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Real-time energy exchange strategy of optimally cooperative microgrids for scale-flexible distribution system

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ABSTRACT

This paper presents an optimal coalition formation mechanism of microgrids in a smart distribution system and analyzes the characteristics from the *coalitional game* theoretical perspective. Microgrids coalitions can (1) minimize the energy burden and dependency on the utility grid, (2) minimize the overall grid network power loss, and (3) maximize intra-coalition energy transfer. In order to form cooperative microgrids, a Hierarchical priority based Coalition Scheme (*HRCoalition*) is proposed. Given an intra-coalition distance threshold, the proposed *HRCoalition* mechanism can provide the *optimal coalition* that achieves the aforementioned objectives. The optimality is realized by reaching a state of cooperative equilibrium for all microgrids and coalitions. The optimality of the formed coalitions is proved by *Coalitional Game Theory*. A Greedy based strategy is designed to perform network constrained energy exchange *(GreedEnEx)* within a formed coalition. Thus, *HRCoalition* provides a higher level optimization while, *GreedEnEx* yields system level optimization using output of *HRCoalition*. The proposed *HRCoalition* scheme is computationally very efficient and can scale up to a huge number of microgrids and thus makes it suitable for near real-time operation. An equivalent pricing mechanism is designed to provide a form of economic incentive to the microgrids participating coalition formation. The performance of the proposed method is reported to scale up to 500 microgrids with a loss reduction ranging from 26% to 80%. The provided numerical simulation results back the claim of optimality as well as prove the effectiveness of the proposed coalition formation method.

1. Introduction

The power system operation and control took a significant turn after the introduction of deregulation in power market and consequent boom of smart grid technology related research and development. These changes impose challenges (exciting, interesting and more importantly necessary ones) into both research and structural development levels. The activities of developing and deploying smart grid infrastructure further fueled by the continuous depletion of natural energy resources and inevitably growing concerns on greenhouse effect. Moreover, soaring cost of the natural energy resources due to increasing demand for energy with a rise of world population and rapid economic growth of developing countries also fasten the drives towards a smarter grid architecture. With these motivations on mind, the electricity distribution system needs to be renovated by grouping several distributed energy resources (DERs), storages and loads into one interactive and automated entity given a particular network settings and geographical area. Such an entity formation idea incepted the concept of microgrid system (Katiraei, Iravani, Hatziargyriou, & Dimeas, 2008). The DERs contain renewable energy sources in conjunction to energy storages and/or small scale generators. Traditionally, a microgrid operates in grid-connected mode where the energy requirement is fulfilled by purchasing/selling energy between that microgrid and the utility grid. This transfer, however causes power loss due to the transmission/distribution line and transformers. Although, cost minimization (Hernandez-Aramburo, Green, & Mugniot, 2005) in microgrid or smart-grid (Chakraborty, Ito, Senjyu, & Saber, 2013) in the form on unit commitment has been extensively studied, the research related to loss-reduction phenomena in the whole distribution grid as well as attainment of a "net-zero-energy" society are still premature and demand considerable attention. A remedy of aforementioned loss reduction while moving towards a "net-zero-energy" society is envisioned as formation of microgrids coalitions. Microgrids inside a coalition perform necessary energy transfer within the coalition and finally interact with utility grid as the last resort to minimize losses. With the realization of

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Digital-grid (Abe, Taoka, & McQuilkin, 2011) architecture, the interactions among microgrids in power/energy level are readily viable in distribution network. Therefore, microgrid coalition formation is practical and can be thought of an important addition to future smart distribution energy management system.

In recent years, streams of outstanding works are presented in the area of real-time and optimal energy management system for microgrid while focusing on e.g. variable grid price (Velik & Nicolay, 2014), day-ahead market (Marzband, Sumper, Ruizlvarez, Domnguez-Garca, & Tomoiag, 2013), inclusion of distributed generators (Liao, 2012), etc. However, most of these reported works concentrate on the energy management and control inside microgrid considering either islanded or grid-connected mode. That being said, the contributions are focused on the primary and secondary control level. The aggregation or grouping schemes of microgrids for optimal energy exchange in the tertiary level are being ignored. However, the aggregation (dynamic) of multiple microgrids in distribution level is of critically important while designing future smart distribution based services for new independent power producers, stake-holders that rise due to the presence of deregulation in energy market.

The usage of game theory (Shoham & Leyton-Brown, 2008) in smart grid application domain (especially in the area of energy) is getting considerable attention in recent years, e.g. (Saad, Han, Poor, & Basar, 2012) (Microgrid coalition), (Ramchurn, Vytelingum, Rogers, & Jennings, 2012; Chakraborty, Ito, & Senjyu, 2014) (Incentive based demand response), etc. The cooperative game theory has been effectively applied in areas like smart grid, microgrid, forming virtual power plant, energy sector etc. (e.g. (Alam, Ramchurn, & Rogers, 2013)). For example, (Alam et al., 2013) provides a cooperative energy exchange scheme in order to reduce the battery usage as well as improving the efficiency of houses locating in remote communities. In cooperative game theory point of view, a coalition should be formed such a way that each participated microgrid will gain benefit (or at least not lose) by participating in a coalition. Intuitively, a *grand coalition* (i.e. a single coalition of players) always produces the maximized benefit for players (Alam et al., 2013). However, to form a grand coalition of microgrids is practically infeasible because *grand coalition* does not consider inter-microgrid distance. A slightly similar approach to form microgrid cooperation was reported in Saad et al., 2012 (and (Wei, Fadlullah, Kato, & Takeuchi, 2013); apparently applied same basic mechanism) who used merge/split operation. Although, the merge/split operation (Apt & Witzel, 2009) to form coalition can provide stable partition, it was not clear how the model described in (Saad et al., 2012) reacts with the scalability of the problem space (the number of microgrids, in this context). Because, merge/split operation in coalition formation is an *NP-hard* problem (Rey et al., 2010) which yields an exponential computational complexity in the worst case.

We propose a hierarchical priority based strategy to form optimal microgrid coalitions and analyze the characteristics through the eyes of *Coalitional Game Theory* framework (Shoham & Leyton-Brown, 2008). The proposed method can form optimal coalition by reaching an equilibrium state and can scale very high in terms of number of microgrids due to the inherent quadratic computational complexity. We present the hourly interactions among microgrids given their hourly energy status and extend the method up to multiple hours (e.g. 24-h) considering the dynamic energy status (loads/supply) of microgrids.

The proposed method can effectively locate itself within the smart distributed energy management system in order to perform energy exchange operation among microgrids by forming the optimal coalition. The optimality, as we will show, is defined by minimizing the power loss by effectively avoiding the interactions with utility grid. The designed scheme can also be used as one of the analytical tools for setting up new microgrid substations and communication and electric infrastructure. At the miniature level, such method has a potential to dynamic formation virtual aggregator for smart homes. A pricing mechanism is designed to complement the formed coalition which somewhat provides the base line of mechanism design for coalition formation. The proposed method is computationally very efficient and highly scalable in compare with other optimal coalition formation techniques. Therefore, the designed method can be applicable in (near) real-time energy management system.

The rest of the paper is organized as follows. The system model with energy exchange scenario is described in Section 2. Section 2 further briefs the Coalitional Game Theory and how it can be applied in proposed model. Some game theoretic observation, analysis and proofs are provided in Section 3. The optimality of *HRCoalition* scheme is proved in this section as well as the computational and communication complexity are analyzed. Section 4 presents the numerical simulations with associated discussions and analysis. The simulations are carried by initially providing the hourly-interactions among microgrids and formed coalitions. Later the whole scenario is extended up to 24-h in order to incorporate the dynamic energy status of microgrids.

2. System model and coalition formation scheme

A microgrid requires to purchase/sell energy from/to *utility grid (UG) owned by utility company* depending on its internal energy status. Every microgrid requires energy for serving the loads within it. We denote the total demand of a microgrid i (where $i \in N; N$ is the set of microgrids) by D_i. At the same time, internal DERs (which include renewables and storages) of i are responsible of energy supply within i. We assume, i's EMS (Energy Management System) already optimizes the usage of internal DERs. Let assume, the total supply for i is S_i. Therefore, the energy difference for i is E_i $(= S_i - D_i)$. A positive value of E_i denotes, i can sell E_i amount of energy while a negative value denotes, it requires E_i amount of energy to purchase from outside (from the *UG*, in particular). In conventional architecture of microgrid, such energy transfer is conducted between the microgrid and *UG*. Therefore, the transfer has to be conducted through the substation connected with that microgrid which leads to power losses due to the presence of voltage transformer(s). In addition to that, power loss can be more severe due to the I^2R effect if the *UG* is located far way. At the same time, energy transfer of this sort increases the burden to the *UG*. One of the remedies of such situation can be achieved by forming microgrid coalitions. The microgrids within a particular group (or coalition) will share the energy among each other. After conducting the intra-coalition energy management, the surplus or deficit of energy will be compensated with *UG*.

The proposed architecture of the distributed network is shown in Fig. 1. Every microgrid in the distribution system is expected to connect with the utility grid through medium voltage line. A microgrid can be connected with another microgrid with low voltage line. During the time of operation, every microgrid will send their energy status (via microgrid's energy controller unit; ECU) to an Aggregator (can be a service provider or distribution system controller). The Aggregator intelligence system contains Microgrid Cooperation Module (MCM), which is responsible for decide optimal coalition. An energy transfer matrix, resulted from MCM, will be sent to the participated microgrids via wireless communication system. The functionalities of these units will be detailed in the later part of the manuscript. The microgrids will communicate pairwise to initiate the energy transfer and realize the transfer via low-voltage line. We, therefore, assume the microgrids, utility company and the Aggregator are connected via wifi communication infrastructure. Additionally, a database of distributed network profile is also a part

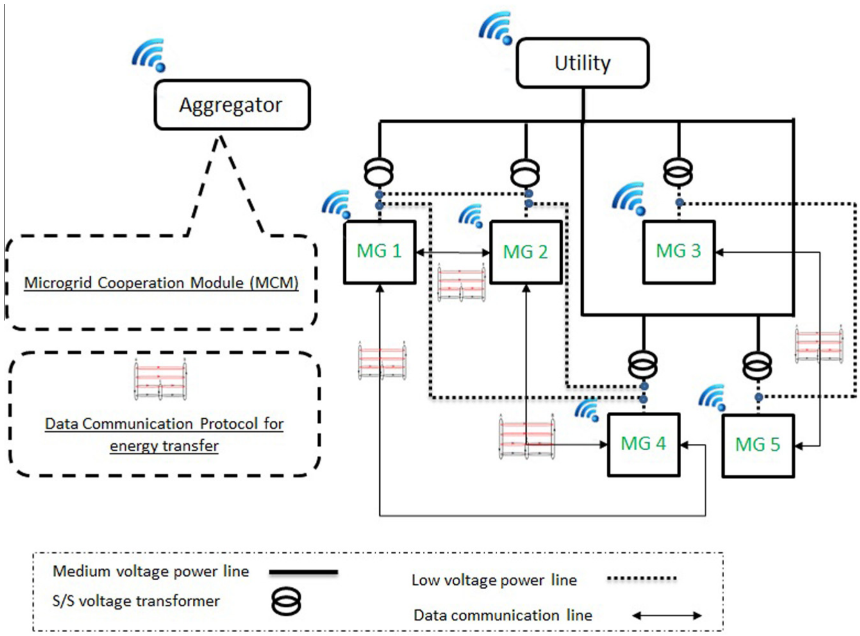

Fig. 1. Distribution system with utility company and several microgrids and the connectivity.

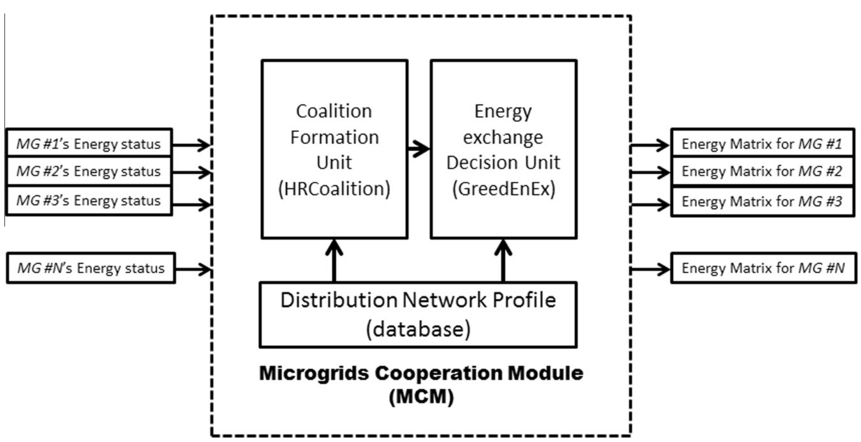

Fig. 2. Microgrid Cooperation Module (MCM) hosted in the Aggregator for performing coalition formation and deciding energy exchange transfer.

of the Aggregator in order to facilitate the MCM. The process outlined in Fig. 2.

2.1. Game design for microgrid coalitions

Coalitional Game Theory is a set of game theoretical tools that deals with players who are performing in an open communicative environment and receive side payments (e.g. share utilities) by intelligently forming coalition. In *Coalitional Game Theory*, the players (microgrids in this context, microgrid agents in particular, defined as intelligent softwares and potentially a part of the microgrid-EMS) will increase their *utility*[1] by forming a coalition (if they can). The designed microgrid coalitional game is a *Convex Utility Game* where player's utility is defined as a convex function. The proof of convexity of the proposed game will be provided. Central to game formation, therefore, is to design the nature of *utility* function(s) of participating players. We can derive two entities from our model, (1) *micrograds* (2) *coalitions*. Note that, the *utilities* will be calculated right before a microgrid makes energy transfer (if it has to) to *UG*.

2.1.1. Utility function for microgrids

The utility of a microgrid depends on the measure of energy exchange amount with *UG* and the associated economic benefit it attains by reducing the energy exchange with *UG*. The effective pricing design is therefore important to ensure the economic benefit of microgrids. The pricing design mechanism is detailed in Section 3.1. Let's define a profit margin *pm* that represents the per-unit profit of a microgrid when it exchange energy with another microgrid. A particular activation point σ is defined that set a desired profit margin. Therefore, the utility factor, *uf* for economic benefit is defined by the following equation

$$uf = \begin{cases} 0 & if \quad pm \leqslant 0 \\ 1 & if \quad pm \geqslant \sigma \\ \frac{pm}{\sigma} & otherwise \end{cases} \tag{1}$$

[1] The definition of utility in the context of *UG* is completely different than that of *utility*. The *utility* of a player in a game measures the *happiness* of the player over some outcome.

The utility of a microgrid should reflect the fact that, the less the energy that microgrid exchanges with *UG*, the more the *utility* that particular microgrid receives. The following utility equation for a microgrid is thus defined as

$$U_i = \frac{uf}{1 + |D_i - S_i|} \tag{2}$$

2.1.2. Utility function for coalitions

In order to define the *utility* of a coalition (conceived as a virtual agent) C, first we define the aggregated energy status of C, E_C as follows

$$E_C = \sum_{i \in N_C} |D_i - S_i| \tag{3}$$

where N_C is the set of microgrids in coalition C. Secondly, we need to define the overall loss of power while power transferring among the microgrids in C and UG. Let's define, ET_C as a set of unique pairs (i,j) (where $i \in \{0 \cup N_C\}, j \in \{0 \cup N_C\}$, 0 represents the UG and $i \neq j$) which states the energy transfer between i and j. Note that, every coalition virtually adds UG as 0-th microgrid to provide or receive additional energy from/to microgrid(s) in the coalition. The overall loss occurs in a coalition is defined as follows

$$L_C = \sum_{(i,j) \in ET_C} loss(i,j) \tag{4}$$

The simplified loss function is defined as the power loss to transfer energy E over the geographical distance between i and j. Point to be noted that, we defined the *loss* as a component of a *coalition* instead of a microgrid's since the power loss occurs only in an energy transaction between two microgrids in a coalition. Mathematically speaking (Saad et al., 2012),

$$loss(i,j) = I^2R + T_{loss} = \left[\frac{P(E)}{\Psi}\right]^2 \times \alpha \cdot dist(i,j) + \beta \cdot P(E) \tag{5}$$

where $P(\cdot)$ is the power required to transfer the energy, Ψ represents the carrying voltage of the transmission line, α is the resistance of the wire per distance unit, $dist(i,j)$ is the geographical line distance (for established network) between i and j, and β is the transformer loss factor. The energy amount E will be decided after managing the intra-coalition energy (described in next subsection). Note that, when both i and j are microgrids (i.e. UG is not involved), β is 0. Moreover, the carrying voltage Ψ changes when UG is involved in the transfer. Typically, we considered Ψ = 22 kV in case of inter microgrid/coalitions transmission while Ψ = 50 kV for any UG transmission. Finally, the *utility function* for a *Coalition* is designed to clearly define the interplay between energy and loss within a coalition (Eq. (6)).

$$U_C = \frac{1}{1 + E_C + L_C} \tag{6}$$

2.2. Shapley value based fair division

For analyzing the benefit of the microgrids in coalitions, Shapley Value based mechanism is adopted. Shapley Value is a widely used technique for fairly dividing surplus/benefit among participating players/agents in a coalition. Shapley Value calculates the average marginal contribution of a player i in a coalition. For a player i in the coalitional game (N, v), where N is the set of players, $S \subseteq N$ is a coalition and v is a characteristic function, the Shapley value for i, $\phi_i(N, v)$ is defined as

$$\phi_i(N, v) = \sum_{S \subseteq N \setminus \{i\}} \frac{|S|!(|N| - |S| - 1)!}{|N|!} [v(S \cup i) - v(S)] \tag{7}$$

The valuation of a coalition in a coalitional game is determined by the characteristic function. In the proposed game, the characteristic function of a particular coalition C is defined as the marginal achievement attained by C. Mathematically speaking,

$$v(C \subseteq 2^N) = \sum_{i \in C} U_i - U_C \tag{8}$$

Algorithm 1. Hierarchical priority based coalition formation (HRCoalition)

Data: microgrid Information *MGs*
Data: Connection matrix *conn*, where $conn(i,j) = 1$ if there is a physical connection between i and j, otherwise 0
Data: Distance matrix *dist*, indexed (i,j)
Data: d = Distance threshold
Result: C = Set of formed coalitions
For all $i \in MGs$, set $C_i = \{i\}$
Find the centroids of C_is
change = True
while *change* **do**
  Set *CPG* = Group of C_is who can provide energy
  Set *CLG* = Group of C_is who require energy
  OLG = *CLG* in descending order of energy demand amount
  OPG = *CPG* in descending order of energy supply amount
  change = False
  for Each $C_l \in OLG$ **do**
    C_p = First coalition in *OPG* whose central is located within the distance d from the central of C_l
    if C_p is None **then**
      continue
    end
    change = True
    $C_l := C_l \bigcup C_p$
    $OPG := OPG\text{-}C_p$
    dissolve C_p
    Update energy status of C_l
    Update centroid location of C_l
    break
  end
end

2.3. Hierarchical priority based Coalition (HRCoalition)

The details of *HRcoalition* formation scheme is provided in this section. The data required for this algorithm is actually the list of microgrids with associated information (stored as *microgrid*). For now, the algorithm only requires the energy status of each microgrid in a particular time. Moreover, a connection matrix *conn* is also needed that depicts the internal connection setup among all pair of microgrids. The algorithm initially starts with assigning a coalition to each microgrid. The coalitions are grouped based on cumulative energy status (provider group and demand group). As the algorithm progresses, it tries to keep pairing up two high priority coalitions (highest aggregated load and highest aggregated supplier), if they are located within certain distance from each other (the distance threshold can be externally provided as the parameter d), until the convergence (or equilibrium) state has encountered. The convergence state is defined by a state where no two coalitions are paired up thereby, confirming the fact that, no changes in the formed coalition is occurred. The key algorithm is shown in Algorithm 1. Given the quadratic nature of the algorithm, it can be showed that, the algorithm always converges at certain point. Therefore, no additional measure needs to be taken to terminate the algorithm (e.g. maximum iteration and so on). The optimality of the algorithm is defined by the minimization of the power loss within a coalition. The proof of optimization of the algorithm is provided in Section 3. Therefore, the formed coalitions contain the minimized potential power loss. The formed coalitions are stored in C.

The *HRCoalition* can be seen as a priority list based heuristic method. The worst case complexity of this method is $O(|N|^2)$, where N can be treated as the number of microgrids. The typical optimal coalition formation method requires exhaustive search over all possible combinations which is computationally very intensive. Thus, the performance of *HRCoalition* is a significant improvement over other optimization methods.

Assuming a coalition has been formed, it needs to manage the proper distribution of energy among the microgrids within that particular coalition. To this end, we have proposed a greedy based heuristic method (Algorithm 1: *GreedEnEx*) that considers the internal distance between two microgrids while managing the energy transfer. The algorithm operates within a coalition and tries to follow the trajectory of power loss set up by *HRCoalition*. The algorithm starts by ordering load group of microgrids (within a coalition). For each of the load microgrid, it will try to find a provider microgrid that located within the distance threshold until its entire load is mitigated. If scanning the near-by microgrids are finished while the load still remains, the microgrid will buy the additional energy from *UG*. The results are stored in a stack defined in the algorithm as *ET*.

Algorithm 2. Greedy energy exchange within a coalition (GreedEnEx)

```
Data: microgrid Coalition C
Data: Connection matrix conn, where conn(i,j) = 1 if there is a
   connection, otherwise 0
Data: Distance matrix dist, indexed (i,j)
Data: d = Distance threshold
Result: ET = Energy transfer matrix between (i,j)
Set PG = Group of energy provider in C
Set LG = Group of energy load in C
SLG = LG in descending order of energy demand
for Each lg ∈ SLG do
  while lg.energy > 0 do
    pg = nearest available microgrid (in PG) from lg
    if pg is None then
      ET(0, lg) = lg.energy
      break
    end
    t = min(pg.energy, |lg.energy|)
    lg.energy := lg.energy - t
    pg.energy := pg.energy - t
    ET(pg, lg) = t
    available(pg, lg) = False
  end
end
for Each pg ∈ PG do
  if pg.energy > 0 then
    ET(pg, 0) = pg.energy
  end
end
```

Note that, while selecting a provider from *PG* (the provider microgrid), an *lg* tries to check the nearest *pg* (which is located within the proximity of the *lg*, set up by a distance threshold, *d*). Moreover, a *pg* locating within the proximity of an *lg* does not necessarily makes that *pg* a candidate provider since the physical connection between *lg* and *pg* might not exist. Therefore, choosing appropriate *pg* for an *lg* has to go through Eq. (9). Obviously, once a *pg* is selected to provide energy to a particular *lg*, it will not be selected in next time for that particular *lg*.

$$pg = \begin{cases} \underset{x}{\operatorname{argmin}} & dist(x,lg) \times conn(x,lg) \\ s.t. & 0 < dist(x,lg) \leqslant d \\ s.t. & conn(x,lg) > 0 \end{cases} \tag{9}$$

Where $conn(i,j)$ represents whether the microgrids i and j are connected via low-voltage line. These two algorithms can be seen as higher level (*HRCoalition*) and lower level (*GreedEnEx*) optimization algorithms. The coalition information formed in *HRCoalition* is transferred to lower level where the actual energy exchange scheme is determined by deciding which microgrid should transfer what amount of energy to which microgrid while bringing down the total power loss in the coalition close to the upper level potential power loss set points. In another words, as the optimal set points (formed coalition in this context) is determined in *HRCoalition*, *GreedEnEx* will try to follow the set point by imposing practical constraints (e.g. physical connection between two microgrids) with associated power loss concerns. The interactions between the proposed algorithms (Algorithm 1:*HRCoalition* and Algorithm 2: *HRCoalition*) is shown in Fig. 3.

On a different note, although, the normal form of game theory requires many self-interested players and associated interactions among them, the coalition game theory (as the name suggests) has dealt with group formation of agents with similar interest (and similar linear utility function). It can, however, be possible to have more autonomous agents/players (microgrids in our context) by developing complex utility function. We can also observe the effect of pricing for a particular coalition and the utility values. Moreover, in order to fully entertain the potentials of *mechanism design*, we have to design a pricing environment. The details pricing model, however, beyond the scope of this research. A simple pricing scheme will be detailed later part of this section.

3. Analysis and pricing

We have analyzed the following important aspect of microgrid coalition formation game and *HRCoalition* scheme using Coalitional Game Theory.

Theorem 1. *HRCoalition produces optimal coalitions if the proposed microgrid coalitional game is a Convex Game without loss consideration.*

Proof. First we try to show the convexity of the game. Recall the characteristic function defined in Eq. (8)

$$\begin{aligned} v(C \subseteq 2^N) &= \sum_{i \in C} U_i - U_c \\ &= \sum_{i \in C} [1 + |E_i|]^{-1} - \left[1 + \sum_{i \in C} |E_i| + L_C\right]^{-1} \\ &\approx \sum_{i \in C} [1 + |E_i|]^{-1} - \left[1 + \sum_{i \in C} |E_i|\right]^{-1} \end{aligned} \tag{10}$$

The third approximation holds by avoiding loss consideration from the game. So, this characteristic function can be re-written as a potential energy exchange maximization within a coalition as follows

$$V(C \subseteq 2^N) = \sum_{i \in C} |E_i| - \left|\sum_{i \in C} E_i\right| \tag{11}$$

Let's define S and T are the two subsets of N (i.e. $S \subset N$ and $T \subset N$). The sum of characteristic functions goes as follows,

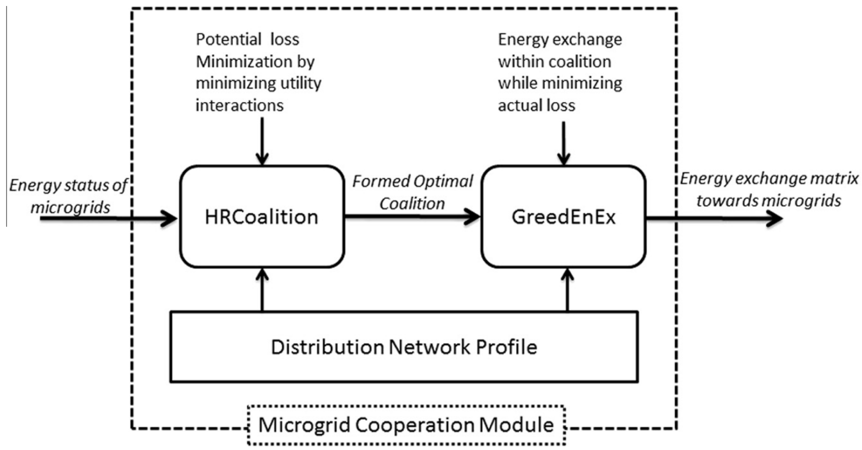

Fig. 3. Interactions between *HRColaition* and *GreedEnEx* Methods.

$$
\begin{aligned}
V(S)+V(T) &= \left(\sum_{i\in S}|E_i| - \left|\sum_{i\in S}E_i\right|\right) + \left(\sum_{i\in T}|E_i| - \left|\sum_{i\in T}E_i\right|\right)\\
&= \left(\sum_{i\in S}|E_i| + \sum_{i\in T}|E_i|\right) - \left(\left|\sum_{i\in S}E_i\right| + \left|\sum_{i\in T}E_i\right|\right)\\
&\leqslant \sum_{i\in S\cup T}|E_i| + \sum_{i\in S\cap T}|E_i| - \left(\left|\sum_{i\in S\cup T}E_i\right| + \left|\sum_{i\in S\cap T}E_i\right|\right)\\
&\leqslant \left(\sum_{i\in S\cup T}|E_i| - \left|\sum_{i\in S\cup T}E_i\right|\right) + \left(\sum_{i\in S\cap T}|E_i| - \left|\sum_{i\in S\cap T}E_i\right|\right)\\
&\leqslant V(S\cup T) + V(S\cap T)V(S\cup T)\\
&\geqslant V(S) + V(T) - V(S\cap T)
\end{aligned} \tag{12}
$$

Therefore, the characteristic function, V defines the proposed microgrid coalitional game, a *Convex Game* (Shoham & Leyton-Brown, 2008). Moreover, the utility functions for both microgrid and coalition are *convex*.

According to Theorem *12.2.15* in Shoham and Leyton-Brown, 2008, in every *Convex Game*, the Shapley value is in the *core*. The *core* measures the stability of a coalition and thereby providing incentive to an agent to stick to a particular coalition. Assuming a mesh networked distribution system architecture with relaxed distance threshold (no loss scenario), according to Eqs. (6) and (11), a coalition's utility/valuation is at its best when the difference of aggregated load and aggregated supply is minimized (i.e. minimizing the $|\sum_{i\in C}E_i|$). *HRCoalition* always tries to pair up the coalition of the highest aggregated load with the coalition of highest aggregated supply until the it converges to an equilibrium state and thereby minimizing $|\sum_{i\in C}E_i|$. Therefore, a microgrid can get the highest "payoff" i.e. its intra-coalition energy exchange is maximized (which in turn minimizes the exchange with *UG*) if it sticks to the coalition formed on the basis of Eq. (8) and having the utility functions as Eqs. (2) and (6), respectively for microgrids and coalitions. □

The *Optimal Coalition* is a binding of microgrids which forms a particular coalition such that every microgrid on that coalition has reached to a cooperative equilibrium state. *Optimal Coalition* is thus always maximizes the characteristic function. The *Equilibrium (in microgrid coalition)* is defined by a state where every microgrid's best *strategy* is to stick to the current coalition. That is, no microgrid can increase its utility by switching coalitions unless at least one of the other microgrids decreases its utility and thereby, decreasing the utility of the coalition where the other microgrid belongs. It is analogous to *Nash Equilibrium* (from non-cooperative game) since the Shapley Value is in the core and *HRCoalition* scheme provides stable and optimal solutions (Theorem 1). We can further say that, after reaching to an equilibrium state, the players (microgrids) are locating in the *Pareto-optimal* frontier (Buchanan & Tullock, 1962) according to Theorem 1. We can also observe the effect of pricing for a particular coalition and the utility values. Moreover, in order to fully entertain the potentials of *mechanism design*, we have to design a pricing environment. The designed pricing environment will be detailed later part of this section.

3.1. Pricing design to support coalition formation

Assumption of pricing is important to form coalitions among microgrids. In another word, the designed microgrid formation scheme should answer the question, *why a microgrid would prefer another microgrid over UG to purchase/sell energy?* Aside from the network loss consideration, the lack of proper pricing mechanism will lead to a disastrous outcome. To put it another way, the designed protocol needs to properly incentivize a microgrid to exchange energy with another microgrid even when it has a chance to exchange energy with *UG*. Therefore, we have proposed a simple *pricing mechanism* which will make sure that forming coalition with another microgrid is always the first choice of a microgrid. For example, consider $a = 0.1$\$ kWh is the selling price of energy to *UG*, $b = 0.4$\$ kWh is the purchasing price from *UG* and $c = 0.12$\$ kWh is the purchasing/selling price within two microgrids.[2] Considering this pricing scheme, a microgrid always tries to purchase from another microgrid since it can save 0.28\$ kWh (0.4−0.12 = 0.28). On the other hand, a microgrid will make little profit of 0.02\$ kWh (0.12–0.1 = 0.02) by selling energy to another microgrid (instead of *UG*). However, the profit a microgrid makes by selling energy should be very small since, otherwise it will try to produce way more extra energy. So, finally we design the pricing relation as follows

$$b \gg c > a \tag{13}$$

where $(c - a) \leqslant e$ is a predefined threshold.[3] In accordance with Eq. (1), σ is set to $b - c$, when the microgrid is purchasing energy and is

[2] Note that, the prices of electricity are tentatively assumed considering the US monthly pricing data which varies from 0.08\$ kWh to 0.37\$ kWh.

[3] In order to fully stop a microgrid to produce extra power, we can transform the pricing variables *a* and *b* as *monotonically decreasing functions* (where the per kWh price decreases as the extra energy increases, and eventually incurs negative value for producing more than a predefined energy level).

$c - a$ when the microgrid is selling energy. Therefore, for a fixed pricing scenario, the utility of a microgrid becomes

$$U_i = \frac{1}{1 + |D_i - S_i|} \tag{14}$$

3.2. Algorithmic complexity analysis

Optimal coalition formation of microgrids will ensure minimized power loss as well as maximized inter-microgrid energy exchange. Forming such coalition, however, is computationally intensive (exponentially proportional with the number of microgrids) and is in inherently complex given a distribution network profile. The conventional mathematical optimization method (such as Linear programming) can ensure the optimality provided the correct mathematical model is formulated. However, the complexity of such method is exponential with the number of microgrid. To be more precise, since the method has to scan all possible combinations, the algorithmic complexity is $O(2^{|N|})$. Thus Optimal Coalition formation is an *NP-Complete* problem (Sandholm, Larson, Andersson, Shehory, & Tohm, 1999).

Therefore, it is computationally almost impossible to perform optimal coalition formation using mathematical optimization methods when the number of microgrids exceeds a particular threshold. Moreover, the game theoretic merge/split operation for forming coalition is an *NP-hard* problem (Rey et al., 2010). Thus, it is impossible to solve the operation in a polynomial time, if the number of agents is higher than a specific number. Applying some heuristics and assumption (Wei et al., 2013), the complexity can be brought down to a tolerable range. However, even the reduced complexity of merge and split is not sufficient enough to be applicable in a real-time operation with a very high number of microgrids. On the other hand, the proposed coalition formation algorithm (namely HR Coalition) is a priority based hierarchical scheme, which tries to form coalition based on the energy status of the microgrid. Since, the coalition formation is based on only one criteria in this context, we can bring down the complexity effectively by iteratively and intelligently choosing the components (microgrids) in a coalition. The computational complexity of *HRCoalition*, therefore, is $O(|N|^2)$.

The communication complexity of merge/split operation used in (Wei et al., 2013) is $O(|N|^3)$ since, it is a distributed approach where every microgrid has to communicate with every other microgrid in order to receive the energy and network information and again in transfer of energy. The proposed method, on the other hand, has a worst case communication complexity of $O(|N|^2)$. Because, after receiving the decision regarding energy exchange from the aggregator, every microgrid has to communicate with every other microgrid (in worst case) to initiate the communication and eventually to conduct the energy transfer.

4. Simulation

For simulation purpose, we assume the *UG* is located on the center (coordinate (0, 0) in 2-D Euclidean space) of the area. The microgrids are scattered randomly over an area. To measure the result qualitatively, we further assume that the distance between two microgrids are proportional to their straight line distance (i.e. Euclidean distance). Moreover, the supply and demand of energy in a microgrid at a particular decisive period are also randomly chosen by keeping their energy ratings on mind. Such assumption can be effectively replaced for real power distribution system by applying real spatial information, energy data, etc. We have developed an equivalent Linear Programming based coalition formation (LP Coalition) and distance based hierarchical clustering

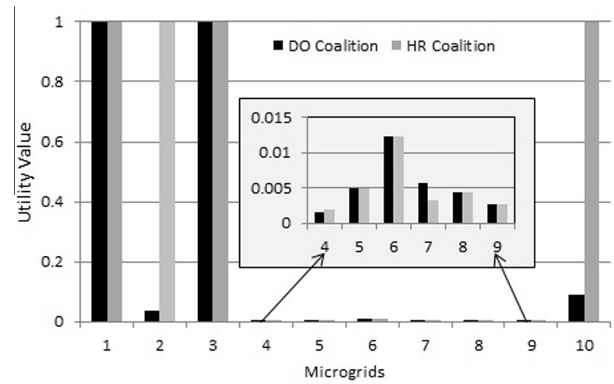

Fig. 4. Increase in utility for microgrids by forming coalition using HR Coalition mechanism.

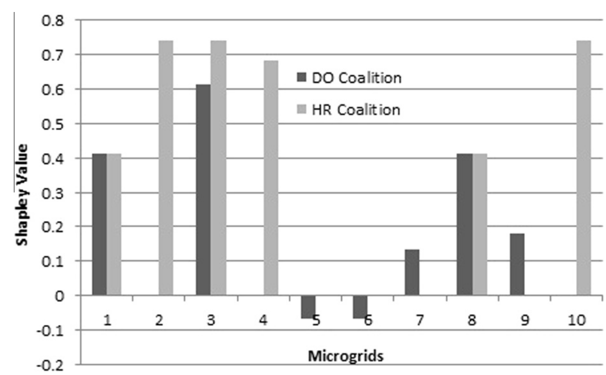

Fig. 5. Shapley value comparison between HR and DO coalition scheme.

Table 1
Initial Energy Status of 10-microgrids.

Microgrid.	Energy (kWh)	Microgrid.	Energy (kWh)
1	−747.74	6	80.65
2	−27.60	7	300.80
3	−123.37	8	973.54
4	667.73	9	375.17
5	201.59	10	−10.18

coalition algorithm (DO Coalition[4]) schemes for comparison purpose. The LP formulation's objective function is maximizing the sum of characteristic function (Eq. (11)) and defined as

$$max \sum_{C \in CS} V(C) \tag{15}$$

where *CS* is the set of formed coalitions by LP Coalition scheme.

4.1. 10 Microgrids with distance threshold 2.5 km

We have randomly scatter 10 microgrids within the vicinity of 5 square km. The centroid distance threshold within a coalition is set to 2.5 km. Fig. 4 shows that the formed coalitions via *HRCoalition* scheme effectively increases (or at least kept same) the utilities of most of the microgrids. *HRCoalition* could not increase Microgrid 7's utility since, Microgrid 7 is alone in the coalition formed by HR

[4] DO Coalition scheme is hierarchical clustering algorithm where distance function is the actual geographical distance between two microgrids. Since, distance is the only measure to determine the coalition, the method is named "Distance only Coalition (DO COalition)".

Source (MG)	Destination (MG)	Energy (E) kWh	Profit (Source) $(0.4 - 0.12) \times E$ [for MG to MG exchange] $	Profit (Destination) $(0.12 - 0.1) \times E$ [for MG to MG exchange] $
8	1	747.74	209.37	14.95
8	0	225.79	0	0
5	0	201.59	0	0
6	0	80.65	0	0
7	0	300.80	0	0
9	0	375.17	0	0
4	3	123.37	34.54	2.47
4	2	27.60	7.73	0.55
4	10	10.18	2.85	0.20
4	0	506.58	0	0

Fig. 6. Energy transfer matrix with associated profits for microgrids.

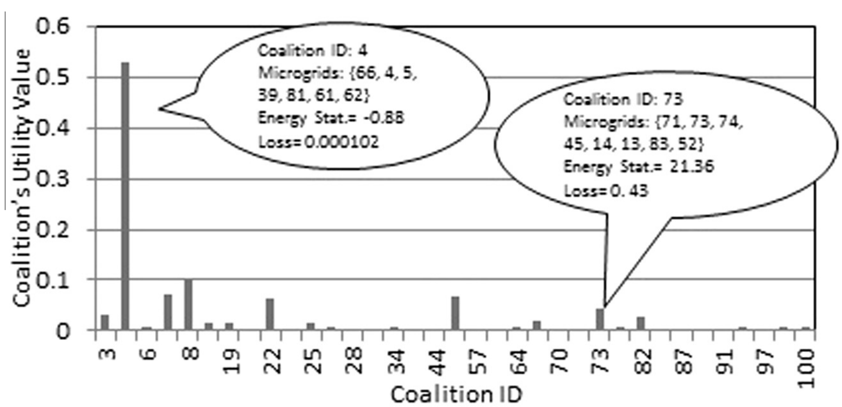

Fig. 7. Utility of coalitions for 100 microgrids (distance threshold d = 1.5 KM.).

scheme. However, as seen in DO coalition, if Microgrid 7 is in any coalition, it will decrease the utilities of other microgrids (e.g. 2, 4 and 10) and thus breaking the equilibrium. Fig. 5 describes the Shapley value phenomena. The microgrids are (except Microgrid 7), once again, gained their marginal contribution by joining the coalition formed by *HRCoalition* scheme. It is, however, computationally intensive to perform Shapley value calculation for bigger coalitions since the number of possible combinations of microgrids grows exponentially with the number of microgrids on that coalition.

The initial energy status of 10 microgrids are presented in Table 1. The LP Coalition forms the coalitions (with corresponding $V(C)$ values) as ({4}:0, {5}:0, {3,9}:246.73, {1,6,8}:1495.49, {2,7,10}:75.57) with total objective value of 1817.79. The

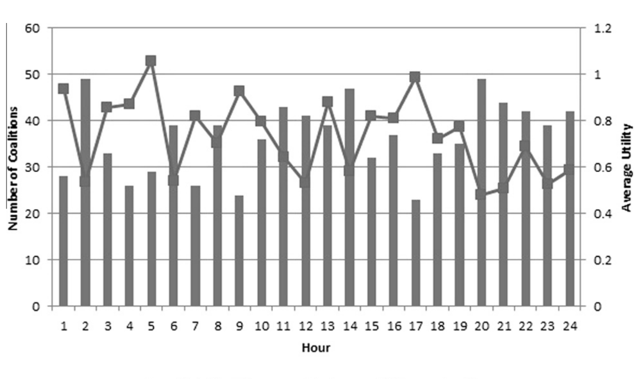

Fig. 8. The average utility of coalitions in 24-h.

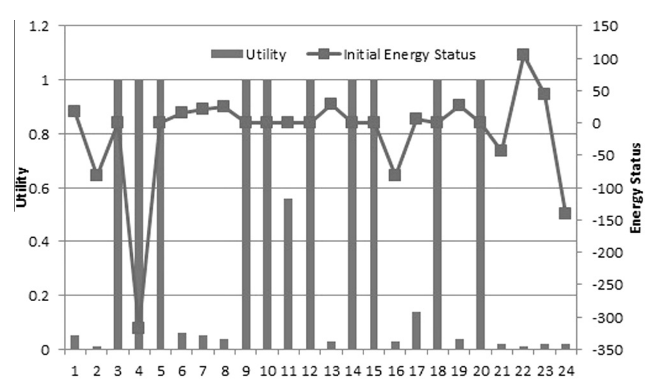

Fig. 9. The utility and initial energy status of microgrid 11 for 24-h.

HRCoalition scheme on the other hand forms coalition as, ({8,1}:1495.49, {5}:0, {6}:0, {7}:0, {9}:0, {2,3,4,10}:322.30) with a total of 1817.79 which is exactly as same as that of LP Coalition scheme. However, LP Coalition scheme becomes computationally expensive since it has to scan through all possible combinations of microgrids, leading the algorithmic complexity towards $O(2^{|N|})$. The energy transfer matrix with associated incurred profit (the per unit pricing is as same as in example related to Eq. (13)) is shown in Fig. 6. The formed coalitions are shown in dashed lines. Here the profit is actually the monetary benefit a microgrid experiences after forming coalition by *HRCoalition* scheme. Note that, the profit margin of the source microgrids are always better than that of destination microgrid (due to the higher per unit profit).

4.2. 100 microgrids with distance threshold 1.5 km

We have considered 100 microgrids spaced over 10 square km with a distance threshold of 1.5 km. The number of coalitions formed is 35. The utility value for each coalition is printed in Fig. 7. This figure also, at the same times, shows three different coalitions with their microgrids inside as well as the total loss and energy status after performing intra-coalition energy management.

4.3. Energy exchange for 24-h

The real-time operation of energy exchange within microgrids and *UG* is ensured by expanding the model up to 24-h. Since, the *HRCoalition* scheme is robust and can provide the microgrids cooperation decision optimally very fast, it can be applied in real-time operation for utility grid. Fig. 8 shows the average utility and number of coalitions in 24 h considering 100 microgrids with a threshold of 1.5 km. Since, the energy status of each microgrid is subjected to change at every hour, the number of coalitions and average utility value also fluctuate dynamically. The energy status and corresponding utility for a particular microgrid (microgrid 11) spans over 24-h is shown in Fig. 9.

4.4. Reduction of loss in distribution system

In this class of simulation, we will show the effectiveness of the proposed HR Coalition scheme as far as *power loss reduction* is concerned. As we mentioned before, one of the motivations of the presented research is to minimize the power loss by coalition formation. The power loss situation employing HR and DO coalition scheme is shown in Fig. 10 for 10 microgrids case. The result is conducted by running both of these methods for 100 times. As it can be seen that, *HRCoalition* scheme effectively reduces the loss of power within the network in almost most of the (86%) times. The average loss reduction is 26%. Fig. 11 shows the loss reduction phenomena when the number of microgrids is 500. It is very interesting to see, in this case, the loss is reduced (significantly) in all of the runs (100%). Moreover, the average loss reduction is also improved to 77%. Therefore, the coalitions formed by *HRCoalition* scheme is scalable and performs better with higher scaled system. The summary of loss reduction phenomena is shown in Fig. 12. This figure portrays the average percentage of power loss reduction after applying *HRCoalition* scheme for different sized system. As the system size grows, the proposed *HRCoalition* scheme reduces the power loss in the network. Another notable point is, the average loss per microgrid is also reduced with the system size. Precisely speaking, the average loss per microgrid in 10-microgrid case is 0.20 while the same in 500-microgrid case is 0.14 by applying *HRCoalition* for both of the cases.

4.5. Average execution time

The pattern of average execution time (AET, in seconds) of forming coalitions is shown in Fig. 13. The processes in *HRCoalition* scheme is executed 100 times each over a hypothetical distribution network containing 5 microgrids to 500 microgrids (with a step size of 5). Fig. 13 suggests that the AET has a quadratic relationship with number of microgrids. Compared with the conventional coalition formation method (which yields an exponential relationship between AET and number of microgrids, shown in Fig. 14), the proposed method is supremely fast. Hence, the proposed *HRCoalition* scheme can be effectively applicable in real time.

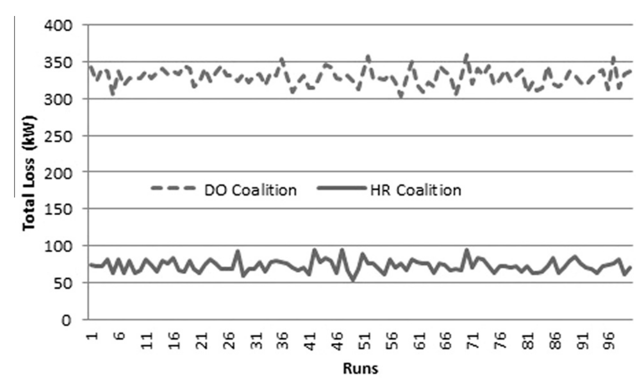

Fig. 11. Comparison of total power loss for 500 microgrids (for 100 runs) between DO and *HRCoalition* scheme.

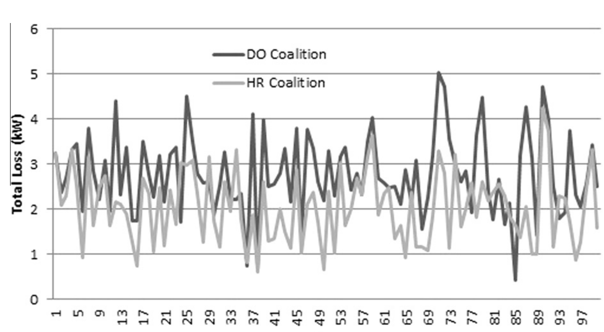

Fig. 10. Comparison of total power loss for 10 microgrids (for 100 runs) between DO and *HRCoalition* scheme.

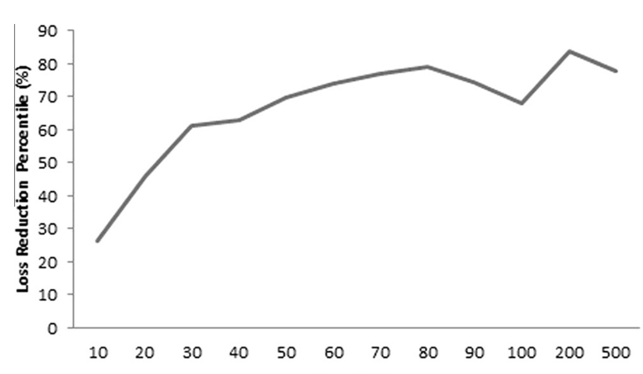

Fig. 12. Percentage of average loss reduction for different number of microgrids.

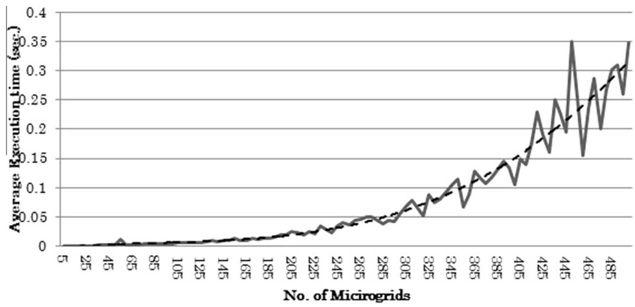

Fig. 13. The pattern of average execution time (AET) vs. the size of the distribution system.

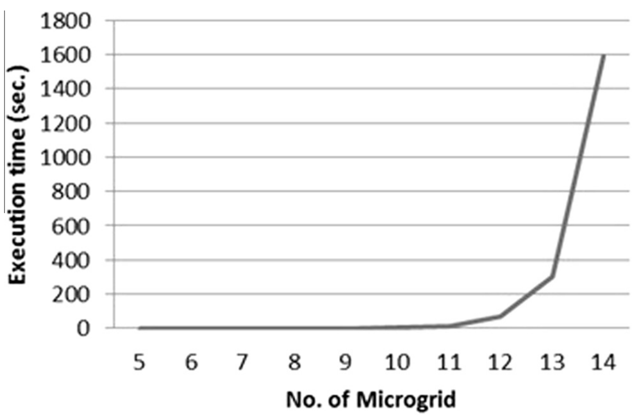

Fig. 14. The pattern of execution time (AET) using LP based coalition formation.

5. Conclusion

A scalable Hierarchical priority based intelligent coalition formation (*HRCoalition*) method is presented to provide the optimal coalition after analyzing the properties using Coalitional Game Theory. We also assume a relative order of pricing that incentivizes the microgrids to form coalitions from economic point of view. The *HRCoalition* is much faster, significantly more scalable yet optimal compared to its LP coalition formation counterpart and thus suitable for real time operation. The dynamic load conditions of microgrids leads to the dynamic formation of coalitions. Coalition formation is proved to be important since it can reduce energy burden from utility grid, the power loss in the network while maximizing the energy transfer between microgrids.

The impact of the proposed method is twofold, (1) it can be directly applied to an existing distribution system (integrated to utility-EMS) by essentially incorporating the geographical locations of microgrids, the inter-connectivity specifications of microgrids and their energy status as system inputs and provides optimized energy transfer matrix which states the amount of energy transferred between a pair of microgrids, (2) it can be used as an analytical tool for setting up potential distribution system with a good number of microgrids in order to provide network connectivity within the microgrids. Even, for a smaller distribution system where the network loss is not so significant, the microgrids are still incentivize to form coalition because of the attainable profit incurring from the designed pricing scheme. The designed method is computationally very efficient and can scale highly with the number of microgrids. The microgrid coalition formation algorithm can be easily transformed into a generic algorithm and be effectively applied while forming smart-home coalitions inside a microgrid.

The method, however, in its current form is a centralized one. That means, we cannot ignore the existence of a centralized entity that is responsible for gathering all energy information, determines the coalition formation in centralized fashion and dispatches the energy exchange information to all involved microgrids. Moreover, the designed pricing scheme is not complete since a microgrid can get away with larger profit by misinforming the system regarding its energy profile. Other economic measures such as strategy-proofness and incentive compatibility are ignored in the current form of designed pricing scheme.

Given a particular distribution system with a sizable number of microgrids, the centralized approach can be effectively transformed into distributed system. Therefore, the future work shall be heading to that direction of distributed and multi-agent based coalition formation of microgrids while keeping the optimality property intact. Moreover, a market based control of microgrid coalition with consideration to detailed and complete pricing design will also be a strong future follow-up research. On the other hand, having a real-time energy exchange method in hand, it will be easy to implement services such as on-line demand response. Another stream of research can also points to this direction.

References

Abe, R., Taoka, H., & McQuilkin, D. (2011]). Digital grid: Communicative electrical grids of the future. *IEEE Transactions on Smart Grid, 2*, 399–410. http://dx.doi.org/10.1109/TSG.2011.2132744.

Alam, M., Ramchurn, S., & Rogers, A. (2013). Cooperative energy exchange for the efficient use of energy and resources in remote communities. In: *Twelfth International conference on autonomous agents and multiagent systems (AAMAS 2013)*.

Apt, K. R., & Witzel, A. (2009]). A generic approach to coalition formation. *International Game Theory Review, 11*, 347–367. http://dx.doi.org/10.1142/S0219198909002352.

Buchanan, J., & Tullock, G. (1962]). *The calculus of consent: Logical foundations of constitutional democracy*. Ann Arbor: University of Michigan Press. Chapter 12.

Chakraborty, S., Ito, T., & Senjyu, T. (2014]). Smart pricing scheme: A multi-layered scoring rule application. *Expert Systems with Applications, 41*, 3726–3735.

Chakraborty, S., Ito, T., Senjyu, T., & Saber, A. (2013]). Intelligent economic operation of smart-grid facilitating fuzzy advanced quantum evolutionary method. *IEEE Transactions on Sustainable Energy, 4*, 905–916.

Hernandez-Aramburo, C., Green, T., & Mugniot, N. (2005]). Fuel consumption minimization of a microgrid. *IEEE Transactions on Industry Applications, 41*, 673–681.

Katiraei, F., Iravani, R., Hatziargyriou, N., & Dimeas, A. (2008]). Micrograds management. *IEEE Power and Energy Magazine, 6*, 54–65. http://dx.doi.org/10.1109/MPE.2008.918702.

Liao, G.-C. (2012]). Solve environmental economic dispatch of smart microgrid containing distributed generation system using chaotic quantum genetic algorithm. *International Journal of Electrical Power and Energy Systems, 43*, 779–787.

Marzband, M., Sumper, A., Ruiz-lvarez, A., Domnguez-Garca, J. L., & Tomoiag, B. (2013]). Experimental evaluation of a real time energy management system for stand-alone microgrids in day-ahead markets. *Applied Energy, 106*, 365–376.

Ramchurn, S. D., Vytelingum, P., Rogers, A., & Jennings, N. R. (2012]). Putting the 'smarts' into the smart grid: A grand challenge for artificial intelligence. *Communications ACM, 55*, 86–97. http://dx.doi.org/10.1145/2133806.2133825.

Rey, A., & Rothe, J. (2010). Complexity of merging and splitting for the probabilistic banzhaf power index in weighted voting games. In: *Proceedings of the 2010 Conference on ECAI 2010: 19th european conference on artificial intelligence* (pp. 1021–1022). Amsterdam, The Netherlands.

Saad, W., Han, Z., Poor, H., & Basar, T. (2012]). Game-theoretic methods for the smart grid: An overview of microgrid systems, demand-side management, and smart grid communications. *IEEE Signal Processing Magazine, 29*, 86–105. http://dx.doi.org/10.1109/MSP.2012.2186410.

Sandholm, T., Larson, K., Andersson, M., Shehory, O., & Tohm, F. (1999]). Coalition structure generation with worst case guarantees. *Artificial Intelligence, 111*, 209–238.

Shoham, Y., & Leyton-Brown, K. (2008]). *Multiagent Systems: Algorithmic, Game-Theoretic, and Logical Foundations*. New York, NY, USA: Cambridge University Press.

Velik, R., & Nicolay, P. (2014]). Grid-price-dependent energy management in microgrids using a modified simulated annealing triple-optimizer. *Applied Energy, 130*, 384–395.

Wei, C., Fadlullah, Z., Kato, N., & Takeuchi, A. (2013]). Gt-cfs: A game theoretic coalition formulation strategy for reducing power loss in micro grids. *IEEE Transactions on Parallel and Distributed Systems*. http://dx.doi.org/10.1109/TPDS.2013.178. PP, 1–1.