Cooperative Energy Management Software for Networked Microgrids

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Abstract: Smart distribution systems are critical cyber-physical energy systems that consists of multiple networked microgrids (MGs) with a distributed architecture. The main problem behind these cyber-physical energy systems is how to manage energy sources to have an efficient and economic energy supply. This paper proposes a cooperative energy management software (EMS) for networked microgrids (MGs) by explicitly modeling the cooperative behavior of MGs. The network of MGs is autonomously self-organized into multiple stable coalitions to achieve an efficient and economic energy exchange. The coalition consists of several MGs that exchange energy with a competitive energy prices to maximize their utility. We formulate the problem of energy management in networked MGs by a coalition formation game between MGs. We develop a merge-and-split-based coalition formation (MSCF) algorithm to ensure the stability of the formed coalitions and maximize the profits of MGs. Then, we design an intra coalition energy transfer (ICET) algorithm for transferring energy between MGs within the same coalition to minimize power loss. The simulation results demonstrate a satisfactory performance in terms of profit maximization that exceeds 21% and in terms of power loss reduction that exceeds 51%, thanks to the proposed cooperative energy management software.

1 INTRODUCTION

The architecture of smart distribution systems is becoming more and more complex after the appearance of networked microgrids (MGs). Smart distribution systems turn into several networked MGs that consists of distributed energy resources (DERs). The smart distribution system must operate in a reliable and safe manner as in manufacturing systems (Gu et al., 2018), (Khalgui et al., 2008) where the control system can reconfigure the operation and adapt its behavior to the related situation (Hafidi et al., 2018). Recently, with the increasing integration of distributed energy resources especially renewable energy, manifold MGs may emerge within the distribution system, which triggers the problem of energy management of multiple networked MGs (Asarias and Pedrasa, 2017). The most practical solution of this problem is to develop an efficient energy management software (EMS) that is responsible for the management of power sources to provide a sufficient power supply to the end users (Naidji et al., 2018).

The EMS has the objective to operate the power generation efficiently and economically to supply the end users and increase the reliability of the system by proactively minimizing blackouts (Meskina et al., 2017), (Meskina et al., 2018). At this point, the energy management problem generates multiple sub-problems such as operational cost optimization, power loss reduction, energy consumption scheduling or power supply availability (Abidi et al., 2017). Thus, an intelligent distributed solution should be looked for (Khalgui and Mosbahi, 2010) under energy constraints (Aissa et al., 2019), (Ghribi et al., 2018) which can be a multiobjective optimization (Lakhdhar et al., 2019) in some situations. Several studies in the literature addressed the energy management in networked MGs by proposing different softwares with different perspectives. The authors in (Wang et al., 2015) propose a coordinated EMS of networked MGs. The coordinated operation between MGs is formulated as a stochastic bi-level problem with the objective to reduce the operational costs of both MGs and DSO. In (Zamora and Srivastava, 2018), a voltage and frequency control algorithm is designed using multi-layer architecture in Networked MGs to regulate volt-

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age magnitude and frequency, as well as output power of the distributed generations (DGs). In (Nunna and Doolla, 2013), a multi-agent system (MAS) based EMS in networked MGs is proposed with the participation of the different entities in the energy market. In (Fathi and Bevrani, 2013), the energy consumption scheduling in networked MGs is studied considering the uncertainty of load demand. In (Wu and Guan, 2013), the energy management in networked MGs is modeled by a decentralized partially observable Markov decision process. A dynamic programming solution is proposed to minimize the MG operational cost.

However, in most of the above existing research efforts, the cooperative behavior of MGs has not been explicitly modeled. Only interactions between MGs and DSO have been considered which limits the gain of MGs. The cooperation between MGs can be ensured by forming several coalitions. The coalition consists of several MGs that exchange energy with a competitive energy prices.

The studies in (Jadhav and Patne, 2017), (Gao et al., 2018), (Cintuglu and Mohammed, 2017), (Ma et al., 2018), (Du et al., 2018) demonstrate that the interconnection of multiple MGs can improve the system operation and control. In (Jadhav and Patne, 2017), a priority-based energy scheduling problem is designed for multiple MGs. A non cooperative energy competition game is designed to solve the problem. In (Gao et al., 2018), a decentralized EMS is proposed to control the operation of power exchange between the DSO and MGs. The alternating direction method of multipliers is used to solve the problem. In (Cintuglu and Mohammed, 2017), a novel bidding behavior and an auction architecture is proposed to enable competitive negotiations between networked MGs and the central aggregator. The authors in (Ma et al., 2018) propose an online EMS for the DSO to control energy scheduling of networked MGs using regret minimization and online alternating direction method of multipliers. In (Du et al., 2018), a cooperative operation model is proposed for multiple MGs where the whole network is considered as a grand coalition to achieve higher operation economy. However, even when the cooperation is addressed, the stability of the formed coalitions is not ensured. These limitations can reduce the gain of MGs and increase the cost including power loss.

In this respect, the main contribution of this paper is the proposal of a new cooperative energy management software in networked MGs using coalitional game theory to self-organize into multiple stable coalitions for maximizing the profits of MGs. We develop a merge-and-split-based coalition formation (MSCF) algorithm based on coalitional game theory and merge and split rules to ensure the stability of the formed coalitions. Then, we develop an intra coalition energy transfer (ICET) algorithm to transfer energy between MGs that are in the same coalition. The ICET algorithm aims to minimize power loss resulting from transferring energy in long distances. Significant gains are obtained with the proposed energy management software in terms of profit maximization, thanks to the designed coalition formation algorithm, and in terms of energy saving, thanks to the energy transfer algorithm. The originality of this paper is threefold:

- The proposal of a cooperative energy management software that ensures the cooperation between MGs by forming several stable coalitions.
- The maximization of the profits of MGs and reduction of power loss by the cooperation between MGs.
- The control of complexity of the energy management problem in networked MGs.

Section 2 presents the system model. Section 3 formulates the problem of energy management in networked MGs with the proposed cooperative game theoretic approach. Section 4 gives the proposed methodology for solving the energy management problem. Section 5 shows the simulation results and finally Section 6 concludes this paper.

2 SYSTEM MODEL

This section describes the networked MGs system architecture, the pricing scheme that allows to apply the coalition formation, and the coalition formation preliminaries.

2.1 Networked Microgrids Architecture

Consider a smart distribution system managed by the distribution system operator (DSO). The system consists of N networked MGs with distributed energy resources (DERs) that are composed of: Distributed generation (DG) units which can be conventional or renewable generators, and energy storage systems (ESSs). The distributed energy resources are responsible for the power supply of the microgrid. We assume that each microgrid has loads to serve. We also assume that each microgrid has an energy management software (EMS) that is responsible for the optimization of power consumption and usage of DERs.

We organize MGs into groups (also called coalitions). Let Θ_i^j denotes the i^{th} MG belonging to the j^{th}

group (i.e., coalition). Let $D(\Theta_i^j)$ be the total demand of Θ_i^j and $S(\Theta_i^j)$ its total supply. The energy status $E(\Theta_i^j)$ of Θ_i^j is given by the difference of total supply and demand, i.e.,

$$E(\Theta_i^j) = S(\Theta_i^j) - D(\Theta_i^j) \quad (1)$$

A positive value of energy status denotes that Θ_i^j can sell $E(\Theta_i^j)$ amount of energy while a negative value denotes that Θ_i^j needs to purchase $E(\Theta_i^j)$ amount of energy from the distribution system. Therefore, the set of all MGs can be grouped into three subsets that are balanced MGs $\Lambda = \{\lambda_1, \ldots, \lambda_{|\Lambda|}\}$, MGs with energy surplus $\Pi = \{\pi_1, \ldots, \pi_{|\Pi|}\}$ and MGs with energy shortage $\Psi = \{\psi_1, \ldots, \psi_{|\Psi|}\}$.

Conventionally, the energy transfer is carried out between MGs and DSO. Consequently, this transfer results in more power loss due to the existence of transformers and the transmission loss due to the Joule effect if the DSO is located within long distances to the microgrid. Furthermore, the energy transfer between MGs and DSO is unprofitable to MGs due to operator policy that imposes disadvantageous energy prices (e.g., the operator buy in low prices and sell in high prices).

An interesting alternative to achieve a cost effective energy management and minimize the power loss is the cooperation between MGs by forming coalitions. The MGs inside the same coalition can exchange energy with a competitive energy price and interact with the distribution system operator as a last resort to minimize the power loss and reduce the energy cost. The networked MGs system is described in Fig. 1. Each microgrid consists of distributed energy resources (DERs) such as distributed generation (DG) units and energy storage systems (ESSs). Furthermore, each microgrid is connected with the distribution system through a voltage transformer while it is connected with the other MGs via a low voltage power line. With this architecture, a microgrid can exchange power with another microgrid if there is a transmission line between them, i.e., a low voltage power line. This energy exchange brings more profit to both MGs since it is cheaper and more efficient than exchanging with the distribution system.

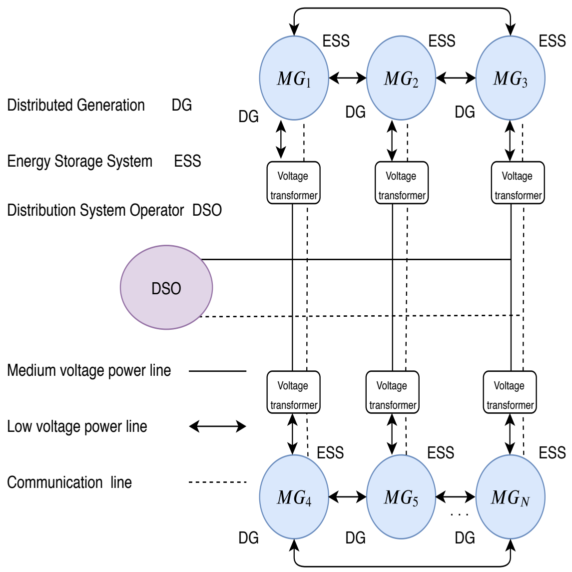

Figure 1: Networked MGs system architecture.

2.2 Pricing Scheme for Coalition Formation

The pricing scheme is an influential factor to perform cooperation between MGs. Particularly, the coalition formation process should justify the preference of MGs over the DSO in energy exchange. The design of an inappropriate pricing scheme will result in disadvantageous outcome. The designed pricing scheme must motivate a microgrid to cooperate with other MGs by exchanging the energy surplus. Thus, we have designed a motivating pricing scheme to ensuring that forming coalitions between MGs is always more rewarding than exchanging with the DSO. For instance, let us assume that $\alpha = 0.2\$/kwh$ is the energy selling price to the DSO, $\beta = 0.4\$/kwh$ is the energy purchasing price from DSO and $\gamma = 0.25\$/kwh$ is the price of selling/purchasing energy between MGs. Hence, a microgrid always prefers to exchange energy with other MGs since it can save $0.05\$/kwh$ in selling and $0.2\$/kwh$ in purchasing by exchanging energy to MGs instead of DSO. Thus, the pricing scheme is designed as follows:

$$\beta > \gamma > \alpha \quad (2)$$

where we define σ as a threshold given by $(\gamma - \alpha) \leq \sigma$.

2.3 Coalition Formation Preliminaries

An interesting framework for coalition formation is given in (Apt and Witzel, 2009) using merge-and-split rules. To run the coalition formation game, the following preliminaries are required.

A coalition Ξ_j^k is a set of players, i.e., MGs that exchange energy in order to maximize their profits, i.e.,

$$\Xi_j^k = \{\Theta_1^j, \ldots, \Theta_{|\Xi_j^k|}^j\} \quad (3)$$

where j is the coalition number and k is the collection that the coalition belongs. A coalition is called the grand coalition G if it is formed by all the set of players N. A collection Ω_k is any family of mutually disjoint coalitions, i.e.,

$$\Omega_k = \{\Xi_1^k, ..., \Xi_{|\Omega_k|}^k\} \tag{4}$$

Various criteria exist in the literature to compare between collections or coalitions. In this paper, the Pareto order is used for comparing collections. The Pareto order is based on a preference operator $\triangleright$ which is an order defined for comparing two collections Ω_k and Ω_l. We assume that we have a subset $A \subseteq N$. Let us take two different partitions of the subset A as a choice that are Ω_k and Ω_l. Therefore, $\Omega_k \triangleright \Omega_l$ denotes that Ω_k is preferred than Ω_l in partitioning A.

In a collection Ω_k, each player, i.e., MG $\Theta_i^j \in \Xi_j^k$ has a utility function $\Phi(\Theta_i^j)$ which defines the payoff of the player in a coalition Ξ_j^k. Here in our case, as more the MG Θ_i^j exchanges energy in a coalition Ξ_j^k, the energy profit increases thus, the utility function is at its best (max) when the energy status of a MG $E(\Theta_i^j)$ in the coalition Ξ_j^k approaches to zero, i.e.,

$$\Phi(\Theta_i^j) = \begin{cases} max, & \text{if } E(\Theta_i^j) = 0, \\ \frac{1}{E(\Theta_i^j)}, & \text{otherwise} \end{cases} \tag{5}$$

$\Omega_k \triangleright \Omega_l$, i.e., Ω_k is preferred than Ω_l by Pareto order, if

$$\Phi(\Theta_i^j) \geq \Phi(\Theta_i^g) \quad \forall\, \Theta_i^j \in \Xi_j^k, \Theta_i^g \in \Xi_g^l \tag{6}$$

with at least one strict inequality, i.e., a collection is preferred by the players over another collection, if at least one player is able to improve its utility without decreasing the utility of the other players. Hence, the merge and split rules for coalition formation can be defined as follows:

Merge Rule: Merge any set of coalitions $\{\Xi_1^k, \Xi_2^k, ..., \Xi_{|\Omega_k|}^k\}$ if $\bigcup_{j=1}^{|\Omega_k|} \Xi_j^k \triangleright \{\Xi_1^k, \Xi_2^k, ..., \Xi_{|\Omega_k|}^k\}$

Split Rule: Split any coalition $\bigcup_{j=1}^{|\Omega_k|} \Xi_j^k$ if $\{\Xi_1^k, \Xi_2^k, ..., \Xi_{|\Omega_k|}^k\} \triangleright \bigcup_{j=1}^{|\Omega_k|} \Xi_j^k$

3 PROBLEM FORMULATION

This section gives the formulation of the energy management problem in networked MGs. Since the networked MGs system is a cyber-physical one, the problem of energy management here needs to be solved by an efficient software. The main problem here consists of two sub-problems that are coalition formation and energy transfer. The first sub-problem consists of forming several stable coalitions between MGs to optimize the power supply availability economically and efficiently. A coalition formation game is formulated for the cooperation between MGs to optimally exchange the power surplus. The second sub-problem consists of transferring energy in each formed coalition. The energy transfer problem is formulated as a power loss minimization problem to optimally transfer energy in each coalition.

3.1 Coalition Formation Game

3.1.1 Challenge

Instead of sharing the power surplus with the DSO, MGs can cooperate with others by forming several coalitions to exchange their power surplus. Unbalanced power of each microgrid is purchased or sold within coalition. After performing the energy transfer within coalition, the rest of energy surplus or shortage can be balanced by the DSO as a last resort.

3.1.2 Formalization

The coalitional game can be defined with the following pair (N, v) that consists of a finite set of players N (MGs in our case) and a characteristic function or value v. The carachteristic function $v : 2^N \rightarrow \mathbb{R}$ associates a payoff $v(\Xi_j^k)$ for each coalition Ξ_j^k, i.e.,

$$v(\Xi_j^k) = \min \mid S(\Xi_j^k) - D(\Xi_j^k) \mid \tag{7}$$

The characteristic function v of a coalition Ξ_j^k is defined by the aggregated energy status in this coalition. Thus, $v(\Xi_j^k)$ has its best value when the difference between the total power demand and supply is minimized. The members of the coalition Ξ_j^k can distribute this payoff among themselves. Here, as less as a microgrid exchanges energy with the distribution system operator, it receives more payoff. A distributed coalition formation game is given by specifying a value for each coalition. The set of the formed coalitions form the coalition structure CS, .i.e,

$$CS = \bigcup_{j=1}^{|\Omega_k|} \Xi_j^k \tag{8}$$

The coalition structure payoff $\rho(CS)$ is the sum of the local coalition payoffs, i.e.,

$$\rho(CS) = \sum_{j=1}^{|\Omega_k|} v(\Xi_j^k) \tag{9}$$

3.2 Energy Transfer

The energy transfer (ET) among MGs in a coalition should have a minimum power loss $P_L^{\Xi_j^k}$. The overall power loss $P_L^{\Xi_j^k}$ of a coalition Ξ_j^k while transferring power among MGs is given by

$$P_L^{\Xi_j^k} = -\sum_{i,e \in \Xi_j^k} P_L(i,e) \tag{10}$$

where $P_L(i,e)$ is the power loss resulting from transferring energy over transmission lines between Θ_i^j and Θ_e^j. Note that, the power loss is defined as a characteristic function of a coalition Ξ_j^k instead of a microgrid Θ_i^j, since loss occurs during power transfer between MGs in the same coalition. Technically, the power loss according to (Gao et al., 2018) is given by

$$P_L(i,e) = I^2 R = \left[\frac{P(E)}{\mathcal{V}}\right]^2 . \alpha . d(i,e) \tag{11}$$

where $P(E)$ is the power required for energy transfer, $\mathcal{V}$ is the carrying voltage on the transmission line, α is the line resistance and $d(i,e)$ is the distance between Θ_i^j and Θ_e^j. The characteristic function of the coalition formation game is designed to consider a trade-off between power supply and loss. Overall, the energy management problem of networked MGs can be formulated with the following equations:

$$\max \rho(CS) \tag{12}$$

$$\min \sum_{\Xi_j^k \in CS} P_L^{\Xi_j^k} \tag{13}$$

4 METHODOLOGY

This section gives the solution of the energy management problem formulated in the previous section. The originality of this work is the proposal of a cooperative energy management software for networked MGs which is based on two algorithms: the coalition formation algorithm and energy transfer algorithm that are detailed hereafter. The software ensures the cooperation between MGs by forming several stable coalitions which lead to a significant technical and economical gains.

4.1 Coalition Formation

4.1.1 Motivation

As some MGs might fail to generate/consume the predicted amount of energy, they are required to exchange energy with other MGs at more beneficial prices than the DSO. For this reason, the energy management is executed in two consecutive steps that are coalition formation and then energy transfer. A coalition formation game is designed to form a stable coalition structure in order to maximize the profits of MGs. After that, the energy transfer process is executed to exchange energy in each coalition with the objective to minimize power loss. The proposed software is globally illustrated in Fig. 2 and detailed in the next subsections.

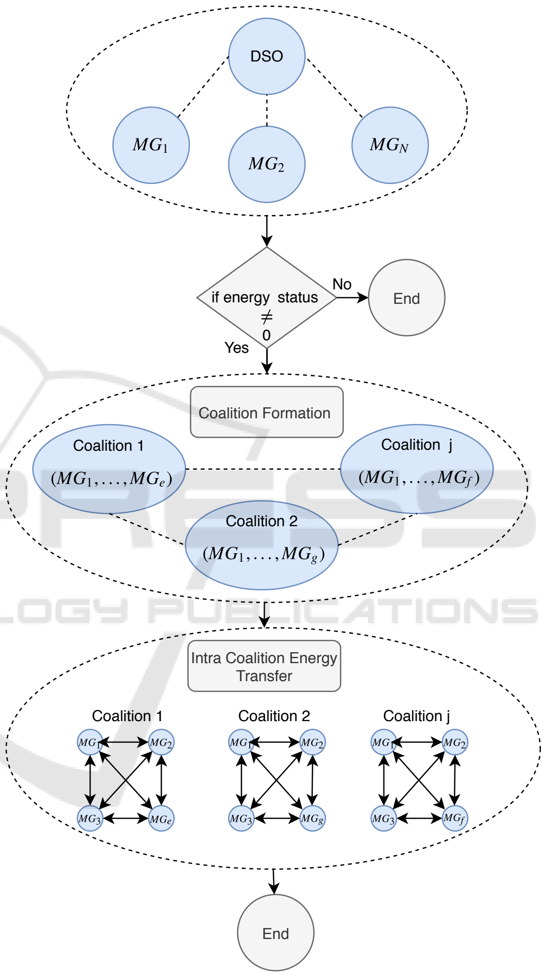

Figure 2: Flowchart of the proposed cooperative EMS.

The software starts by checking the energy status E of each microgrid in the network, if it is equal to zero, then the microgrid does not participate in the coalition formation game, else, the microgrid participates. After that, the coalition formation process starts forming several coalitions until the network is stabilized. Then, the intra coalition energy transfer starts transferring energy in each coalition in order to minimize the power loss.

4.1.2 Formalization

The set of balanced MGs Λ will not participate in the coalition formation game while MGs with energy surplus Π and energy shortage Ψ participate in the coalitional game. If $|\Pi| = 0$, then all of the MGs with energy shortage purchase power from the DSO, and if $|\Psi| = 0$, then all of the MGs with energy surplus sell power to the DSO. Thus, in such case, the MGs cannot cooperate. Specifically, the required condition for the coalition formation game is given by

$$|\Pi| \,.\, |\Psi| \neq 0 \tag{14}$$

The coalition formation game aims to find the best coalitions that maximize the profit from energy exchange, i.e.,

$$\Omega_k = \arg\max \sum_{j=1}^{|\Omega_k|} v(\Xi_j^k) \tag{15}$$

4.1.3 Implementation

Alg. 1 presents the proposed merge-and-split coalition formation algorithm (MSCF). The algorithm can be executed by a trusted third party that coordinates between coalitions and MGs. It assumes that MGs report their energy status to this party.

The first collection Ω_k is initialized with every singleton microgrid Θ_i^j as a coalition $\Xi_j^k \in \Omega_k$. A matrix called *visited* is used to memorize all pairs of the visited coalitions for merge process. The matrix has the structure of an adjacency matrix. Initially, the *visited* matrix is set to false for all coalitions, after that, the merge process starts. The collection Ω_k is submitted for merging, i.e., a random pair of coalitions (Ξ_j^k, Ξ_l^k) is chosen from Ω_k to check if $\Xi_j^k \bigcup \Xi_l^k \triangleright \{\{\Xi_j^k\}, \{\Xi_l^k\}\}$, then coalitions Ξ_j^k and Ξ_l^k decide to merge. $\Xi_j^k \bigcup \Xi_l^k$ is saved in Ξ_j^k, and Ξ_l^k is removed from Ω_k, then Ξ_j^k enters in the next merge step. So, the *visited* matrix is updated. Ω_k continues for merging by searching non-visited coalitions. After the test of all the combinations, if there is no merge, the merge process ends.

The resulted Ω_k is then passed to split process. Every coalition $\Xi_j^k \in \Omega_k$ having more than one member, i.e., microgrid, is subject to splitting. The algorithm tries to split Ξ_j^k into two disjoint coalitions Ξ_l^k and Ξ_m^k where $\Xi_l^k \bigcup \Xi_m^k = \Xi_j^k$. The splitting occurs only if one of the MGs belonging to the coalition can improve its individual payoff, without hurting the payoff of the other MGs.

If one or more split occurs, then merge process starts again. Multiple successive merge-and-split processes are repeated until the coalition formation game

Algorithm 1: Merge-and-Split Coalition Formation (MSCF).

Input: $\Theta_1^0, \Theta_2^0, ..., \Theta_N^0$ (set of microgrids)
Output: CS\{coalition structure\}
for $j \leftarrow 1$ **to** N **do**
    $\Xi_j^k = \Theta_j^j$;
end
initialization $\Omega_k = \{\Xi_1^k, \Xi_2^k, ..., \Xi_N^k\}$
repeat
    finish= *true*;
    forall $\Xi_j^k, \Xi_l^k \in \Omega_k, j \neq l$ **do**
        visited $[\Xi_j^k][\Xi_l^k] \leftarrow$ False
    end
    \{Merge process\}
    repeat
        $\Omega_k = Merge(\Omega_k)$
        update *visited* matrix
    until *(no merge occurs)*;
    \{Split process\}
    repeat
        $\Omega_k = Split(\Omega_k)$
    until *(no split occurs)*;
    if *(one or more split occurs)* **then**
        $finish = false$;
    end
until *(finish == true)*;
$CS = \Omega_k$;

terminates. The termination criteria is that there are no merge or split to execute for all existing coalitions in Ω_k.

4.1.4 Proof of Stability of the Proposed MSCF Algorithm

We demonstrate the stability of the formed coalitions regardless the environmental changes of the networked MGs system. We provide the concept of defection function given in (Apt and Witzel, 2009), to prove the stability of the formed coalitions.

Definition 4.1. A defection function $\mathbb{D}$ assigns to each partition P of the grand coalition G a group of collections.

The players in P can only form the collections assigned by $\mathbb{D}$. If no group of players is interested in leaving the partition P, then P is $\mathbb{D}$-stable. Apt and Witzel proposed in (Apt and Witzel, 2009) a defection function $\mathbb{D}_P$ that allows to form all partitions of P in the grand coalition G, such that, $\mathbb{D}_P$-stability is defined based on this defection function. $\mathbb{D}_P$ allows any group of players to leave P through merge-and-split rules to form another partition. Thus, $\mathbb{D}_P$-stability means that no coalition has a motivation to merge or split.

Running Example. In order to demonstrate the stability of the proposed algorithm, let us consider a simple example with three MGs with the following energy status $E = \{20, -5, -10\}$. Ω_k is initalized with every microgrid as a coalition Ξ_j^k, i.e., $\Omega_k = \{\Xi_1^k, \Xi_2^k, \Xi_3^k\}$. Ξ_2^k and Ξ_3^k cannot form coalition because they cannot improve their payoff since E is negative for both of them. Consider that Ξ_1^k communicates with Ξ_2^k in order to merge. Based on the values of E, $\{\Xi_1^k, \Xi_2^k\} \triangleright \{\{\Xi_1^k\}, \{\Xi_2^k\}\}$ since $\{\frac{1}{15}, max\} \triangleright \{\{\frac{1}{20}\}, \{-\frac{1}{5}\}\}$, such that both of Ξ_1^k and Ξ_2^k improve their payoff.

Now, there are two coalitions $\{\Xi_3^k\}$ and $\{\Xi_1^k, \Xi_2^k\}$. $\{\Xi_3^k\}$ communicates with $\{\Xi_1^k, \Xi_2^k\}$ in order to merge. $\{\Xi_1^k, \Xi_2^k, \Xi_3^k\} \triangleright \{\{\Xi_1^k, \Xi_2^k\}, \{\Xi_3^k\}\}$ since $\{\frac{1}{5}, max, max\} \triangleright \{\{\frac{1}{15}, max\}, \{-\frac{1}{10}\}\}$, so the merge occurs. This is because, Ξ_1^k and Ξ_3^k improve their payoff while Ξ_2^k keeps its previous payoff. Now $\{\Xi_1^k, \Xi_2^k, \Xi_3^k\}$ tries to split. Ξ_1^k will not split to from a coalition with Ξ_2^k or even with Ξ_3^k. Thus, there are no coalitions to be able to merge or split any further. As a result, the final coalition structure $CS = \Omega_k = \{\Xi_1^k, \Xi_2^k, \Xi_3^k\}$ is $\mathbb{D}_P$-stable.

The proposed algorithm is repeated periodically, enabling the MGs to autonomously self-organize in structured coalitions until no merge or split occurs, i.e., until the stability of the network.

4.1.5 MSCF Algorithm Complexity

The complexity of the proposed MSCF algorithm is determined by the number of merge-and-split attempts. In the worst case of merge process, each coalition attempts to merge with all the other coalitions in Ω_k. Thus, the first merge process occurs after $\frac{N(N-1)}{2}$ attempts, the second after $\frac{(N-1)(N-2)}{2}$ attempts and so on. In such case, the complexity is $O(N^3)$. However, the merge process significantly requires less number of attempts since a merge of two coalitions occurs, it does not need to search for other merge attempts.

Splitting a coalition Ξ_j^k in the worst case is $O(2^{|\Xi_j^k|})$ involving to find all the possible partitions of the considered coalition. To avoid this scenario, one of the two partitions of size $\mid \Xi_j^k - 1 \mid$ and 1, respectively, should be feasible. If none of them is feasible, the split process stops. So, the complexity of the split process depends on the size of the formed coalitions and not on the total number of MGs. As a result, in some cases the complexity of the split process is reduced to $O(\mid \Xi_j^k \mid)$. Therefore, the complexity of the proposed MSCF algorithm can be reduced by limiting the size of the formed coalitions, thus allowing to control the complexity of the proposed algorithm.

4.2 Energy Transfer

After the coalition formation process, the energy transfer among coalitions members is executed. Alg. 2 aims to find the optimal energy transfer between MGs in the same coalition by transferring energy between the closest MGs in order to minimize the power loss.

Algorithm 2: Intra Coalition Energy Transfer (ICET).

Input: Coalition Ξ_j^k, distance matrix $dist$
Output: Energy transfer matrix ET
Π = set of energy seller within Ξ_j^k;
Ψ = set of energy buyer within Ξ_j^k in decreasing order;
foreach $\psi \in \Psi$ **do**
    π = argmin $dist(\psi, \pi)$; %nearest MG seller %
    if ψ *is None* **then**
        $ET(0, \psi) = \psi.energy$;
        break;
    end
    $dif = \pi.energy - \mid \psi.energy \mid$;
    $\psi.energy \ -= dif$;
    $\pi.energy \ -= dif$;
    $ET(\pi, \psi) = dif$;
end
foreach $\pi \in \Pi$ **do**
    if $\pi.energy > 0$ **then**
        $ET(\pi, 0) = \pi.energy$;
    end
end

Initially, for each MG buyer, we search for the nearest MG seller. After that, we subtract the given amount of energy from the energy buyer and seller and the energy transfer matrix ET is filled with the energy sellers in rows and with energy buyers in columns and so on until we supply all the MGs that have energy shortage. Finally, if an amount of energy rests, it is saved in ET indexed with energy sellers in rows and zero in columns.

5 SIMULATION RESULTS

In this section, the proposed cooperative energy management software is applied on a case study consisting of multiple networked MGs and some simulation results are given.

5.1 Case Study

The networked MGs system is modeled with a mesh structure which ensures a high level of service. Fig. 3 shows the networked MGs system considered in our case study. The figure shows the distribution of microgrids around the distribution system operator.

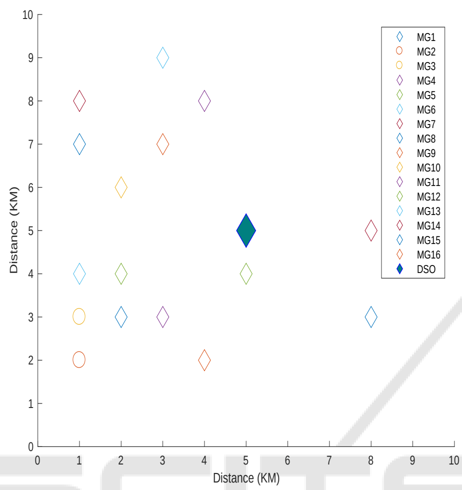

Figure 3: Networked MGs system.

We assume that the distribution network covers an area of 100 km^2 and consists of N MGs. We assume also that the MGs are randomly located around the distribution system operator (DSO) which is located in the center of the network. We have randomly scatter 16 MGs which is a reasonable number of MGs in real smart grids.

5.2 Coalition Structure

Fig. 4 shows the coalition structure of the proposed MSCF algorithm which is applied on our case study. Tab. 1 illustrates the coalition structure by specifying the MGs that belong to each formed coalition. We compare the performance of our merge-and-split Coalition Formation (MSCF) algorithm, with that of three other algorithms: 1) Grand Coalition Formation (GCF) algorithm (Du et al., 2018), which consider the grand coalition as an optimal solution for the coalitional game, 2) Random Coalition Formation (RCF) algorithm (Ray and Vohra, 2015), (Okada, 2011), which forms a random size of coalitions, where the members of that coalitions are randomly selected, 3) Same-Size Coalition Formation (SSCF) algorithm (Vatsikas et al., 2011), which forms coalitions with

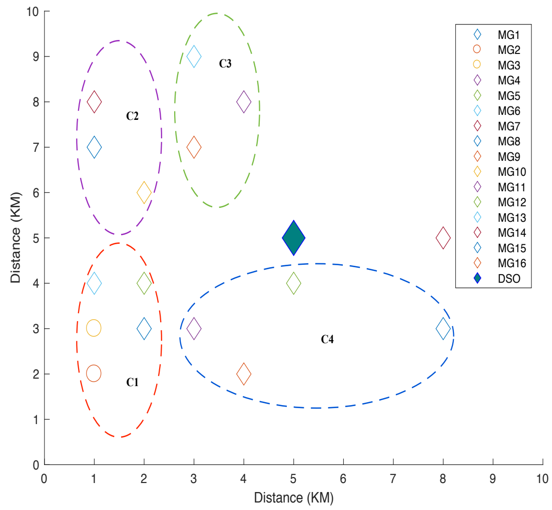

Figure 4: Coalition structure.

Table 1: Stable coalitions.

Coalition	Members	Exchanged energy with DSO (kw/h)
Ξ_1^k	$\{\Theta_1^1,\Theta_2^1,\Theta_3^1,\Theta_5^1,\Theta_6^1\}$	13
Ξ_2^k	$\{\Theta_7^2,\Theta_8^2,\Theta_{10}^1\}$	21
Ξ_3^k	$\{\Theta_9^3,\Theta_{11}^3,\Theta_{13}^3\}$	2
Ξ_4^k	$\{\theta_4^4,\Theta_{12}^4,\Theta_{15}^4,\Theta_{16}^4\}$	18

the same size where the members of that coalitions are also randomly selected. In Fig. 5, we show the performance of the coalition structures (CS) payoff with different size of the networked MGs. The figure shows that the MSCF gives the highest global payoff for MGs compared with the other algorithms. In fact, the less power exchange with the DSO, the more profit from power exchange. The proposed MSCF algorithm creates a stable coalitions that minimize the power exchange with the DSO. The significant difference between the MSCF and the SSCF is in the decision making in coa-

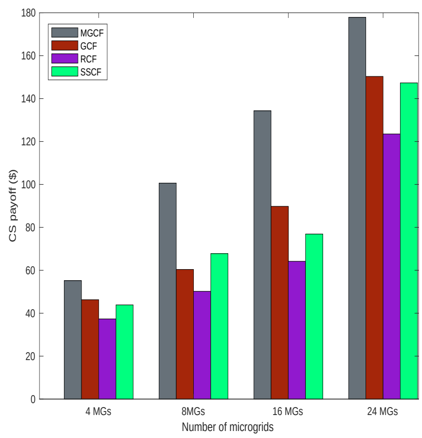

Figure 5: Coalition structure payoffs.

coalition formation process. The proposed MSCF algorithm forms coalitions based on merge-and-split rules. The decision making in SSCF and RCF is random which yields to a very high standard deviation. As a result, the formed coalitions are unable to perform energy exchange efficiently and the coalition members receive less payoff. On average, the global CS payoff of MSCF exceeds the payoff of the RCF, GCF and SSCF about 18.24%, 21.33% and 17.15%, respectively.

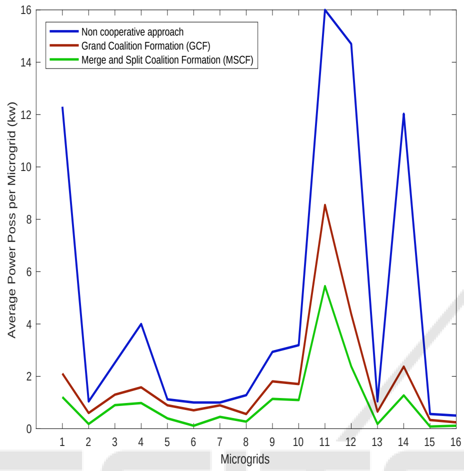

Figure 6: Power loss per microgrid.

Fig. 6 shows the average power loss for individual MGs with non cooperative approach as in (Jadhav and Patne, 2017), and with a cooperative approach. In the cooperative approach, the GCF algorithm as in (Du et al., 2018) and the proposed MSCF algorithm are compared. In the non-cooperative approach, a high level of power loss is observed due to the long distances between MGs and DS and the existence of power transformers resulting in more power loss. A significant decrease in power loss is observed with the cooperative approach in the case of GCF algorithm where MGs inter-exchange power. The power transfer between MGs reduces the power loss caused by transporting power in long distances which is the case of the non-cooperative approach. With the proposed MSCF algorithm, the power loss is less than the GCF algorithm. The proposed MSCF algorithm forms many small size coalitions resulting in short distances of power transfer which reduce the power loss compared with the GCF algorithm that forms the grand coalition resulting in long distances of power transfer compared with the proposed MSCF algorithm, so, more power loss.

In order to demonstrate the scalability of the proposed cooperative approach, the total power loss of MGs for different sized networked MGs systems is compared in Fig. 7 where the number of MGs is up to 100. The result is obtained after executing a non-cooperative and cooperative energy exchange (GCF and MSCF). The loss is significantly reduced with the cooperative approach. As more as the network size increases, the MSCF algorithm further reduces the power loss (about 72%) and the reduction is significantly high compared with the GCF algorithm (about 51%).

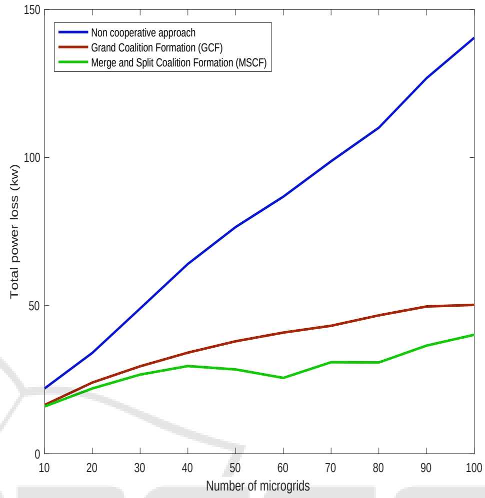

Figure 7: Total power loss.

5.3 Discussion

Tab. 2 presents the execution time of the coalition formation algorithm in two cases that are: 1) limiting the size of the formed coalitions, 2) without limiting the size. The proposed coalition formation methodology is quite inexpensive in terms of computational burden, its heaviest task is the split process, which is executed in few seconds even for large networks. As expected, the execution time taken by the proposed methodology is of the order of seconds regardless of the number of existing microgrids in the distribution system. Thus, the results confirms that the execution time does not depend on the number of microgrids, i.e., the network size but depends on the size of the formed coalitions which is a controllable parameter.

Table 2: Execution time of MSCF algorithm.

Number of microgrids	10	50	100	200	300	500
Execution time in seconds (case 1)	2	2	2.3	2.3	2.7	2.9
Execution time in seconds (case 2)	2	3.3	5.9	10.5	12.6	21.7

6 CONCLUSION

An efficient cooperative energy management software for networked MGs is proposed. A motivating pricing scheme is designed to encourage the MGs for cooperation by forming several stable coalitions. This cooperation is beneficial from the economic and technic point of view. We develop a scalable merge-and-split based coalition formation (MSCF) algorithm that ensures the stability of the network. The proposed MSCF algorithm performs better in over sized systems where the power loss reduction is greater and the payoff is more. Furthermore, we control the complexity of the proposed MSCF algorithm by limiting the size of the formed coalitions. Finally, we design an intra coalition energy transfer (ICET) algorithm to transfer energy in each coalition. The ICET algorithm gives the best results in terms of power loss reduction thanks to the stability of the coalitions formed by MSCF algorithm. As a perspective, we will study additional choices of decision-making models for networked MGs and consider other behaviors of MGs in energy management softwares.

REFERENCES

Abidi, M. G., Smida, M. B., Khalgui, M., Li, Z., and Wu, N. (2017). Multi-agent oriented solution for forecasting-based control strategy with load priority of microgrids in an island mode–case study: Tunisian petroleum platform. *Electric Power Systems Research*, 152:411–423.

Aissa, Y. B., Bachir, A., Khalgui, M., Koubaa, A., Li, Z., and Qu, T. (2019). On feasibility of multichannel reconfigurable wireless sensor networks under real-time and energy constraints. *IEEE Transactions on Systems, Man, and Cybernetics: Systems*, pages 1–16.

Apt, K. and Witzel, A. (2009). A generic approach to coalition formation. *International Game Theory Review*, 11(03):347–367.

Asarias, F. N. and Pedrasa, M. A. A. (2017). Resilient distributed generation dispatch in multi-microgrid systems. In *IEEE Innovative Smart Grid Technologies - Asia (ISGT-Asia)*, pages 1–6.

Cintuglu, M. H. and Mohammed, O. A. (2017). Behavior modeling and auction architecture of networked microgrids for frequency support. *IEEE Transactions on Industrial Informatics*, 13(4):1772–1782.

Du, Y., Wang, Z., Liu, G., Chen, X., Yuan, H., Wei, Y., and Li, F. (2018). A cooperative game approach for coordinating multi-microgrid operation within distribution systems. *Applied Energy*, 222:383–395.

Fathi, M. and Bevrani, H. (2013). Adaptive energy consumption scheduling for connected microgrids under demand uncertainty. *IEEE Transactions on Power Delivery*, 28(3):1576–1583.

Gao, H., Liu, J., Wang, L., and Wei, Z. (2018). Decentralized energy management for networked microgrids in future distribution systems. *IEEE Transactions on Power Systems*, 33(4):3599–3610.

Ghribi, I., Abdallah, R. B., Khalgui, M., Li, Z., Alnowibet, K., and Platzner, M. (2018). R-codesign: Codesign methodology for real-time reconfigurable embedded systems under energy constraints. *IEEE Access*, 6:14078–14092.

Gu, C., Li, Z., Wu, N., Khalgui, M., Qu, T., and Al-Ahmari, A. (2018). Improved multi-step look-ahead control policies for automated manufacturing systems. *IEEE Access*, 6:68824–68838.

Hafidi, Y., Kahloul, L., Khalgui, M., Li, Z., Alnowibet, K., and Qu, T. (2018). On methodology for the verification of reconfigurable timed net condition/event systems. *IEEE Transactions on Systems, Man, and Cybernetics: Systems*, (99):1–15.

Jadhav, A. M. and Patne, N. R. (2017). Priority-based energy scheduling in a smart distributed network with multiple microgrids. *IEEE Transactions on Industrial Informatics*, 13(6):3134–3143.

Khalgui, M., Carpanzano, E., and Hanisch, H.-M. (2008). An optimised simulation of component-based embedded systems in manufacturing industry. *International Journal of Simulation and Process Modelling*, 4(2):148–162.

Khalgui, M. and Mosbahi, O. (2010). Intelligent distributed control systems. *Information and Software Technology*, 52(12):1259–1271.

Lakhdhar, W., Mzid, R., Khalgui, M., Li, Z., Frey, G., and Al-Ahmari, A. (2019). Multiobjective optimization approach for a portable development of reconfigurable real-time systems: From specification to implementation. *IEEE Transactions on Systems, Man, and Cybernetics: Systems*, 49(3):623–637.

Ma, W.-J., Wang, J., Gupta, V., and Chen, C. (2018). Distributed energy management for networked microgrids using online ADMM with regret. *IEEE Transactions on Smart Grid*, 9(2):847–856.

Meskina, S. B., Doggaz, N., Khalgui, M., and Li, Z. (2017). Multiagent framework for smart grids recovery. *IEEE Transactions on Systems, Man, and Cybernetics: Systems*, 47(7):1284–1300.

Meskina, S. B., Doggaz, N., Khalgui, M., and Li, Z. (2018). Reconfiguration-based methodology for improving recovery performance of faults in smart grids. *Information Sciences*, 454:73–95.

Naidji, I., Smida, M. B., Khalgui, M., and Bachir, A. (2018). Non cooperative game theoretic approach for residential energy management in smart grid. In *The 32nd Annual European Simulation and Modelling Conference*, pages 164–170, Ghent, Belgium.

Nunna, H. K. and Doolla, S. (2013). Multiagent-based distributed-energy-resource management for intelligent microgrids. *IEEE Transactions on Industrial Electronics*, 60(4):1678–1687.

Okada, A. (2011). Coalitional bargaining games with random proposers: Theory and application. *Games and Economic Behavior*, 73(1):227–235.

Ray, D. and Vohra, R. (2015). Coalition formation. In *Handbook of game theory with economic applications*, volume 4, pages 239–326. Elsevier.

Vatsikas, S., Armour, S., De Vos, M., and Lewis, T. (2011). A distributed algorithm for wireless resource allocation using coalitions and the nash bargaining solution. In *2011 IEEE 73rd Vehicular Technology Conference (VTC Spring)*, pages 1–5. IEEE.

Wang, Z., Chen, B., Wang, J., Begovic, M. M., and Chen, C. (2015). Coordinated energy management of networked microgrids in distribution systems. *IEEE Transactions on Smart Grid*, 6(1):45–53.

Wu, J. and Guan, X. (2013). Coordinated multi-microgrids optimal control algorithm for smart distribution management system. *IEEE Transactions on Smart Grid*, 4(4):2174–2181.

Zamora, R. and Srivastava, A. K. (2018). Multi-layer architecture for voltage and frequency control in networked microgrids. *IEEE Transactions on Smart Grid*, 9(3):2076–2085.