2020 IEEE 3rd International Conference on Renewable Energy and Power Engineering

Renewable Energy Integration through Coalition Formation for P2P Energy Trading

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Abstract—**Renewable energy sources are highly unreliable; hence prosumers connected to renewable energy sources find unreliable energy surplus and demands which should be managed frequently within neighbourhoods. Peer-to-peer(P2P) energy trading has emerged as the next-generation energy management mechanism to manage unreliability concerns within local communities. This process needs a prosumer with energy demand to join with a set of prosumers with energy surpluses to fulfil the energy need. Finding the optimal set of prosumers with energy surpluses is a challenge that is not yet duly addressed in literature considering the unreliability of energy sources and constraints in local communities. This paper presents a game-theoretic approach, applies coalition formation game theory supported by a clustering-based approach and solves an optimisation problem to find optimal coalitions. The optimal coalitions are the winning coalitions found from our coalition formation game. This game considers frequent change of energy surpluses and demands, distance to prosumers, the quantity of energy sale, and dynamic clustering on potential coalitions. The payoff will calculate the quantity of energy sale. We used a multi-threading and parallel computing approach to find the optimal size of the cluster that gives winning coalitions. We implemented our clustering-based coalition formation algorithm in Java. We tested for the efficiency and success rate using a residential PV energy production and consumption data set from California state in the USA. We compared the number of successful coalitions resulted from our algorithm with the hierarchical coalition formation algorithm(HCF) in literature. Our experimental results showed that both the sizes of the neighbourhood and sizes of the cluster have a significant impact on the number of successful coalitions and the proposed algorithm has a higher success rate compared to the HCF algorithm.**

Keywords-renewable Energy Integration, through coalition formation for p2p, energy trading

I. Introduction

Renewable energy generators are not reliable because they are profoundly affected by changing environmental factors; for example, the amount of sunshine and wind speed. The unreliable energy sources create unreliable energy surplus and energy demands. The P2P energy trading has emerged as the next-generation energy management mechanism to manage unreliable energy surplus and demands within local communities. This process needs a prosumer with energy demand to join with a set of prosumers with energy surpluses to fulfil the energy need. Prosumers consume and produce renewable energy.

The P2P energy trading among local prosumers and users is an exciting concept to manage unreliable distributed energy resources[1], [2]. The energy transfer in conventional micro-grid architecture is between micro-grids and the Utility Grid(UG), which involves energy transfer through substations and voltage transformers, resulting in a power loss. P2P Energy trading goes from prosumer to prosumer rather than large commercial enterprise to consumer, and prosumers can sell their excess power for profit. In this approach, there is no middle man making deals on own terms, everyone saves money, the size of the generator or prosumer is not essential, and deals are direct and transparent.

Cooperative game theory involves three stages of cooperative action, coalition formation(i.e., agreement of who will work together), team formation (i.e., agreement of who does which task with which resources), and coordinated, cooperative action (i.e., agreement on how to dynamically coordinate)[3]. We have explored the literature in detail essentially HCF in [4], P2P energy trading using a game-theoretic approach in [5], robust coalition structure generation in [6], coalitional games to fulfill group efficient solutions in [7], cooperative strategy-based coalition formation in [8], and generic approach to coalition formation in [9]. However, finding the optimal set of prosumers with energy surplus for a prosumer with energy need is a challenge which is not yet duly addressed in literature considering the unreliability of energy sources and constraints in the local community. We have observed, at least the following concerns should be addressed when creating coalitions:

- Coalition formation needs to find optimal coalitions. This process may need to look into all the possible distinct combinations of potential prosumers. However, a large number of prosumers can create an exponential number of coalitions and could be relatively unrealistic.
- Coalition formation and energy trading should be done frequently within small intervals because energy sources

978-1-7281-9452-3/20/$31.00 ©2020 IEEE

are unreliable.
- Coalition formation needs to consider the distance between prosumers to minimise energy loss at transmission in low-voltage networks.

Our methodology directed towards clustering-based coalition formation, solving an optimisation problem using multi-threading and parallel computing approach to find the optimal coalitions, and P2P energy trading using the optimal coalitions. We modelled coalition formation using cooperative game theory[6], [10] to create coalitions of prosumers to fulfil energy requirements of them. Prosumer with excess energy at time t is called PG_t and prosumer with energy need at time t is called NG_t. A set of MGs at time t within neighbouring distance d from an NG is called coalition members. A large number of coalition members can create an exponential number of coalitions and could be relatively unrealistic. We propose a clustering-based approach that creates clusters from coalition members and creates all the possible distinct combinations of prosumers in each cluster. These distinct combinations in different clusters join together to form potential coalitions which can fulfil the energy need of an NG. The optimal coalition can fulfil the energy need of an NG with minimum excess energy. We further vary the size of the cluster, consider the maximum time for coalition formation, and solve an optimisation problem to find the optimal coalitions. In other words, the optimal coalition is the winning coalition found from our coalition formation game. We implemented our algorithm in Java and tested using a data set in the California state. We compared our coalition formation results with HCF in [4] that creates coalitions among microgrids.

We organised this paper as follows: In section II, we discussed the relevant literature. Section III described the proposed clustering-based coalition formation game. In section IV, we discussed the implementation, experimental evaluation, and results. Finally, in section V; we presented findings and future research.

II. Literature Review

Game theory is the study of mathematical models of strategic interaction among rational decision-makers[11]. Game theory attempts to abstract out elements that are common to many conflicting and(or) cooperative encounters and analyse them mathematically[12]. A cooperative game focuses on how one can provide incentives to independent decision-makers so that they act together as one entity to improve their position (or utility) in the game[5].

We have explored HCF in [4], P2P energy trading using game theory in ([5], [13]), robust coalition structure generation in [6], coalitional games to fulfill group efficient solutions in [7], cooperative strategy-based coalition formation in [8] and generic approach to coalition formation in [9] to review and advance state of the art of coalition formation.

The primary task of managing prosumers is dynamically balancing energy requirements (local supply and power demands) due to the unreliable nature of renewable energy resources and the variability of load demand during the day. In [8], agents associated with each micro-grid implement a cooperative strategy and generate coalitions to fulfil the energy requirements of them having a minimum power loss. A TU game $(\mathcal{N}, v)$ was defined to have a cost function proportional to the power loss[8]. Coalitional games fulfil group-efficient solutions to problems involving strategic actions. In coalition formation games, forming coalitions bring advantages to its members, but the cost for forming coalitions limit the gains[7]. Authors in [6] have discussed a robust coalition structure generation that partitions a set of agents into coalitions and maximises the social surplus (i.e., the sum of the rewards obtained by each coalition). Collaborative spectrum sensing as a coalitional game is presented in [14]. The typical optimal coalition formation method requires exhaustive search over all possible combinations, which is computationally very expensive[9]. This paper advances the state of the art by introducing a clustering-based game-theoretical coalition formation supported by an optimisation problem.

III. Clustering-based Coalition Formation Game

This section explains how do the prosumers with energy surplus find their positions in optimal coalitions to trade energy to prosumers with energy needs. In a coalition formation game for P2P energy trading, prosumers form coalitions to improve their respective utilities. The strategic interaction among prosumers is needed to identify the distance between them, find energy requirements, find all the possible distinct coalitions and find the optimal coalitions. The optimal coalitions contribute to P2P energy trading.

Let $A = \{a1, a2, ..., a_n\}$ be a set of prosumers including PGs and NGs. The quantity of energy need is defined as $Q(NG)$. For an NG, potential coalition members should be found based on the neighbourhood distance. The neighbourhood distance can be varied based on the geographical and network constraints [15]. Coalition members consist of PGs from A within a neighbourhood of an NG. The distinct combinations of coalition members will form coalitions. The winning coalition is the optimal coalition (s^*) for an NG found from all the coalitions.

Definition 1 - Coalition Formation Game.
The coalition formation game can be defined by a pair $CFG_{NG_i} = \langle N, v \rangle$ where $N = \{PG_k, PG_{k+1}, ..., PG_n\}$ is a finite set of prosumers (the set of players), and v is a real-valued function on $s \subset N$ (s is a coalition) with $v(\emptyset) = 0$. $v : 2^{|N|} \rightarrow \mathbb{N}$ and i,k and n are positive integers. A mutually disjoint coalition $s \in S$ where S is the total number of coalitions (distinct combinations of PGs).

The function v is called a game or a game on N. G^N denotes the set of all games on N; G^N is a Euclidean space of dimension $2^{|N|} - 1$, where $|N|$ is the cardinality of N. This process excludes the empty set. The value (or utility) of a coalition s, denoted by $v(s)$ is given by the real-valued function v. $v(s)$ finds the total energy of coalition s when its members act together. If $s = MG_i, MG_{i+3}, ..., MG_j$ then $v(s) = Q(MG_i) + Q(MG_{i+3}) + ... + Q(MG_j)$ where i, j are positive integers.

Definition 2 - the Optimal Coalition for a NG. The optimal coalition s^* is the coalition where $(v(s) - |Q(NG)|) >= 0$ and $(v(s) - |Q(NG)|) = Q^{diff}_{min}$ for $s \in S$. Q^{diff} is a quantity of energy measured in a given unit. The $Q^{diff} = v(s) - |Q(NG)|$ for $s \in S$ and Q^{diff}_{min} is the minimum quantity. That is, the optimal coalition s^* finds when $v(s)$ is higher than and the nearest to $|Q(NG)|$. The optimal coalition is the winning coalition for the NG.

In a coalition formation game, it is crucial to distinguish the real-valued function v and the payoff function ϕ. In this work, we assume the unit price of energy is equal to all the prosumers in the neighbourhood, and the payoff is proportional to the quantity of energy sale in the optimal coalition. When $v(s^*) = Q(MG_{i+1}) + Q(MG_{i+4}) + ... + Q(MG_{j+4})$ then the payoff function $\phi(MG_i) = \eta * Q(MG_i)$ can be described as follows:

- $\phi_{MG_{i+1}} = \eta * Q(MG_{i+1})$
- $\phi_{MG_{i+4}} = \eta * Q(MG_{i+4})$
- $\phi_{MG_{j+4}} = \eta * Q(MG_{j+4})$ where η is the unit price of energy.

$$\eta(s^*) = \phi_{MG_{i+1}} + \phi_{MG_{i+4}} + ... + \phi_{MG_{j+4}}$$

Definition 3 - the Optimal ζ $\forall$ $NG \in A$. Let $\psi(A, \zeta) \rightarrow Map(NG, s^*)$ $\forall$ $NG \in A$ during the time $\tau < \tau_{max}$ then ζ has the optimal value. The optimal ζ fulfil energy needs of most of the NGs from PGs in A.

In this work, we use $\tau_{max} = 4Minutes$ because coalition formation is happening every 5 minutes based on the energy requirement of prosumers. However, τ_{max} can have various values based on the application and various other constraints (for example, distribution system operator constraints, infrastructure constraints, and policy constraints)[15]. The transaction monitoring and testing at the real deployment of P2P trading system enable deciding the most appropriate τ_{max}.

This coalition formation game will play until most of the NGs find optimal coalitions from PGs. If an NG cannot find a coalition, then connectivity to the utility grid is needed to fulfil its energy need.

Using above definitions, we define algorithm1 to find the optimal coalitions for NGs in a set of prosumers $A = \{a1, a2, ..., a_n\}$. Here we explain the algorithm 1 as follows:

1) Find prosumers with energy surplus for trading (PGs)
2) Find and Sort prosumers with energy need for buying in the ascending order (NGs)
3) Find coalitions for NGs. for each NG :
   a) Find the energy load from NG, that is Q(NG)
   b) Find a set of PGs from the neighbourhood of NG. PGs are organised in clusters of size $\zeta \in \mathbb{Z}^+$. The value of ζ should provide a reasonable number of distinct PG combinations. However, A relatively large ζ can make an exponential number of coalitions and could be relatively unrealistic. Therefore we solve an optimisation problem to find ζ for different settings.
   c) Find energy surpluses based on all the possible combinations of PGs in clusters. For a cluster, $\{\{Q(PG1)\}, \{Q(PG2)\}, ..., \{Q(PG1) + Q(PG2)\},$
   $..., \{Q(PG1) + Q(PG2) + Q(PG3)\}, ...\}$
   d) Find a PG or a set of PGs where the total energy surplus is the nearest and greater than Q(NG). When connecting clusters, firstly we check the first cluster if it can fulfil $Q(NG)$ (i.e. if $|Q(NG)| <= Q^{total}_{1stCluster}$). If NG needs further consideration, we check the next cluster to fulfil the remaining balance (i.e. $(|Q(NG)| - Q^{total}_{1stCluster}) <= Q^{total}_{2ndCluster})$). If we can fulfil the remaining balance from the 2nd cluster, then we find the best coalition from the 2nd cluster for the remaining balance. This process repeats until finding the energy need for the NG.
4) Return a set of best coalitions of MGs for NGs. In the best coalition, the total energy surplus of the coalition is the nearest and higher than Q(NG).
5) Return optimal coalitions for NGs. All the previous steps will run for various $\zeta \in \mathbb{Z}^+$ within τ_{max} on parallel threads and select the optimal coalitions for NGs. The optimal ζ provides optimal coalitions that are the best coalitions for the highest number of NGs. We solve the optimisation problem here to find optimal coalitions.

Algorithm 1 : Clustering-based Coalition Formation (CBCF)

Input : $A = \{a1, a2, ..., a_n\}$
Output: S^*; a set of optimal coalitions

$PGs \leftarrow energyExcessProsumers(A)$
$NGs \leftarrow energyRequiredProsumers(A)$
$NGs \leftarrow sortAscOrder(NGs)$
for each $NG \in NGs$ **do**
    $Q_{NG} \leftarrow energyLoad(NG)$
    $CMPGs \leftarrow findCoalitionMembers(PGs, NG)$
    $CCs \leftarrow allCoalitionCombinations(CMPGs, \zeta)$
    $BC \leftarrow bestCoalitionCombination(CCs, Q_{NG})$
end for
$B^*_{\zeta} \leftarrow bestCoalitionsForNGs()$
$S^* \leftarrow optimalCoalitionsForNGs(B^*, \mathbb{Z}^+, \tau_{max})$

The optimal coalitions decide energy transfer and transactions between NGs and PGs. If the optimal coalition of an NG is empty, the NG needs a connection to the utility grid (UG) for the energy need. The algorithm 1 executes at every 5 minutes throughout 24 hours to fulfil the energy requirements of prosumers.

A. P2P Trading

Our clustering-based coalition formation algorithm finds optimal coalitions for NGs at frequent time intervals throughout the day considering neighbourhood distance, size of the cluster ζ, and τ_{max}. Let NG_j find an optimal coalition $s^* = \{PG_i, PG_{i+1}, PG_{i+2}\}$ where i and j is a positive integer. NG_j needs a set of transactions between PGs to fulfill its energy need. Our payoff function ϕ will calculate the payoff of each transaction between NG and PGs.

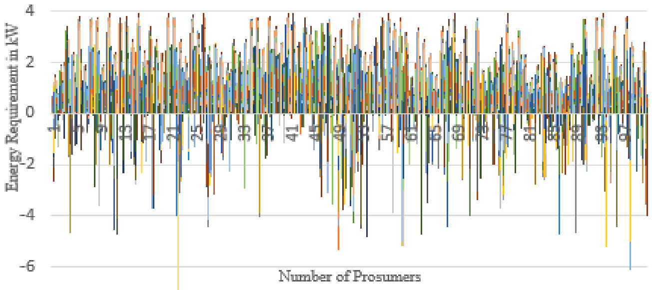

Fig. 1. Total Energy Requirement for 100 prosumers

- $\phi_{(NG_j,PG_i)} = \eta * Q(PG_i)$
- $\phi_{(NG_j,PG_{i+1})} = \eta * Q(PG_{i+1})$
- $\phi_{(NG_j,PG_{i+2})} = \eta * Q(PG_{i+2})$ where η is the unit price of energy.

Our future work will record these transactions in a blockchain as decentralised, secure, immutable and transparent records.

IV. Evaluation and Testing

A. Data Processing

We used road network data from the California state from [16] and processed locations, demand profiles(energy needs for houses) and PV profiles(energy generation information) of houses fitted with PVs using data sources in [17], [18]. We have selected 100 houses in the range of latitudes between 33 and 34, and longitudes between -119 and -118. Then we created demand profiles and PV production profiles for each house every 5 minutes for 24 hours. Using this information, we created an excess energy profile for each house in every 5 minutes for 24 hours. We created two types of energy requests (Buying request, Selling request) for each house based on the excess energy profile. We consider these houses as prosumers. Prosumers with energy surplus create Selling requests and prosumers with energy demand create Buying requests.

The total energy requirement for 100 prosumers from 6 am to 6 pm is illustrated in figure 1. The total energy requirement is calculated for each prosumer by summing energy demand and energy needs every 5 minutes from 6 am to 6 pm. The results show that most of the prosumers have up to 4 kW of energy surplus during the day time, and this energy surplus can contribute to creating coalitions to fulfil the energy needs of NGs.

B. Experimental Evaluation

We implemented our proposed clustering-based coalition formation algorithm in Java and tested for various scenarios using the above data set of 100 prosumers for 24 hours. This process creates coalitions for NGs using PGs every 5 minutes for 24 hours. Coalition formation considers the distance to the neighbouring PGs and the energy requirement of NGs. If there is (n) number of coalition members available, then there is $2^n - 1$ number of potential distinct coalitions available. As defined in definition 3, finding the Optimal $\zeta \ \forall \ NG \in A$ needs to solve a cluster-based optimisation problem. For a selected neighbourhood distance, We run our algorithm in parallel threads considering $\zeta \in \mathbb{Z}^+$ and τ_{max} and select the optimal ζ that gives the best coalitions for the highest number of NGs. We created a set of neighbourhood distances as $\{2, 4, 6, 8, 10, 12\}$ in km and clusters of various sizes as $\{2, 4, 8, 12, 16, 20\}$. We tested our algorithm using these variations, and the above sample data set for 24 hours in 5 minutes intervals, counted all the successful coalitions. We could observe that the neighbourhood distance and ζ has a significant impact when creating successful coalitions as illustrated in figure 2 hence finding optimal ζ is essential.

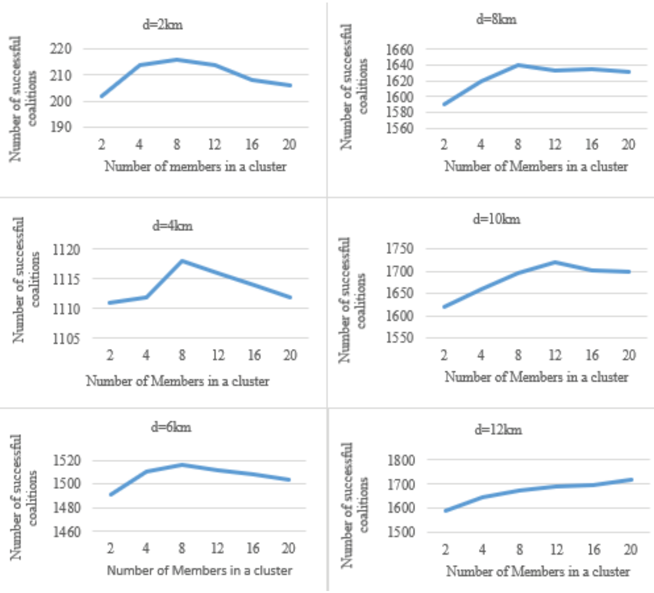

Fig. 2. Coalition Generation for neighbourhoods and clusters

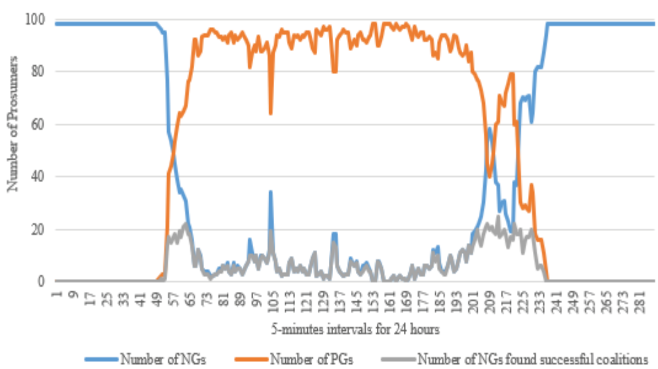

Fig. 3. CBCF: Number of PGs, NGs and NGs found coalitions

In testing, we had observed that the optimal ζ was 8 when neighbourhood distance was 8 km. We monitored the behaviour(number of NGs, number of PGs and number of the best coalitions) of our algorithm every 5 minutes for 24 hours when $\zeta = 8$ and neighbourhood distance is 8 km and illustrated in figure 3. A successful NG creates a coalition joining with a set of PGs mostly during the day time from 6 am to 6 pm.

We tested and compared the HCF and the proposed CBCF for successful coalitions using the above data set throughout the day when $\zeta = 8$ and neighbourhood distance is 8 km. The

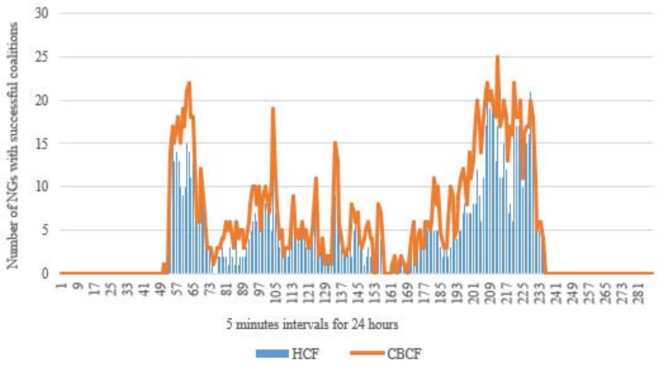

Fig. 4. Compare the Number of NGs with Successful Coalitions

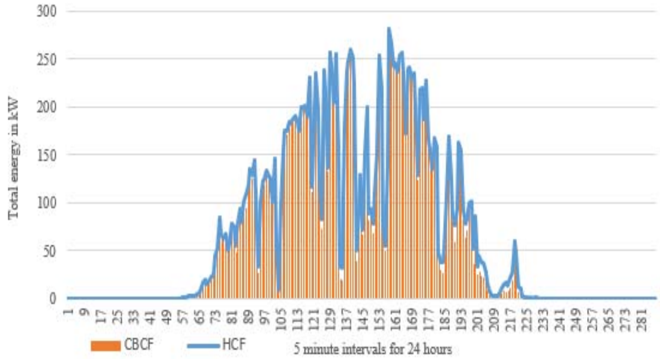

Fig. 5. Total energy of PGs did not participate for coalitions

results are illustrated in figure 4. This result shows that our clustering-based coalition formation algorithm has a higher success rate than the HCF throughout the day.

Not all PGs can participate in coalitions because of several reasons. For example, when there is no NG available within the neighbourhood distance at time t, and when the total energy available in the neighbouring PGs is not enough to fulfil the energy need of the NG at time t. We implemented our CBCF algorithm and HCF algorithm to compare the total energy of PGs which did not participate in coalitions. The figure 5 illustrates the results for 24 hours. This result shows that the proposed CBCF algorithm has a higher success rate than the HCF algorithm throughout the day. In other words, the total energy resulted from unsuccessful trading using HCF is higher than that of CBCF trading throughout the day.

V. Conclusion

This paper presents a game-theoretic approach, applies coalition formation game theory supported by a clustering-based approach, and solves an optimisation problem to find optimal coalitions. We modelled a coalition formation game and developed an algorithm for NGs to find optimal coalitions. This work monitors the frequent change of energy surpluses and demands of prosumers to address unreliability concerns and assesses the neighbourhood distance to minimise energy loss at the transmission. We perform P2P energy trading based on the optimal coalitions. We implemented our coalition formation algorithm and tested for efficiency and success rate using a real PV energy production and consumption data set from California state. We compared the successful coalition generation of our algorithm with the HCF algorithm. Our experimental results showed that the proposed algorithm has a higher success rate compared to the HCF algorithm. Moreover, we have observed that the optimal ζ and the size of the neighbourhood have a significant impact on the successful coalition generation. Our future work will consider network constraints in the neighbourhoods and use blockchain technology to improve the security and trust of winning coalitions.

VI. Acknowledgment

This publication has emanated from research supported by Science Foundation Ireland (SFI) under Grant Number SFI/12/RC/2289_P2 (Insight).

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