]. Shapley value can be taken as a measure of the contribution each

Algorithm 1

while there are buyers not satisfied **do**
  choose buyer $b_i \in S_b$ according to order Ω
  while there are available sellers in S_s **do**
    choose the seller $s_j \in S_s$ that is closest to b_i
    if seller s_l can satisfy the demand $-Q_{b_i}$ of buyer b_i **then**
      b_i buys energy $-Q_{b_i}$ from s_l
      b_i does not require other power transaction and go to 1
    else
      b_i buys all the energy s_j can sell and tries to buy from the next closest seller s_{j+1}
    end if
  end while
end while

Fig. 2 *Algorithm 1: Maximise payoff of the coalition S*

MG makes. For our coalitional game $(\mathcal{N}, \nu, \boldsymbol{\phi})$, the shapley value of each MG_i is denoted as $\phi_i(\nu)$ and can be calculated as

$$\phi_i(\nu) = \sum_{S \subseteq \mathcal{N}\setminus\{i\}} \frac{|S|!(|\mathcal{N}| - |S| - 1)!}{|\mathcal{N}|!} (\nu(S \cup \{i\})) - \nu(S)) \quad (11)$$

where each subset of coalition S without player i is considered, and the corresponding profit $\nu(S \cup \{i\})) - \nu(S))$ that player i gains under different joining order are added up, then the average value over all possible conditions is calculated. The calculated shapley value of each MG_i is the profit it obtains after distribution.

4.3 Find optimal coalition structure

Next, the coalition formation strategy by the MS is discussed. It can be seen from (3) and (6) that sometimes the transaction between MGs costs more than the trading with MS. Thus, the grand coalition (the coalition includes all the players) is not optimal in many cases.

When forming the optimal coalition structure, each MG prefers to attend in the coalition which will bring most profits to it, while not the total coalition value. To this end, the comparison relation [17] which is called 'pareto order' based on the individual payoff is introduced. Consider two collections $\mathcal{K} = \{K_1, K_2, \ldots, K_k\}$ and $\mathcal{L} = \{L_1, L_2, \ldots, L_l\}$ consisting of the same set of players. For collection $\mathcal{K} = \{K_1, K_2, \ldots, K_k\}$, the individual payoff of player j in a coalition $K_j \in \mathcal{K}$ is denoted as $\phi_j(\mathcal{K}) = \phi_j(\mathcal{K}_j)$, where $\phi_j(\mathcal{K}_j)$ can be calculated by (11). Collection $\mathcal{K}$ is preferred over $\mathcal{L}$ by pareto order if and only if the following relation satisfies:

$$\begin{aligned} &\mathcal{K} \triangleright \mathcal{L} \Leftrightarrow \phi_j(\mathcal{K}) \geq \phi_j(\mathcal{L}), \quad \forall j \in \mathcal{K}, \mathcal{L} \\ &\text{and } \phi_k(\mathcal{K}) > \phi_k(\mathcal{L}), \quad \exists k \in \mathcal{K}, \mathcal{L} \end{aligned} \quad (12)$$

As (12) shows, a collection $\mathcal{K}$ is a preferred structure than $\mathcal{L}$ if at least one player is able to gain a better payoff without reducing other players' payoffs.

On the basis of the individual comparison relation, we propose a three-stage algorithm by the MS in a centralised way involving two rules [11]: merge and split.

- *Merge*: Merge any set of coalitions $\{S_1, S_2, \ldots, S_k\}$ to $\bigcup_{j=1}^{k} S_j$ if $\{S_1, S_2, \ldots, S_k\} \triangleright \bigcup_{j=1}^{k} S_j$.
- *Split*: Split any coalition $\bigcup_{j=1}^{k} S_j$ to $\{S_1, S_2, \ldots, S_k\}$ if $\bigcup_{j=1}^{k} S_j \triangleright \{S_1, S_2, \ldots, S_k\}$.

Applying the merge and split rules, coalitions will change their structure and yield better individual payoffs of each MG, thus improving the whole profits. In [1, 17], the convergency of the merge-and-split operation has been proved. The detail of our algorithm is shown in Algorithm 2 (Fig. 3). It is to be noted that merge and split are rules for the centralised algorithm to determine the optimal coalition structure rather than real operations of MGs such as synchronisation or desynchronisation in the real distribution network.

The proposed algorithm includes three stages: request exchange, merge-and-split and cooperative transaction. In the first stage, the agent of each MG send their information to MS, comprising their position, power surplus or need Req_i and demand D_i. By using the information collected from the MGs, the MS then perform the merge-and-split operation to form optimal coalition structure. Our algorithm starts with a partition $\mathcal{S}$ where each MG_i is an individual coalition S_i. For each coalition S_i, it tries to merge with other coalition S_j in the partition. If the pareto order is held, then S_i and S_j merged into one larger coalition. The merge process continues until there is no possible coalition pair S_i and S_j that can be merged. Subsequently, the split process starts. For each coalition of S_i of the partition S after merge operation, all its possible partition of two disjoint coalition $\{S_p, S_q\}$ are considered. Here, to find all the possible partitions, a binary representation is used to indicate the players in the coalition [18]. For an example of three MGs, one possible splitting can be represented as $111 = 001 + 110$, which means $\{MG_1, MG_2, MG_3\}$ is split into $\{MG_3\}$, $\{MG_1, MG_2\}$. If the split two coalition S_p and S_q satisfy the pareto order, then the former coalition S_i will be deleted from the partition $\mathcal{S}$ while S_p and S_q will be added. Once a success split is found, the split process will terminate and restart from the merge process. After the merge-and-split operation converges, a final partition $\mathcal{S}_{\text{final}}$ can be obtained which maximises the individual payoff for all the MGs. Finally, cooperation transaction will take place based on the formed coalition structure. The MS will send the determined formation information and related ordering to agents of each MG. Then, the MGs in the same coalition will exchange energy as the joining order determined by Fig. 2. If there remains power surplus or need for the coalition, it will trade with the MS.

5 Performance evaluation

In this section, a set of simulation experiments are performed to validate our proposed ET-scheme. For the simulation, a distribution network of an area $20 \times 20\ \text{km}^2$ is set up. As Fig. 1 shows, MS is located at the centre of the upper border and the MGs are deployed randomly in the network. Under the MS lies a common distribution power line, to which all MGs are connected in a radial pattern. In fact, our ET-scheme can be applied to any other topological structures. Similarly, as [15], the power generation G_i and demand D_i of MG_i are assumed to be Gauss random variables distributed from 1 to 3 MW. Therefore, the power surplus or need Req_i of MG_i is a random variable distributed from −2 to 2 MW. It is to be noted that our economic power transaction can be applied in real cases by changing the proportion of MGs with power surplus or power deficient in the distribution network.

The resistance on the distribution line of the network is set as $R = 0.2\ \Omega/\text{km}$ and the power transfer fraction of the MS as $\alpha = 0.02$ [19]. The medium voltage of the distribution line is set to $U_0 = 50$ kV [19]. The ampacity of the distribution network is assumed as 100 A, which is a typical value in distribution network. The retail price for the MS and the generation cost of MGs are derived from the prices in California in 2014 [20]: $C_{\text{b}} = 10$ cents/kW and $C_{\text{g}} = 4$ cents/kW, respectively. Here, we do not consider different generation price C_{g} for each MG with different energy mix so as to simplify the numerical simulation. The transmission cost is set to 0.01 cents/kW km. The communication cost per unit distance is set to 0.1 cents/km. Compensation price for load shedding is set to 1 cents/kW and the maximum capacity percentage of the interruptible loads $\theta_{\max}$ is set to 10%. The simulation results are average values obtained after ten runs of the experiment with random deployment of the MGs.

Fig. 4 depicts the normalised total expenditure for all MGs to manage their power surplus or need. Three schemes are considered here: non-cooperative scheme, proposed ET-scheme and ET-scheme without load shedding for a total number of MGs varying from 10 to 50. As shown in the figure, our ET-scheme achieved a significant cost reduction compared with the non-cooperative scheme and the ET-scheme without considering load shedding. The resulting cost reduction is ascribed to the direct trading within MGs, which requires less cost than the power transaction with MS. Furthermore, the power losses are decreased by cooperative transaction since the distance within MGs are usually smaller than with MS.

With the increasing number of MGs, the reduction rate also increases, as more MGs in the distribution network implies a higher possibility to find MGs which have complementary surplus or demand and require lower purchase costs. Moreover, the ET-scheme considering load shedding achieved lower total expenditure compared with the case not performing load shedding when compensation cost is relatively low. In essence, load shedding reduces the power need of MGs and hence decreases the power transaction between MGs and the MS.

Algorithm 2

Input: G_i, D_i of each MG_i, a partition $\mathcal{S} = \{S_1, S_2, ...S_N\}$, initially each S_i only consists of MG_i

Output: Final partition $\mathcal{S}_{final}$

1. Request exchange stage
for each MG_i **do**
  MG calculate its Req_i based on G_i, D_i and θ_{max}
  Send Req_i, D_i to the MS
end for
2. Merge-and-split stage
repeat
  Merge process starts
  for each $S_i \in \mathcal{S}$ **do**
    coalition S_i tries to merge with coalition S_j
    if $S_i \cup S_j \triangleright \{S_i, S_j\}$ **then**
      $S_i \leftarrow S_i \cup S_j$, $\mathcal{S} \leftarrow \mathcal{S} \backslash \{S_j\}$
    end if
  end for
  Split process starts
  for each $S_i \in \mathcal{S}$ **do**
    for all partitions $\{S_p, S_q\}$ of S_i **do**
      if $\{S_p, S_q\} \triangleright S_i$ **then**
        $S_i \leftarrow S_p$, $\mathcal{S} \leftarrow \mathcal{S} \cup \{S_q\}$
        break
      end if
    end for
  end for
until Merge-and-split operations converge to a partition $\mathcal{S}_{final}$
3. Cooperative transaction stage
All MG agents receive coalition formation from MS
for each $S_i \in \mathcal{S}_{final}$ **do**
  MGs in S_i exchange power sequentially as the order of joining the coalition
end for
If any $S_i \in \mathcal{S}_{final}$ still has power surplus or demand, perform power transaction with MS
return $\mathcal{S}_{final}$

Fig. 3 *Algorithm 2: Three-stage algorithm for economic power transaction*

Fig. 5 shows the relationship between the retail price of the utility grid and the cost reduction rate when the number of MGs is 10 and 50. In Fig. 5, it is shown that when the retail price is higher, the cost reduction rate becomes larger. It is identical with the fact that existing price difference brings cost reduction to MGs. Therefore, the higher the retail price of MS is, the more benefit it will produce by energy trading within MGs. Considering the price fluctuation during a whole day, since the electricity price of peak periods is larger than the peak-off periods, the MGs are more willing to form coalition to perform direct trading and thus gain more monetary profit in the peak periods than peak-off periods.

Fig. 6 illustrates how the transmission cost affects the cost reduction rate in the case when $N = 10$ and 50. With a higher transmission cost, the reduction rate decreases sharply and

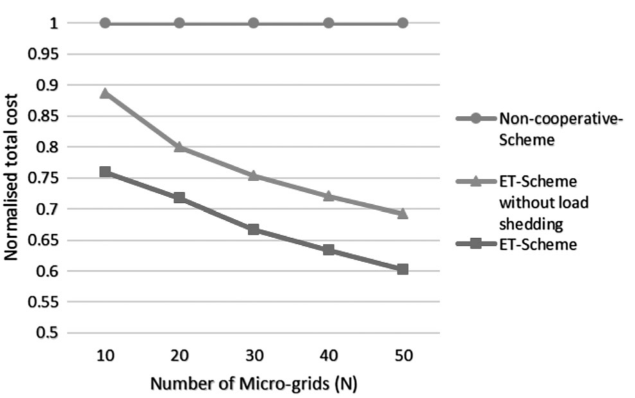


Fig. 4 *Comparison of non-cooperative scheme and cooperative scheme*

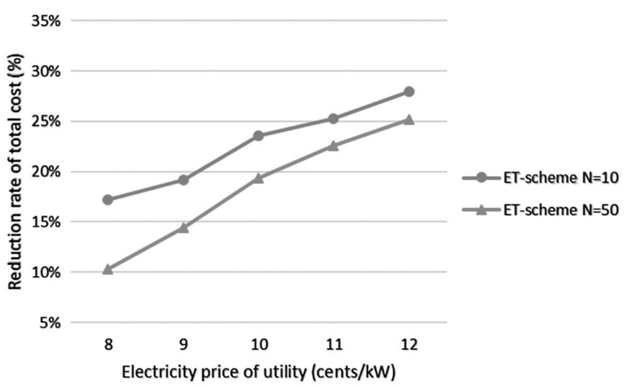


Fig. 5 *Reduction rate of cost versus retail price*

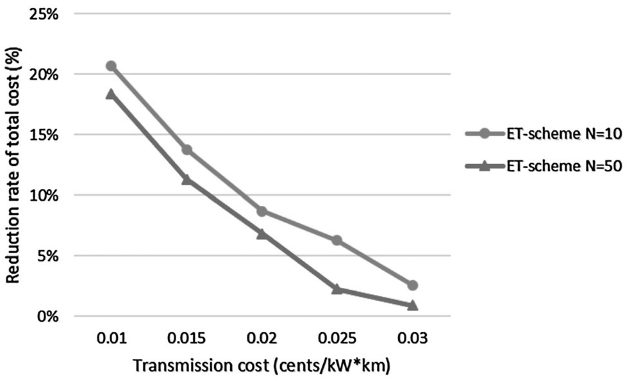


Fig. 6 *Reduction rate of cost versus transmission cost*

becomes near 0. When the transmission cost gets higher, the expenditure for MGs to perform local transfer increases. Consequently, there is no more benefit to trade energy within MGs than with MS. This result indicates the importance of the pricing scheme of the utility grid. Cater to the trend of developing renewable energies, direct trading within MG should be encouraged because it can effectively increase the utilisation of the generated renewable energy and also reduce the energy request to MS, which definitely decreases the generation of traditional plants and thus reduces the pollution. In this respect, the utility grid is expected to price a low transmission fee for MGs so as to increase the incentive for MGs to perform direct energy trading.

Figs. 7 and 8 demonstrate how the efficiency of load shedding changes when the maximum capacity percentage of allowable load shedding and the compensation price for the cut off loads vary, respectively. In Fig. 7, the compensation price C_{shed} is set as 1 cent/kW and the maximum capacity percentage $\theta_{\max}$ varies from 5 to 25% for each MG. It can be seen that the total cost decreases with the increase of $\theta_{\max}$. This is simply because with more loads cut down, the power need of each MG decreases and hence the total purchase cost decreases. Fig. 8 shows the total expenditure of the ET-scheme with load shedding when compensation price changes, where $\theta_{\max}$ is set to 10% and C_{shed} is changed from 1 to 5 cents/kW. As it shows, with the increasing of C_{shed}, the total expenditure increases because the expenditure for compensating the cut off loads become larger. When the compensation price becomes too high, our ET-scheme considering load shedding might lead to a higher expenditure than that without load shedding. In practical, there are different levels of interruptible loads which correspond to different compensation prices of load shedding. Based on our scheme, it is expected to perform load shedding of those interruptible loads with lower compensation prices so as to maintain economic efficiency.

Fig. 9 depicts the proportion of each type of cost to total cost. The total cost is listed on the top of each cluster (unit is dollar). Compared with the other three items (power loss cost, load shedding cost and communication cost), purchase cost has the largest percentage up to 70% in average. It identifies with our main concern to reduce the purchase cost by direct trading within MGs. As it shows, the proportion of purchase cost and the power loss cost decreases along with the increase of number of MGs N while the communication cost increases. With the increase of number of MGs N in the square area of the distribution network, the average distance within each MG is shortened. Therefore, the proportion of the purchase cost decreases because there are more MGs closer to each other and the transmission cost decreases so that the direct trading price is reduced. Similarly, the power loss cost decreases because it is more likely for closer MGs to form coalition and reduce the power transfer distance. On the other hand, the ratio of communication cost increases since the increase of number of MGs leads to more communication within each coalition. On the other hand, the ratio of load shedding cost almost remains the same. It is because the load shedding capacity is set to a constant in our numerical experiment so that the load shedding cost also maintains nearly unchanged.

Fig. 10 gives the comparison result of a greedy scheme and our economic scheme when applied to the network shown in Fig. 11 in Appendix. Here, the greedy algorithm only considers purchase

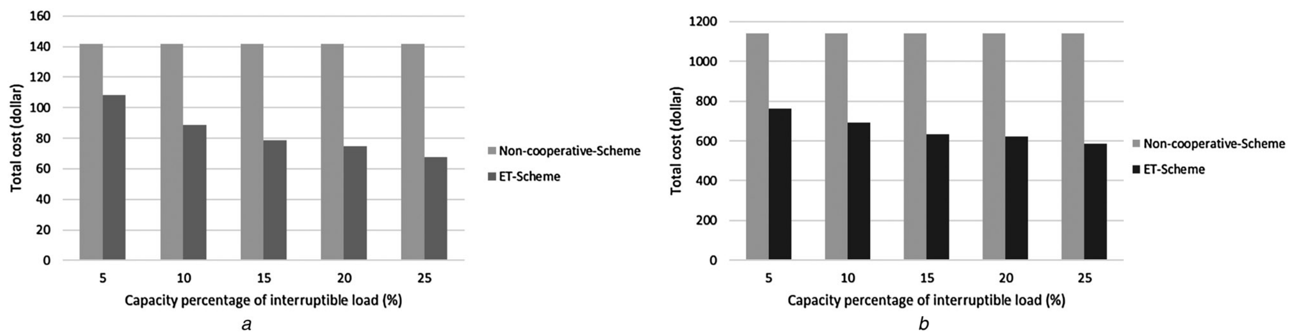


Fig. 7 *Improved total cost versus different capacity percentages of load shedding*

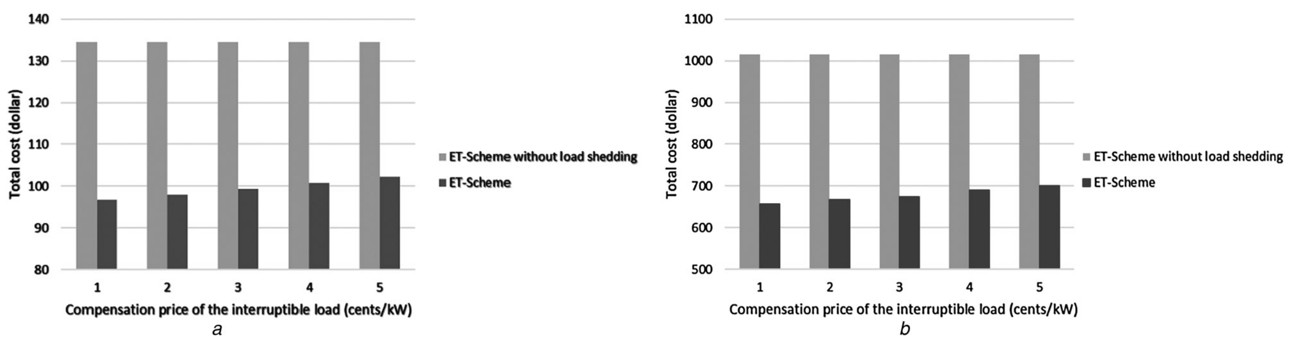


Fig. 8 *Improved total cost versus different compensation prices for cut off loads*

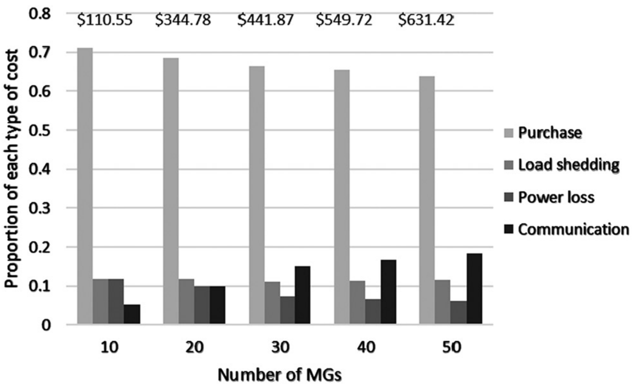
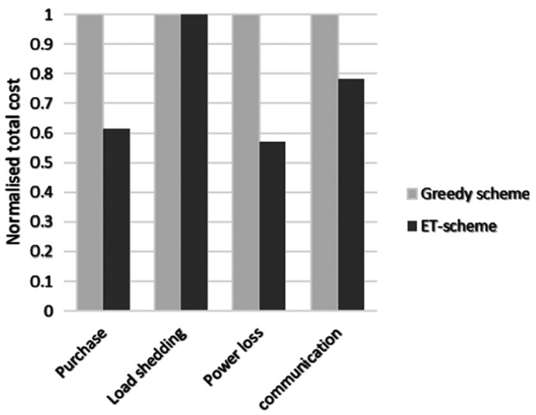


Fig. 9 *Proportion of each type of cost to total cost*



Greedy scheme	\$81.23	\$19.52	\$64.93	\$16.61
ET-scheme	\$49.93	\$19.52	\$37.05	\$12.99

Fig. 10 *Comparison of greedy scheme and proposed ET-scheme (N = 10)*

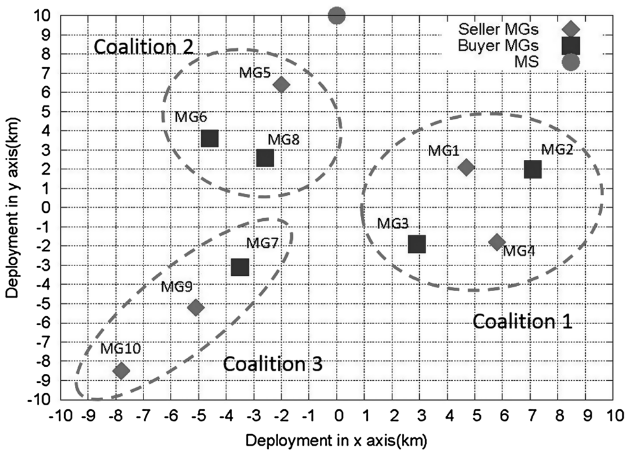


Fig. 11 *Deployment of MGs and MS (N = 10)*

cost as the choosing criteria. Specifically, each MG will choose to trade with those MGs that have lower transmission costs subsequently while not considering other costs such as power loss cost and communication cost. Compared with the greedy algorithm, our economic scheme can take a whole view of all MGs and obtain a more reasonable coalition structure, which makes each MG lower its cost. The histograms show the normalised total cost of two algorithms and the table lists the real value. It can be seen that our proposed scheme achieve lower total cost than the greedy algorithm. Specifically, the purchase cost, power loss cost and communication cost are further reduced.

6 Conclusions

In this work, we focused on the economic power transaction in a multiple MG network with MASs. A coalitional game theory-based centralised algorithm is proposed consisting of three stages: request exchange, merge-and-split and cooperative transaction. This algorithm enables MGs to exchange information through agents and form coalitions where they can perform direct energy trading to satisfy their power surplus and demand. Since the direct trading of MGs avoids paying the price difference of wholesaler, it requires lower cost than trading with MS. Besides, MGs with shorter distances tend to form coalition and therefore reduces power losses and other costs. In this respect, direct power trading among the MGs brings monetary benefits and optimise the total expenditure of the whole MG network. Simulation results show the effectiveness of our ET-scheme over the non-cooperative method, with a significantly expenditure reduction up to 34.7%. Moreover, comparison results demonstrate that load shedding further improves the cost reduction rate. In future work, it will be interesting to study on the pricing policy of the MGs network in the case that MGs with power surplus attend the electricity market and act as sellers. Further numerical simulations will be implemented on real-field data.

7 Acknowledgment

This work was supported by National Natural Science Foundation of China (no. 51577115).

8 References

1 Wei, C., Fadlulah, Z.M., Kato, N., *et al.*: 'CT-CFS: a game theoretic coalition formulation strategy for reducing power loss in micro grids', *IEEE Trans. Parallel Distrib. Syst.*, 2014, **25**, (9), pp. 2307–2317
2 Darghouth, N.R., Barbose, G., Wiser, R.: 'The impact of rate design and net metering on the bill savings from distributed PV for residential customers in California', *Energy Policy*, 2011, **39**, (9), pp. 5243–5253
3 Vasirani, M., Ossowski, S.: 'Smart consumer load balancing: state of the art and an empirical evaluation in the Spanish electricity market', *Artif. Intell. Rev.*, 2013, **39**, (1), pp. 81–95
4 Lee, W., Xiang, L., Schober, R., *et al.*: 'Direct electricity trading in smart grid: a coalitional game analysis', *IEEE J. Sel. Areas Commun.*, 2014, **32**, (7), pp. 1398–1411
5 Wang, Y., Saad, W., Han, Z., *et al.*: 'A game-theoretic approach to energy trading in the smart grid', *IEEE Trans. Smart Grid*, 2014, **5**, (3), p. 1439C145
6 Nguyen, D.T., Negnevitsky, M., de Groot, M.: 'Walrasian market clearing for demand response exchange', *IEEE Trans. Power Syst.*, 2012, **27**, (1), p. 535C544
7 Rahimiyan, M., Baringo, L., Conejo, A.J.: 'Energy management of a cluster of interconnected price-responsive demands', *IEEE Trans. Power Syst.*, 2014, **29**, (2), p. 645C655
8 Nunna, H.S.V.S.K., Doolla, S.: 'Multiagent-based distributed energy-resource management for intelligent microgrids', *IEEE Trans. Ind. Electron.*, 2013, **60**, (4), p. 1678C1687
9 Erol-Kantarci, M., Kantarci, B., Mouftah, H.T.: 'Cost-aware smart microgrid network design for a sustainable smart grid'. IEEE GLOBECOM Workshops, 2011, pp. 1178–1182
10 Gregoratti, D., Matamoros, J.: 'Distributed energy trading: the multiple-microgrid case', *IEEE Trans. Ind. Electron.*, 2015, **62**, (4), pp. 2551–2559
11 Saad, W., Han, Z., Poor, H.V.: 'Coalitional game theory for cooperative micro-grid distribution networks'. IEEE Int. Conf. on Communications Workshops (ICC), 2011, pp. 1–5
12 Wei, C., Fadlulah, Z.M., Kato, N., *et al.*: 'On optimally reducing power loss in micro-grods with power storage devices', *IEEE J. Sel. Areas Commun.*, 2014, **32**, (7), pp. 1361–1370
13 Ochoa, L.F., Harrison, G.P.: 'Minimizing energy losses: optimal accommodation and smart operation of renewable distributed generation', *IEEE Trans. Power Syst.*, 2011, **26**, (1), pp. 198–205
14 Deilami, S., Masoum, A.S., Moses, P.S., *et al.*: 'Real-time coordination of plug-in electric vehicle charging in smart grids to minimize power losses and improve voltage profile', *IEEE Trans. Smart Grid*, 2011, **2**, (3), pp. 456–467
15 Li, H., Zhang, W.: 'Qos routing in smart grid'. Proc. of IEEE Global Telecommunications Conf., Miami, FL, USA, 2010, pp. 1–6
16 Lai, H.Q., Chen, Y., Liu, K.J.: 'Energy efficient cooperative communications using coalition formation games', *Comput. Netw.*, 2014, **58**, pp. 228–238
17 Apt, K.R., Witzel, A.: 'A generic approach to coalition formation'. Proc. of Int. Workshop COMSOC, Amsterdam, UK, 2006, pp. 1–21

18 Mashayekhy, L., Grosu, D.: 'A merge-and-split mechanism for dynamic virtual organization formation in grids', *IEEE Trans. Parallel Distrib. Syst.*, 2014, **25**, (3), pp. 540–549
19 Machowski, J., Bialek, J.R., Bumly, J.R.: 'Power systems dynamics: stability and control' (Wiley, New York, NY, USA, 2008)
20 http://www.eia.gov/electricity/

9 Appendix

We have given the concrete data of the system in one run of the numerical simulation as Table 2 shows. The first column shows the id of each MG and the second column shows the deployment position of each MG. Columns 3, 4 and 5 show the total generation, total demand and power surplus or shortage of each MG, respectively. As it shows, we do not assume identical MGs at equal distances. The distance of each MG to the MS and its position is determined randomly based on Gauss distribution, within a square of 20×20 km^2. The power surplus and shortage of each MG are also considered to be Gauss random variables distributed from −2 to 2 MW.

Fig. 11 gives the deployment of each MGs and MS based on the data listed in Table 2. The diamond corresponds to each seller MG, the square corresponds to each buyer MG and the grey spot represents the MS. The spotted circle shows the final coalitions. It can be seen that for each coalition there exists seller and buyer MGs which have complementary power surplus and demand. Besides, MGs in the same coalition have a smaller distance with each other than with the MS.

Table 2 Parameters of MGs in one run of numerical experiments

MG id	Deployment position	Total generation, MW	Total demand, MW	Surplus shortage, MW
1	(4.7, 2.1 km)	1.324	1.901	−0.577
2	(7.1, 2 km)	2.589	1.168	1.421
3	(2.9, −1.9 km)	1.622	1.458	0.164
4	(5.8, −1.8 km)	2.057	2.827	−0.769
5	(−4.6, 3.6 km)	1.331	1.305	0.026
6	(−2, 6.4 km)	2.204	2.652	−0.448
7	(−3.5, −3.1 km)	1.526	2.077	−0.551
8	(−2.6, 2.6 km)	2.308	2.992	−0.684
9	(−5.1, −5.2 km)	2.378	1.156	1.222
10	(−7.8, −8.5 km)	2.496	1.885	0.611