GT-CFS: A Game Theoretic Coalition Formulation Strategy for Reducing Power Loss in Micro Grids

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***Abstract*—In recent years, research attention on smart grid comprising distributed power generators has increased. To produce electricity in the smart grid, many micro grids (MGs) may exploit various renewable energy resources. Because the production capacity of renewable resources cannot be controlled, the MGs often require the power plants to provide power for them. However, the power loss between each MG and the power plant is larger than that among the MGs. To alleviate this power loss, we propose a game theoretic coalition formulation strategy for the MGs dubbed GT-CFS. Our proposed GT-CFS allows the MGs (belonging to the same macro station (MS)) to autonomously cooperate and self-organize into a partition composed of disjoint MG coalitions. Also, GT-CFS enables the MGs, in a distributed manner, to decide whether they will remain in the coalitions or not upon environmental changes, e.g., the variation of the power demand of the MGs. Within every coalition, MGs coordinate the power transfer among themselves as well as with the MS, in a fashion to optimize a utility function, which captures the total losses over the power distribution lines. MGs in the same coalition will distribute the extra profits (i.e., payoff) produced from forming coalitions by their "Shapley value". Through computer simulations, we demonstrate that the proposed GT-CFS reduces the average power loss per MG significantly in contrast with the conventional non-cooperative approach.**

***Index Terms*—Coalition Game, Shapley value, micro grid, cooperative game.**

I. INTRODUCTION

RCENTLY, the consumption of electricity has increased leaps and bounds with the immense growth of technology. The demand of electricity is, however, not balanced during a day. Indeed, there are large gaps among the demands during different times of the day. Therefore, it is possible to divide a day into two parts, namely the peak and off-peak periods [1]. During a day, the peak demand consists in the busiest (i.e., the heaviest electricity consumption) time while the remaining time is referred to as the off-peak period. Furthermore, the peak period differs in various seasons. For example, in the summer, the peak period is usually observed in the noon/afternoon due to the heavy usage of air conditioners. On the other hand, in the spring and autumn, the afternoon represents off-peak time. It is difficult for the traditional power plants to effectively deal with the variation of peak and off-peak power demands. If the power plants are able to consistently maintain high generation of electricity, they may meet the peak demand. However, the high production of electricity, especially obtained from the non-renewable energy resources (e.g., coal), usually wastes a lot of energy. Therefore, we require a new type of intelligent power grid (i.e., smart grid), which can help the power plants to effectively meet the peak and off-peak demands, and avoid the unnecessary power generation and/or distribution loss.

Micro grids (MGs) comprising distributed power generators have been introduced recently to construct smart grid to reduce power loss. MGs are able to supply electricity to the end-users (i.e., homes, companies, schools, and so forth) which are linked to the corresponding MGs. The MGs can exchange power with others. In addition, they are also capable of transferring power with the Macro Station (MS), which is the primary substation of the smart grid. The MGs can also be deployed near the users so that long-distance power loss may be avoided. They produce electricity from different resources, especially by using a number of renewable resources, e.g., wind, water, solar, and so on. Although these resources are easily procurable and depicted as "green" energy resources, they present a significant shortcoming since they cannot guarantee stable production of electricity at all times. For example, solar energy generation through deployed solar panels in the MGs can be seriously hampered on rainy days. When a MG needs additional power, it can buy electricity from the wholesaler (i.e., the MS) and/or from neighboring MGs.

The objective of our paper is to allow the MGs to collaborate with each other to optimally decrease the power loss while procuring electricity. Toward this end, we propose a game theoretic coalition formulation scheme, referred to as GT-CFS, whereby the MGs can form coalitions or leave the old coalition to join a new one to increase their payoffs. And two problems need to be solved, namely, how to motivate the MGs to form coalitions, and how to appropriately distribute the extra profits (e.g., payoff) produced through forming the coalitions. In case of the first problem, we show that by using the proposed algorithm, the MGs are able to autonomously cooperate and self-organize into a distributed partition, which is composed of disjoint coalitions. The MGs in the same coalition can exchange power with other MGs or the MS, and the power transfer among the MGs alleviates the power loss over the distribution line. In addition, the MGs can adjust decisions accordingly upon environmental change. To address the second problem, we calculate the "Shapley value" of the MGs in the coalition. The Shapely value means the weight of

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the contribution of the MGs to their coalition. Based on their Shapley values, the MGs distribute the extra profits.

The remainder of our paper is organized as follows. The background and related works are discussed in Section II. The system model is discussed in Section III. In Section IV, coalition game between MGs is discussed and we propose our GT-CFS for forming MGs coalitions. We prove that the GT-CFS is stable, convergent and optimal in Section V. The optimal number of MGs is discussed in Section VI. In the Section VII, the simulation result is presented, and the conclusion is drawn in Section VIII.

II. Background and related works

The MS, which typically represents the wholesaler in the power market, usually need fossil-based resources. These non-renewable resources, upon combustion, produce excessive amounts of greenhouse gases that are vented into the atmosphere contributing to air pollution. In addition, the daily maintenance cost of the MS is significantly high. On the other hand, the MGs, distributed in different areas of the smart grid, are able to exploit renewable resources. Compared with traditional grids, the MGs are more flexible as they can quickly adjust their power production according to the demands of the users. When a MG is not self-sufficient, it can purchase additional power from the wholesaler (i.e., the MS) or the nearby MGs for meeting the power demands of customers who are linked to this MG. By this way, the MGs can serve as a strong complement to the traditional macro station. S. A. Arefifar *et al.* presented systematic and optimized approaches for the distribution system into a set of micro grids with optimized self-adequacy [2].

Although there has been a significant progress in the development of the MGs recently, the power loss between the MGs and that between an individual MG and the MS have not been addressed much in literature. In their work in [3], D. Niyato *et al.* proposed an algorithm optimizing the transmission strategy to minimize the total cost. The problem of minimizing power losses in distribution networks has traditionally been investigated using a single, deterministic demand level. L. F. Ochoa *et al.* presented a novel algorithm to solve this problem [4]. B. Kantarci *et al.* proposed the "cost-aware smart micro grid network design", which enables economic power transactions within the smart grid [5]. The problem of power loss minimization was discussed in the work conducted by Meliopoulos *et al.* [6] whereby a real-time and coordinated control scheme was proposed with the participation of distributed generation resources that can be coordinated with the existing infrastructure. The objective of the work was to operate the distribution system with minimized power losses. S. Deilami *et al.* proposed a novel load management solution for coordinating the charging of multiple plug-in electric vehicles (PHEVs) in a smart grid system [7]. A. Vargas *et al.* presented an efficient optimal reconfiguration algorithm for power loss minimization [8]. T. Erseghe *et al.* showed that the power loss reduction is possible without central controllers, by taking advantage of the local measurement, communication and control capability in the MGs [9]. A simple and effective solution to achieve cooperative operation of electronic power processors were described in [10][11]. M. Kirthiga *et al.* proposed a detailed methodology to develop an autonomous micro grid for addressing power loss in [12]. Furthermore, some researchers have addressed power loss in the works in [13]-[15].

At present, game theory is an important tool for Micro Grid research as described in the work in [16]-[18]. Saad *et al.* presented an algorithm based on the cooperative game theory to study novel cooperative strategies between the micro-grids of a distribution network [19].

Note that the afore-mentioned power loss minimization techniques did not take into account the entire smart grid comprising the MS and numerous MGs. They usually adopted a localization approach, e.g., how to reduce the power loss within an individual MG, or how to reduce the power loss between the MG and the MS. However, in our paper, we focus on a scalable power minimization approach across the entire smart grid and consider a fair payoff distribution of the MGs for the coalition.

III. System Model

In this section, system model of the smart grid is presented. As shown in Fig. 1, we consider that the users are supplied electricity by the MS and/or a number of MGs (e.g., wind farm, solar panel, PHEVs, and so on), each of which is linked to the MS. The users include residential customers, schools, companies, and so forth. Because a user is only linked to one MG at a time, for convenience, we assume the MG and the users are linked to this MG are considered as a whole. Smart meters are assumed to be installed at the user-end. The smart-meters measure the power consumption of the users, and they also have the capability to notify the MG about the users' demands. Because the power loss between the MS and a MG is more than that between two MGs, the MGs can alleviate the power loss through forming coalitions. If a sufficient number of MGs to form the coalition does not exist, the coalition will only have a MG (e.g., the coalition 2 in Fig. 1). All MGs are connected by power lines (this is why MGs can change their partners (MGs) to form coalitions). Therefore, if the sum of demands of the users is more than the production of a MG, this MG will obtain power from other MG(s) or the MS to meet demands of users.

Let $\mathcal{N}$ denote the set of MGs. In the given time period (e.g., one hour), every MG_i ($i \in \mathcal{N}$) is able to produce power G_i and supply power to satisfy D_i, which is the sum of demands from all users linked to MG_i. For MG_i, we define the real function $Req_i = (G_i - D_i)$ as the power demand or surplus of MG_i. It means that MG_i wants to get power to meet its demand ($Req_i < 0$), MG_i has a power surplus to sell ($Req_i > 0$), or its demand equals its production ($Req_i = 0$). The MGs can be divided into two types, namely "sellers" and "buyers". The "sellers" have surplus to sell while the "buyers" need additional amount of power to meet the demands of users. If the request of MG_i is zero ($Req_i = 0$), MG_i is considered to be either a "seller" or a "buyer", and it cannot affect the result. In fact, demand D_i and production G_i are always considered as random numbers in the real Smart Grid networks [20]. As a consequence, the value of Req_i is seen as a random number with a certain observed distribution. For convenience, we assume that a "seller" will sell all the power to the "buyer(s)" and/or the MS while a "buyer" has enough "money" to buy the power from the "seller(s)" and/or the MS for meeting its demand. Furthermore, the concept of "buyers" and "sellers" can also be extended to the group or coalitions formed by a number of MGs.

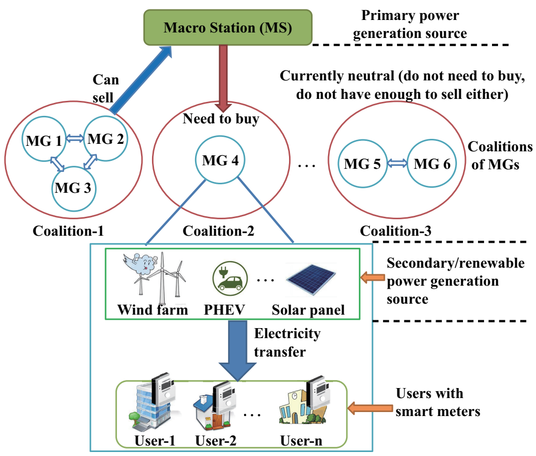

Fig. 1. The construction of Micro Grids

A. Existing Non-cooperative Coalition Model

Before we design the payoff function of coalition, let us see a non-cooperative case. In this case, each MG only exchange power with the MS. In general, the medium voltage of power transfer between the MG and MS is U_0. Any power transfer between MG and MS is accompanied with the power loss. In this process of power transfer, we only consider two kinds of power loss, namely (i) the power loss over the distribution lines inside the network, and (ii) the power loss due to other factors in the MS such as voltage conversion, dust, and so forth. If MG_i wants to sell Req_i to MS $(Req_i > 0)$ or buy Req_i from MS $(Req_i < 0)$, we are able to express the power loss P_{i0} as follows.

$$P_{i0} = R_{i0} I_0^2 + \alpha Q_i, \tag{1}$$

where R_{i0} is the distribution line resistance between MS and MG_i, and α is a fraction of power loss caused by other factors. For simplicity, α is treated as a constant. Q_i is the power that MG_i wants to buy or sell. $I_0 = \frac{Q_i}{U_0}$ is the current flowing over the distribution line when there is a power transfer between the MS and MG_i. Therefore, we can transform eq. (1) into a new quadratic equation with respect to Q_i as shown below.

$$P_{i0} = \frac{R_{i0} Q_i^2}{U_0^2} + \alpha Q_i. \tag{2}$$

The value of Q_i is any of the following.

$$Q_i = \begin{cases} Req_i & : \quad Req_i > 0 \\ L_i^* & : \quad Req_i < 0 \\ 0 & : \quad Req_i = 0, \end{cases} \tag{3}$$

where L_i^* denotes the total amount of power that needs to be produced (or be made available to the system) to ensure that MG_i is able to obtain the power required to meet its demand, Req_i. In case of no power loss, $L_i^* = |Req_i|$. Therefore, the power L_i^* is more than the demand $|Req_i|$ $(L_i^* > |Req_i|)$. L_i^* is the solution of following quadratic equation.

$$L_i = P_{i0} + |Req_i| = \frac{R_{i0} L_i^2}{U_0^2} + \alpha L_i - Req_i. \tag{4}$$

For a given Req_i, three possible solutions of eq. (4) exist, namely none (zero), one, and two solutions. Because we want to minimize the value of Req_i, if eq. (4) has two roots, the smaller one is to be used. For the cases that eq. (4) has no solution, we assume that the root is the same as eq. (4) having a single root, which is $L_i^* = \frac{(1-\alpha)U_0^2}{2R_{i0}}$.

Because in the non-cooperative case each MG can be regarded as a coalition, the payoff of MG is equal to that of coalition. Thus, we are able to define the non-cooperative payoff (utility) of each MG_i as the total power loss due to the power transfer, as follows:

$$u(\{i\}) = -w_2 P_{i0}, \tag{5}$$

where w_2 is the price of a unit power in MS. Because the objective is to minimize $u(\{i\})$, the negative sign is able to convert the problem into a problem of seeking the maximum.

B. Cooperative Coalition Model

In the remainder of this section, the cooperative coalition model is considered for managing the MGs acting as "buyers" and "sellers". Also, the functions of power loss and utility in the cooperative case along with how to form the coalitions are proposed. Toward the end of the section, the concept of "Shapley" function is presented.

Besides exchanging power with the MS, the MGs can exchange power with others. Because the power loss during transmission among the neighbouring MGs are always less than that between the MS and a MG, the MGs can form cooperative groups, referred to as coalitions throughout this paper, to exchange power with others, so as to alleviate the power loss in the main smart grid and maximize their payoffs in eq. (5).

Before formally studying the cooperative behaviour of the MGs, the framework of coalition game theory is firstly introduced in the work in [20]. A coalition game is defined as a pair $(\mathcal{N}, v)$. The game comprises three parts, namely the set of players $\mathcal{N}$, the strategy of players, and the function v: $2^{\mathcal{N}} \rightarrow \mathbb{R}$. In this game, v is a function that assigns for every coalition $S \subseteq \mathcal{N}$ a real number representing the total profits achieved by S. We divide any coalition $S \subseteq \mathcal{N}$ into two parts: the set of "sellers" denoted by $S_s \subset S$ and the set of "buyers" represented by $S_b \subset S$. S_s and S_b satisfy that $S_s \cup S_b = S$. Therefore, for a $MG_i \in S_s$, $Req_i > 0$ and it means that MG_i wants to sell power to others. On the other hand, an arbitrary $MG_j \in S_b$ having $Req_j < 0$ indicates that MG_j wants to buy power from others. It is obvious that any coalition $S \subseteq \mathcal{N}$ should have at least one seller and one buyer.

In order to calculate the payoffs of all the coalitions, players of which are MGs $\in \mathcal{N}$, we need to define the payoff function *v(S)* for each S $\subseteq \mathcal{N}$. Subsequently, for any coalition $S = S_s \cup S_b$, we study the local power transfer between the sellers S_s, the buyers S_b, and the MS.

In a formed coalition, there are many MGs, which are to exchange power with others or even with the MS. Let a "seller" and a "buyer" be denoted by $MG_i \in S_s$ and $MG_j \in S_b$, respectively. If MG_i and MG_j want to exchange power, the power loss function P_{ij} can be expressed as follows.

$$P_{ij} = \frac{R_{ij} Q_{ij}^2}{U_1^2}, \tag{6}$$

where R_{ij} is the resistance of the distribution line between MG_i and MG_j. U_1 denotes the transfer voltage between MG_i and MG_j and it is less than U_0. Because there is no voltage conversion between two MGs, when power is transmitting among MGs, we only calculate the transfer power loss among MGs. In other words, eq. (6) is the special case of eq. (2), when $\alpha = 0$. Also, Q_{ij} is as follow,

$$Q_{ij} = \begin{cases} Q_i & : \quad |Q_i| \leq |Q_j| \\ Q_j & : \quad otherwise, \end{cases} \tag{7}$$

where Q_i and Q_j are given by eq. (3). It means that if MG_i (i.e, the "seller") cannot meet the demand of MG_j (i.e., "the buyer"), then the seller only sells Q_i to MG_j. In addition, since there is power loss between the MGs, MG_j will buy power $\frac{U_1^2}{2R_{ij}}$ (due to the power loss between MG_i and MG_j) from MG_i at least.

In any given coalition S, the total payoff function is consists of three terms, namely (i) the power loss between the MGs which can be obtained from eq. (6), (ii) the power loss caused by the MG selling power to the MS, and (iii) the power loss caused by the MG buying power from MS. (ii) and (iii) are given by eqs. (2) and (3). Therefore, the total payoff function of the coalition S is as follows.

$$u(S, \Omega) = -(w_1 \sum_{i \in S_s, j \in S_b} P_{ij} + w_2 \sum_{i \in S_s} P_{i0} + w_2 \sum_{j \in S_b} P_{j0}), \tag{8}$$

where $\Omega \in \mathcal{S}_S$ is the join order of the MGs, which decide to join the coalition S, and $\mathcal{S}_S$ is the set of the MGs' order in S. w_1 and w_2 represent the price of a unit price of power in the coalition and that in the MS, respectively. P_{i0} and P_{j0} are given by eqs. (2) and (3). P_{ij} is given by eq. (6). By using eq. (8), which represents the total power loss incurred by the different power transfers for S, we can define the value function for the MGs ($\mathcal{N}$,v) coalition game:

$$v(S) = \max_{\Omega \in \mathcal{S}_S} u(S, \Omega) \tag{9}$$

IV. Envisioned Game Therotic Coalition Formulation Strategy (GT-CFS)

In a game, players can make different choices, e.g., which coalitions to join and which coalition/MGs/MS to buy the power from. Each player confronts the best possible choice for him. Note that this is the reason behind our motivation to propose an adequate algorithm to help the MGs to choose the best decision. Therefore, an effective strategy is essential to ensure that the sum of the power transfers between the coalitions and the MS is the minimum, so as to maximize the payoffs of the MGs. To achieve this objective, we want to increase the utilities of the coalitions. In eq. (8), $u(S, \Omega)$ is made up of three terms. Generally speaking, the power loss between the MS and MGs is much higher than that between the MGs. Hence, the first term is much lower than the second term and the third term in the same condition. In other words, we can minimize the power transfer between the coalition and the MS to alleviate the power loss out of the coalition. Therefore, in order to maximize eq. (9), a strategy will be designed that can find the coalition having the MGs so as to ascertain the minimum power loss between the coalition and the MS, or obtain the maximum profit from forming the coalition. To achieve this target, MGs can calculate the value of Difference of Power loss per unit Power (*DPP*) between within coalition and out of the coalition. It is obvious that the greater difference will bring greater payoff for the coalition. If MG_i wants to form coalition with MG_j and the quantity of transfer is Q_{ij}, the function of DPP between them is as follow.

$$DPP(i, j) = \frac{P_{0i}(Q_{ij}) + P_{0j}(Q_{ij}) - P_{ij}(Q_{ij})}{Q_{ij}} \tag{10}$$

where P_{0i}, P_{0j}, and P_{ij} are given by eqs. (2) and (6). In other words, the function of *DPP* is the marginal value of a MG for the coalition. For maximizing the profit of coalition, MGs will find the partners which are able to maximize the eq. (10). In this vein, our envisioned strategy is as follows.

- Initialization: sort S_s and S_b in descending order, according to the requests of MGs (selling or buying), i.e., $S_b = \{b_1, ..., b_k\}$, and calculate the sum of sets respectively and find the less one of two sets. To facilitate the description of the algorithm, we may assume that S_b is the less one. Then, select $b_l \in S_b$ as the objective.
- Step 1: depending on the demand of objective, based on eq. (10), find the *appropriate* MGs in S_s or S_b to form coalition S with objective, which can ensure that the profit of coalition S is the maximum. Thus, this step indicates that the power loss of MGs in coalition S is less than that between the MS and the MGs belonging to the coalition S.
- Step 2: If the remainder of S_s is less than that of S_b, select the biggest one in S_s as the objective. Go to step 1, until there is no availability in the sets or one of the sets is an empty set.
- Step 3: If the remainder of S_s is more than that of S_b, select the biggest one in S_b as the objective. Go to step 1, until no availability in the sets or one of sets is empty set.

Again refer back to eq. (9), which represents the maximum total utility produced by any $S \subseteq \mathcal{N}$. This represents that the minimum power loss over the distribution lines. Therefore, comparing with the non-cooperative case (described in Sec. III-A), the sum of utilities of MGs in the considered coalitions increase. That is to say, the MGs produce the extra profits through forming the coalition. Upon completion of the coalition formation, the MGs belonging to the same coalition face the problem of how to distribute the extra profits appropriately in the coalition. If the allocation of profits is not appropriate, the coalition will be split into parts. Thus, we need an appropriate allocation for the profits.

For this purpose, we choose the "Shapley" value concept from cooperative game theory [21]. In each the cooperative game, it assigns a unique distribution (among the players) of a total surplus produced by the coalition of all the players. When a MG joins in a coalition, it will bring income for the coalition. However, different order that MGs join in the coalition means different income. Shapley value is average income, which is generated by a MG join in a coalition. In other words, the Shapley value of a MG is the contribution of that MG to its coalition. Profit distribution totally depends on the MGs' contribution for the coalition. Furthermore, the "Shapley" value of a MG is the contribution of this MG. Therefore, if all the "Shapley" values of MGs are given, the profit may be distributed. If there is a coalition game $(\mathcal{N}, v)$, the Shapley value of player i (MG_i) can be calculated by following formula:

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

where *n* is the total number of players and the sum extends over all the subsets *S* of $\mathcal{N}$ without the i^{th} player, and $v(S)$ is given by eq. (9). The formula can be interpreted as follows. Imagine that the coalition is formed one player at one time, each player demands their contribution $v(S \cup \{i\}) - v(S)$ as an appropriate compensation, and then averages over the possible different permutations in which the coalition can be formed. In Section III, the function *v* of MG is given. Hence, the "Shapley" value can be calculated.

Furthermore, since the payoffs depend upon the MGs' order in the coalition, the payoffs are likely to be different in different orders. In fact, the contribution of a player to the coalition is independent of the order. Therefore, the fraction in eq. (11) attempts to calculate the average of the payoffs in all conditions, and this average is the contribution of the player to the coalition. Additionally, the Shapley value has nothing to do with the costs of the players. For example, consider three players, costs of whom are 10, 20, 30, respectively. Then, the payoff function is as follows.

$$v(S) = \begin{cases} 1 & : \quad S = \{1, 2, 3\} \\ 0 & : \quad otherwise, \end{cases}$$

The number of orders is six. Different orders mean different payoffs. Now, let us calculate the Shapley value of the 1^{st} player. From Table I, we can find the value of the 1^{st} player to be $\frac{1}{3}$. Similarly, note that the values of the 2^{nd} and 3^{rd} players are the same as the 1^{st} player. All the values are $\frac{1}{3}$. Thus, their contributions for the coalition are same, although their costs are different.

From eq. (11), we can see that if two MGs have equal contributions to the coalition, their corresponding Shapley values are the same, although their individual values are different. Furthermore, the value is independent of the order of MG in the coalition. At the first glance, the result may appear to be unfair; however, it indicates the practical contribution of the players to the coalition. Therefore, MGs in the same coalition may distribute the extra payoff, based on eq. (11).

TABLE I
THE SHAPLEY VALUE OF PLAYER 1

Order	$v(S \cup \{1\}) - v(S)$
Order 1,2,3	$v(\{1\}) - v(\emptyset)$=0-0=0
Order 1,3,2	$v(\{1\}) - v(\{\emptyset\})$=0-0=0
Order 2,1,3	$v(\{2,1\}) - v(\{1\})$=0-0=0
Order 3,1,2	$v(\{3,1\}) - v(\{1\})$=0-0=0
Order 2,3,1	$v(\{2,3,1\}) - v(\{2,3\})$=1-0=1
Order 3,2,1	$v(\{3,2,1\}) - v(\{3,2\})$=1-0=1

Algorithm 1 COALITION FORMING ALGORITHM OF MGs

Initial State

Each coalition is one MG, which means that all MGs cannot form coalition with others. Therefore the network is partitioned by $\mathcal{S} = S_1, S_2, ..., S_N$.

Stage 1 Coalition Formation:

repeat

a)$\mathcal{M} = Merge(\mathcal{S})$: the MGs will form coalition or merge small coalitions to big one.

b)$\mathcal{S} = Split(\mathcal{M})$: the MGs will decide to leave from the coalitions to form new coalitions through the Pareto Order in (8).

until no MGs can do merge-and-split operation to get more payoffs, and the network is partitioned by S'.

Stage 2 Power transfer:

repeat for every $S_i \in S'$

the MGs $\in S_i$ will exchange power with others by the order of forming coalition.

until no local power transfer is possible.

if every $S_i \in S'$, any seller or buyer, which has not meet its demand or has power surplus to sell, can exchange power with MS.

Based on the envisioned strategy for objective selection and the concept of Shapely value for extra profit distribution in a coalition, we propose an algorithm to formulate distributed coalitions of MGs in the remainder of this section. First, we need to introduce an important definition from [20].

Definition 4.1: Consider two collections of disjoint coalitions $\mathcal{A} = \{A_1, ..., A_i\}$ and $\mathcal{B} = \{B_1, ..., B_j\}$ which are formed out of the same players. For one collection $\mathcal{A} = \{A_1, ..., A_i\}$, the payoff of a player *k* in a coalition $A_k \in \mathcal{A}$ is $\phi_k(\mathcal{A}) = \phi_k(A_k)$ where $\phi_k(A_k)$ is given by (9) for coalition A_k. Collection $\mathcal{A}$ is preferred over $\mathcal{B}$ by *Pareto order*, i.e. $\mathcal{A} \triangleright \mathcal{B}$, if and only if

$$\mathcal{A} \triangleright \mathcal{B} \Leftrightarrow \{\phi_j(\mathcal{A}) \geq \phi_j(\mathcal{B}), \forall k \in \mathcal{A}, \mathcal{B}\} \quad (12)$$

with at least one strict inequality (>) for a player *k*.

The Pareto order means that a group of players prefer to join a collection $\mathcal{A}$ rather than $\mathcal{B}$, if at least one player is able to improve its payoff when the structure has been changed from $\mathcal{B}$ to $\mathcal{A}$ without cutting down the payoffs of any others.

In order to form the coalition, two distributed rules are needed: *merge* and *split* [22] defined as follows:

Definition 4.2: **Merge:** Merge any set of coalitions $\{S_1, ..., S_l\}$ where $\{\cup_{i=1}^{l} S_i\} \triangleright \{S_1, ..., S_l\}$, hence,$\{S_1, ..., S_l\} \rightarrow \{\cup_{i=1}^{l} S_i\}$.

Definition 4.3: **Split:** Split any coalition $\{\cup_{i=1}^{l} S_i\}$ where $\{\{S_1, ..., S_l\} \triangleright \cup_{i=1}^{l} S_i\}$, hence,$\{\cup_{i=1}^{l} S_i\} \rightarrow \{S_1, ..., S_l\}$.

From the definitions of merge and split, we find that some MGs and some MGs coalitions will join a new coalition or merge with a bigger coalition, respectively, if at least one of them can improve its payoff and do not cut down the payoffs of any other MGs and coalitions, respectively. On the other hand, a big coalition will be split into some small coalitions (or even disappear) if the MGs find that they can leave the coalition or merge with a smaller coalition, so as to get more payoffs than that in the current coalition. Hence, a merge or split decision by Pareto order will ensure that all the involved MGs agree on it.

Because the MGs act as players of a cooperative game, we propose a coalition formation algorithm called Game Theoretic Coalition Formulation Strategy (GT-CFS) by exploiting the merge and split operations as shown in Alg. 1. First, in our envisioned algorithm, each MG could obtain information of others (e.g., position, neighbour MGs, and so on) by using the communication infrastructure or communication technology of smart grid (i.e., smart meters). Second, the MGs will produce the power, meet the demands of the users, and decide to buy or sell the power. Third, the forming coalition stage starts when the merge process occurs as follows. Given a partition $\mathcal{S} = \{S_1, ...S_k\}$, each coalition $S_i \in \mathcal{S}$ will communicate to its neighbours. Using these negotiations, the coalitions will exchange the information with others. MGs want to find the best partners MGs to form coalitions, so as to get more profits (payoff). The rules of merge and split will help them to deal with it. The coalitions or MGs calculate their payoffs by employing eqs. (8) and (9), find that the payoffs of all of them will increase, and this is the Pareto order in eq. (12), if they can form a coalition. They will do it with the rule of the merge operation. For example, consider that there is a MG, which is able to sell power. Assume that the power loss between it and the MS is 0.2. If it can find a coalition, which needs power, and the power loss between them is 0.15, the MG will join the coalition. But during the next time interval, the surrounding circumstances of the MG may change, such as the coalition does not want to buy power from the MG, or there exists another coalition for the buyer such that the power loss is lower than that in the current coalition. Therefore, the MG will leave this coalition to find a new one so as to alleviate its power loss.

For any MG, the decision of merge and split is a distributed operation, and it is not be affected by other MGs or the MS. Most importantly, a MG is able to make it individually by following Alg. 1. After the merge and split iterations, the network will compose of disjoint coalitions, and no coalitions may have any incentive to perform further merge or split operation. Upon such convergence, the MGs within each formed coalition will start its power transfer stage.

In next section, a proof on the stability, convergence, and optimality of proposed GT-CFS algorithm is presented.

V. Proof of stability, convergence, and optimality of GT-CFS

It is important to show that our proposal is stable regardless of the environmental changes in the grid. Furthermore, it is also important to prove that it converges to an optimal solution. We begin our proof by providing a definition of stability followed by two theorems. The proof of each of the theorems is provided separately.

Definition 5.1: A coalition C: = $\{C_1, ..., C_k\}$ is $\mathbb{D}_{hp}$-stable if the following two conditions are satisfied.

(a) for each $i \in \{1, ..., k\}$ and for each partition $\{P_1, ..., P_l\}$ of the coalition C_i: $v(C_i) \geq \sum_{j=1}^{l} v(P_j)$.

(b) for each set T $\subseteq \{1, ..., k\}$: $\sum_{i \in T} v(C_i) \geq v(\cup_{i \in T} C_i)$.

Theorem 5.1: The coalition formed by proposed algorithm is $\mathbb{D}_{hp}$-stable.

Proof: From the Definition 5.1, we know that if a coalition formed by our proposed GT-CFS is $\mathbb{D}_{hp}$-stable, it must satisfy two conditions. At first, let us see the first condition. Assume $\{P_1, ..., P_l\}$ is an arbitrary partition of any stable coalition C_i. Select partition P_k arbitrarily from coalition C_i where $k \in \{1, ..., l\}$. Because each coalition and partition must have a "seller" and a "buyer", there exists a MG_j belonging to both P_k and C_i at least. If the payoff of MG_j in P_k is more than that in C_i, MG_j will use the proposed algorithm to split the coalition C_i into smaller coalitions so that the coalition C_i will not exist. Therefore, for any stable coalition C_i, which is formed by the proposed algorithm, condition (a) must be satisfied.

Then, let us discuss the second condition. For each coalition C_i which is formed by the proposed algorithm, if there exists a bigger coalition C' which is satisfied $C_i \subseteq C'$ and $v(C_i) < v(C')$, the MGs in C_i make use of the proposed GT-CFS to *merge* other coalitions with a bigger coalition C' where the MGs are able to get more payoffs than that in the smaller coalition C_i. However, C_i is formed by GT-CFS, and it is the final result. Hence, C' cannot exist. It contradicts the assumption of stable coalition C'. Therefore, for each coalition C_i formed by the proposed algorithm, condition (b) must be satisfied. ■

Remark: The first condition in Theorem 5.1 means that if a coalition is formed by the proposed algorithm, one cannot find its subsets, which are satisfied as the sum of subsets' payoffs is more than that of the coalition. Similarly, in the second condition, it means that it is not possible to find a bigger coalition C', which satisfies $C_i \subseteq C'$ and $v(C_i) < v(C')$. In other words, coalition C_i cannot provide extra profits for others when C_i joins a bigger coalition. As a consequence, another coalition does not want to merge with C_i to formulate a bigger one. Therefore, by using the proposed GT-CFS repeatedly, the final result becomes stable (regardless of the initial value).

Theorem 5.2: In the studied ($\mathcal{N}$,v) MGs coalition game, the proposed GT-CFS converges to the Pareto optimal $\mathbb{D}_{hp}$-stable partition, if such a partition exists. Otherwise the final partition is merge-and-split proof [23].

Proof: It is an immediate consequence of Theorem 5.1. ■

From theorems 5.1 and 5.2, we can see that the $\mathbb{D}_{hp}$-stable partition is an outcome of the algorithm of formation coalition based on merge-and-split iterations. In other words, the Pareto optimal one is only stable situation. Therefore, the MGs can exploit the operation of merge or split to change the coalitions until they get the $\mathbb{D}_{hp}$-stable.

Finally, by using GT-CFS, the MGs will make a decision regarding merge and split operations to finally determine whether the MGs will stay in the coalition or not, so as to increase their payoffs upon environmental changes (i.e., the variations in the surplus or the need of power due to the changes in the demand or production of one or more MGs). To deal with it, GT-CFS is repeated periodically so that it allows the MGs to make a new decision of merge or split to adapt to the environment which has been changed.

VI. Optimal number of MGs in a region

In the previous section, our proposed algorithm of forming coalitions dubbed GT-CFS is presented. MGs will supply the users with the power to meet their demands. However, an excessive number of MGs will increase the maintenance cost, and this will raise the costs of users. Therefore, a key question arises in terms of the appropriate number of MGs in a given region to participate in the coalitions formation. This issue is addressed in this section.

Assume that the total demands of the users in a region are fixed to D_{total} and the maintenance cost of the MG is a constant C_0. Additionally, assume that the maximum production of MGs are the same, denoted by G. From eq. (6), when *m* power is transmitted, the average power loss is:

$$P_1(m) = \frac{R_{avg1} m^2}{U_1^2}, \tag{13}$$

where R_{avg1} refers to the average resistance among MGs and it is an area-related constant. When the electricity production *m* does not meet the demand D_{total}, the users need to buy power from the MS. Based on eq. (13), the request function $R_{MS}(m)$ is:

$$R_{MS}(m) = D_{total} - m + P_1(m). \tag{14}$$

By using eqs. (2), (3), and (4), we can calculate the average power loss between the MGs and the MS, when power $R_{MS}(m)$ is transmitted between the MGs and the MS. The power loss function $P_2(m)$ is given as follows.

$$P_2(m) = \frac{R_{avg2} m^2}{U_0^2} + \alpha m, \tag{15}$$

where R_{avg2} is the average resistance between the MG and the MS. It is also an area-related constant. When the production of electricity from the MGs is less than the demands of users, the users are able to buy the rest from the MS. The total cost C_1 can be expressed as:

$$C_1(n) = w_1(nG) + w_2(R_{MS}(nG) + P_2(R_{MS}(nG))) + nC_0, \tag{16}$$

where $n \in \mathbb{N}$ denotes the number of MGs. Similarly, when the production is not less than the demands, the cost can be expressed as C_2 as below.

$$C_2(n) = w_1(D_{total}) + nC_0. \tag{17}$$

Therefore, when the number of deployed MGs is $n \in \mathbb{N}$, the COsting Money for Electricity (*COME*) is given by:

$$COME(n) = \begin{cases} C_1(n) & : \ nG \leq D_{total} + P_1(nG) \\ C_2(n) & : \ otherwise \end{cases} \tag{18}$$

If *N* is the optimal number of MGs, *COME(N)* will satisfy

$$COME(N) = \min_{n \in \mathbb{N}} COME(n) \tag{19}$$

The next theorem will guarantee that the function *COME(n)* exists with a minimum.

Theorem 6.1: The function *COME(n)* exists with a minimum.

Proof: If a minimum of COME(n) exists, it must satisfy $(\min COME(n) = \min(C_1(m), C_2(l)) \ \forall n, m, l \in \mathbb{N})$. If C_1 and C_2 exist with their minimum, the minimum of *COME* exists. It is obvious that $C_2(n)$ is an increasing function of n. Therefore, a minimum of $C_2(n)$ exists. Let us consider the function $C_1(n)$. Note that $n \in [1, \lceil \frac{D+P_1(NG)}{G} \rceil]$, when $COME(n) = C_1(n)$. Hence, the minimum of $C_1(n)$ exists. As a consequence, the function *COME(n)* exists with a minimum. ■

Thus, if the afore-mentioned parameters are known, the optimal number of MGs can be calculated.

When we know the maximum of demand, based on our algorithm, the maximum number of MGs is given. When the demand below the maximum, MGs will decrease their productions, or may not even generate additional power for some period. Therefore, our algorithm is able to adjust the number in a real system.

In the following section, the effectiveness of our proposal is evaluated.

VII. Performance Evaluation

In this section, simulation results are presented to evaluate the effectiveness of our proposed GT-CFS. Our considered simulation scenario comprises a power distribution grid topology, area of which is $10 \times 10 \ km^2$. The MS is placed at the center of the grid, and the MGs are deployed randomly in the topology. For convenience, the MG and the users linked to this MG are regarded as a whole. Therefore, the demands of user is equal to the demand of MG. The power requirement parameter of MG_i denoted by Req_i is assumed to be a random variable distributed from -200 MW to 200 MW (note that the negative and positive signs of Req_i imply that MG_i is a "buyer" or a "seller", respectively). The resistance between the MGs is the same as that between the MS and any MG, and its value $R = 0.2 \ \Omega$ per km. The fraction number of power transfer $\alpha = 0.02$ according to the assumption in [24]. The voltage values of U_0 and U_1 are set to 50 kV and 22 kV, respectively, which represent practical values in a variety of smart grid distribution networks [24]. The price of the each of the unit power loss parameters is set as $w_1 = 1$ and $w_2 = 3$. These values are set arbitrarily and do not affect the fundamental observations in the conducted simulation. The simulation results are presented in the remainder of this section.

Fig. 2 depicts the average power loss per MG for varying number of MGs from two to 100 in case of the non-cooperative

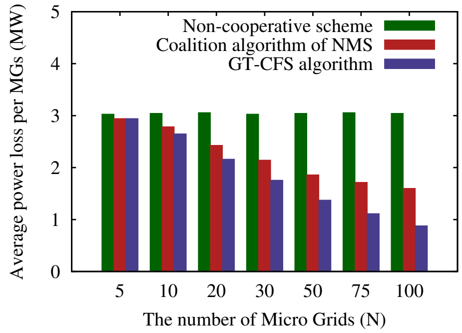

Fig. 2. The comparison of Noncooperative case and coalition case

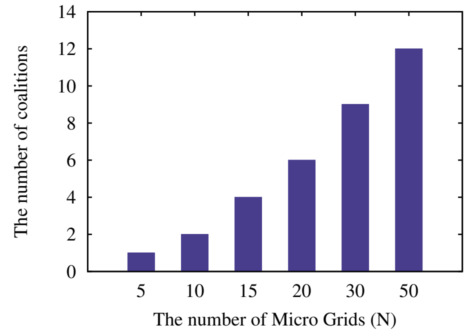

Fig. 4. The number of coalitions

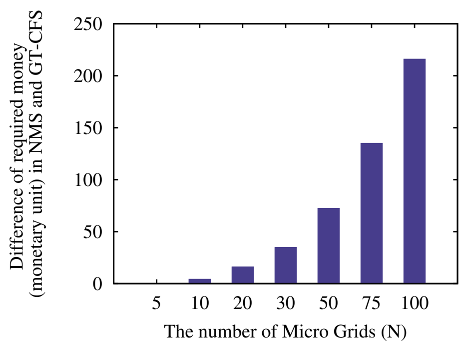

Fig. 3. The comparison of NMS case and GT-CFS case

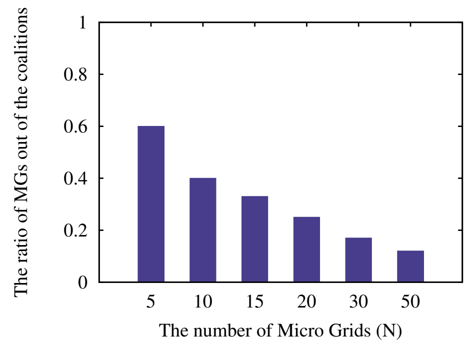

Fig. 5. The ratio of Micro Grids out of coalitions

model, a conventional algorithm called NMS [19] (MG will find the nearest neighbour MG to form coalition), and our proposed GT-CFS. The results in the figure indicates that when the number of MGs increases, the average power loss changes just a little in the non-cooperative game case. However, in the cooperative coalition cases, i.e., in our GT-CFS and the conventional NMS, the power losses decrease (sharp initial drop followed by gradual descent) with the increasing number of MGs. For instance, when the number of MGs is 100, the power loss in GT-CFS reaches up to significant reduction in contrast with the non-cooperative game case, and exhibits better performance compared to the cooperative NMS approach. The good performance of GT-CFS can be attributed due to the fact that the power losses within its formed coalitions are much lower than those between the MS and MG(s). Hence, when most of the MGs are in the coalitions, the whole costs of the users decrease. However, power losses exist in the coalition, when power has been transmitted. Therefore, the average power loss does not always fall, as verified by the shape of the curve demonstrated in Fig. 2.

Furthermore, in GT-CFS, the sum of power losses in the coalitions is less than that in the NMS. This is because GT-CFS helps coalitions to select MGs, marginal values of which for the coalition are the maximum. In other words, the value of DPP is the maximum. On the other hand, when the power loss between the MGs remain the same, the coalition selects the MGs which are further away from the MS, and thus, the coalition gets more profit from the selected MGs. However, NMS only selects the nearest MG to form coalition and it cannot guarantee the profit of coalition is maximum. As a consequence, GT-CFS outperforms NMS in terms of improvement of the average power loss.

Fig. 3 demonstrates the difference of the money required for buying power in case of NMS and that in our proposed GT-CFS. As shown in the figure, when the number of MGs increases, the difference of the required money (i.e., saved money by using GT-CFS) becomes larger. It is because GT-CFS will help coalition to find the MGs which can bring maximum payoff with coalition while NMS only considers finding the nearest MG to decrease the power loss. Coalitions are able to obtain more profit from GT-CFS than that from NMS. Hence, our algorithm may help the MGs to save a significant amount of money in contrast with the NMS algorithm.

Next, from Fig. 4, we can see that the number of coalitions increases with the number of MGs increasing. This supports intuition. If we analyse numerically, the number of coalitions increases from 1 (for 5 MGs) to 12 (for 50 MGs). Note that the positions of MGs are fixed since their random deployment in the simulation grid topology. Hence, the power losses between the MGs and MS are fixed when they want to transmit the same power. However, with the increasing number of MGs, the distance between them becomes shorter and shorter and the power losses among the MGs decrease. Therefore, in order to decrease the power loss, the MGs can form the coalitions and exchange power with others.

In Fig. 5, the result demonstrates that with the increasing of number of MGs, less and less MGs are left without being inside coalitions. Also, it indicates that the MGs can form coalitions easily, because of the shortened distance among

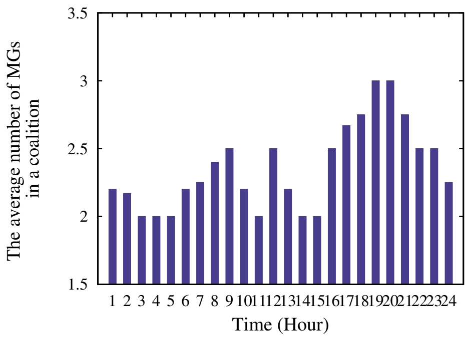

Fig. 6. The average number of Micro Grids in coalitions

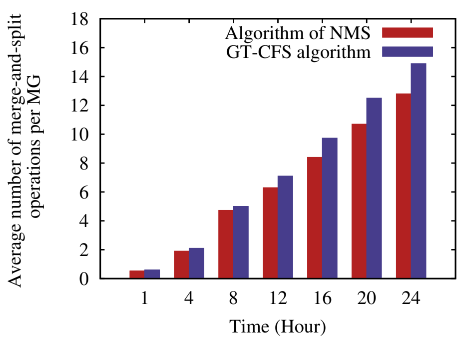

Fig. 7. Average number of merge-and-split operations per MG versus the frequency of changes in the power needs of the MGs over a period of 24 hours

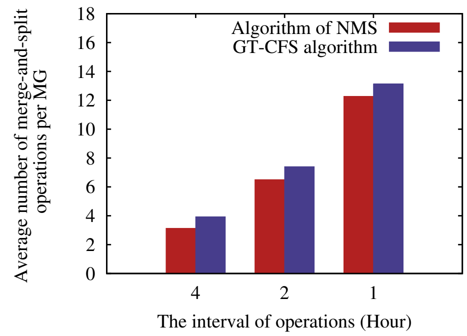

Fig. 8. Average number of merge-and-split operations per MG versus the different interval over a period of 24 hours in the different algorithms

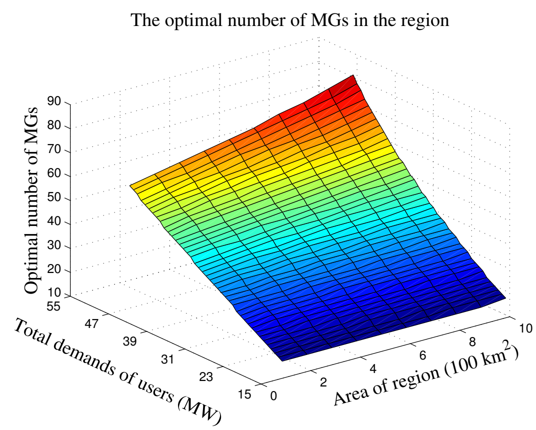

Fig. 9. The optimal number of MGs in the region

them. Furthermore, it also reflects the fact that the MGs can sell or buy power easily from other MGs than the MS. However, from this figure, we find that some MGs are out of the coalitions. There are two reasons that a MG is not part of a coalition. The first reason is that the MG is far away from other MGs. In this case, the power losses among this MG and others are larger than that between this MG and MS. Therefore, no coalition will allow this MG to join any of the coalitions. The second reason is that the demands of MGs is zero (e.g., the coalition 3 in Fig. 1). It means that the MG does not need to exchange power with others.

Assume, for example, that the peak period in the power grid is observed twice a day, namely in the morning (from 6 AM to 9 AM) and in the evening (from 4 PM to 9 PM). Furthermore, the number of MGs is 15 whose situations remain fixed since their initial random deployment in the simulated grid. Fig. 6 shows the variation of the average number of MGs in a coalition in a day. The average number of MGs per coalition during the peak period is 2.58 while during the off-peak period it has a lower value of 2.11. It is because that during peak time, the users need more electricity to meet their demands than that in off-peak time, and the MGs will not exchange power when they belong to different coalitions. Therefore, the MGs need to change coalitions to buy power from others. Thus, it also becomes obvious that forming coalition is a good choice for the MGs, regardless of whether they act as “buyers” or “sellers”.

In Fig. 7, we plot the average number of merge and split operations per MG (i.e., overhead) versus the frequency of changes in the power needs of the MGs over a period of hours, for N = 15 MGs in the different algorithms. Here, an interval of one hour is considered. Comparing with the conventional NMS approach, the number of operations in our proposed GT-CFS is slightly higher per day. It is because that the MGs need to change coalitions during different time periods to get an optimal power loss improvement. Indeed, in our proposal, the MGs form the coalitions based on the minimization of the total power loss during power transfer within the coalitions. Therefore, the average number of merge and split operations is found to be slightly higher than that in the NMS algorithm. However, from earlier sections, we also know that there exists a minimum power transfer between the MGs and the first part of eq. (8) is significantly less than the others in the same condition. In other words, to choose the nearest MG in a coalition does not mean the total power loss is minimum. The proposed GT-CFS is able to guarantee maximization of the total power in the coalitions and minimization of the power loss between the considered MGs or between the MS and MG(s). Hence, GT-CFS exhibits better performance in contrast with NMS.

Next, Fig. 8 demonstrates that, as the dynamics of the environment change and become faster, i.e., the frequency of changes increases, the MGs require a higher number of merge and split operations to adapt to the updated network structure. For instance, while 3.13 and 3.93 merge-and-split operations are required when the power needs change 6 times every 24 hours (for N = 15 MGs) by using the different algorithms respectively, these numbers increase to 12.26 and 13.13 when the power needs change roughly every hour. Nevertheless, in smaller time intervals, the difference of merge and split operations in existing NMS algorithm and proposal is not high. In fact, our proposed GT-CFS saves a significant amount of power loss with a slight higher overhead.

In terms of saving money of the users, Fig. 9 depicts the optimal number of MGs in different cases. Remember that the optimal number of MGs depends on the area of the considered region and the demands of users in that area. For this reason, with their increasing demands, users need more electricity from the MGs to reduce their costs. For example, the optimal number becomes from 15 to 50, when the demands change from 15 MW to 55 MW in the the simulated grid area of $10 \times 10\ km^2$. Additionally, a higher resistance means a higher power loss. Hence, when the area is larger, more MGs are wanted to minimize this higher power loss. When the area changed from 100 km^2 to 1000 km^2 and the demands are 15 MW, the number of MGs becomes from 15 to 17. Thus, it is evident from Fig. 9 that the increasing speed of demands is more than that of the power loss.

VIII. Conclusion

In this paper, we proposed a novel game theoretic coalition formulation strategy dubbed GT-CFS for distributed micro grids. Our proposal allows the MGs to form coalitions so that the power loss is minimized when power is transmitted from a MG to other MGs or the macro station. The proposed GT-CFS also allows the MGs to make decisions on whether to form or break the coalitions while maximizing their utility functions through alleviating the power loss within power transfer. The proof of stability and optimality of GT-CFS is presented. Also, an analysis on determining an optimal number of MGs required for a given area is conducted. Through simulation results, the effectiveness of GT-CFS is verified. Comparative results demonstrate its superior performance, in contrast with the non-cooperative model and the conventional NMS model, in terms of a significant reduction of the average power loss per MG. In future, it will be interesting to analyse the interactions of the customers with their corresponding MGs to explore possibility of formulating more effective coalitions and reduce further power loss. Additionally, energy storage devices for the MGs can be added to our list of assumptions in the future extension of our work. The energy storages devices for the MGs will store the power in the off-peak periods and release the power to meet the demands of users in the peak time. However, at the same time, the devices will increase the costs of users. Therefore, there should be an optimal result to solve the problem that what is the best choice for the MGs.

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