Fractional Hedonic Coalition Formation Game for Peer to Peer Energy Trading in a Microgrid

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Abstract—**By increasing energy trading in a microgrid, we can reduce the energy burden of the main grid, generate surplus power, reduce transmission and distribution losses, and save electricity bill. One of the options for curbing surplus energy flow, which will help maintain a dynamic equilibrium in the power grid between supply and demand, is Peer to Peer energy trading. When players form a group to strengthen their position and increase their payoff in a game, they are referred to as coalitions. An optimal coalition is designed in this work using the Fractional Hedonic Games mechanism, in which a player's utilities is the average of all the other players in a coalition. The objective of using FHG is to consider each player's preference in the game, as other games in the literature do not consider preference relations. We argued that the proposed coalition is better than the grand coalition and proved optimal and stable with a better payoff.**

Index Terms— **Coalition formation, Energy Trading, Fractional hedonic game, Game Theory, Peer to Peer trading**

I. Introduction

The integration of renewable energy (RE) based distributed energy resources (DER) in the smart grid has gained popularity in the last few years. The innovations of better Information and communication technologies (ICT) in the smart grid make a substantial change of distribution network from a centralized network to a decentralized network. DER is capable of generating renewable energy like solar rooftop, battery energy storage, small wind turbines etc., on a small scale in the distribution network. This shift transforms consumers into prosumers. A prosumer is a consumer capable of generating energy using DER in its premises and trading excess energy to consumers in a distribution network. As a result, consumers can directly purchase electricity from the prosumers without going through the main grid. Consequently, both prosumers and consumers can gain monetary benefits by revenue generation and save on the electricity bill. Peers in the network selects a trading price between the wholesale price and retail price, such that profit obtained from trading can be fairly distributed among peers. Such type of trading is known as Peer to Peer (P2P) energy trading [1],[2] and to enable this trading, a proper cost-sharing mechanism is required to split the payoff among peers. The objective of peers in P2P are peak load shaving, high participation rate, reduction in energy cost, increased green energy usage, reduced CO_2 emissions, increased revenue and minimization of network cost. P2P trading is also used to facilitate power in rural areas where the traditional grid is difficult to reach [3]. To increase the revenue of users in VPP and increase participation in a day-ahead market, [4] used green certificates of 1 MWh each. An optimization model to reduce Microgrid (MG) cost with renewable sources and demand response is illustrated in [5].

Game theory is a formal analytic framework used to study complex interconnected interactions between players with mathematical tools. In recent years, there has been a growing interest in game theory research for energy trading, mainly due to the need for developing stable and optimal coalitions where the peers can take independent decisions. Broadly game theory can be divided into two sections, i.e. Non cooperative game theory and cooperative game theory. The non cooperative game theory focuses on competitive scenarios, whereas the cooperative game theory studies players' formation and behavior in a grand coalition. When players form a cooperating group to strengthen their position and increase their payoff in a game, they are referred to as coalitions. Players in the game form a coalition such that each player shall gain more benefit in a coalition than playing individual [6]. In hedonic games [7], each agent's (player) preference for the coalition depends on the structure of the coalition he belongs to irrespective of the number of agents in a coalition. Fractional Hedonic game (FHG) [8] is a category of hedonic games where an arc linking two players denotes the preference relation between them. Each arc is prescribed with the valuation function that explains how much two players value each other. FHG is symmetric if the players' relationship is simple, and the arc's weight of 2 players is 0 or 1. In this work, we introduce fractional hedonic games for P2P energy trading, where each agent's utility (payoff) is calculated by the average value of all the member in that coalition. The bigger the payoff of the respective coalition, the more preferred is the coalition. In a game to gain more payoff, two coalitions can also merge to form a single coalition. Similarly, a single coalition can split into two smaller ones if the payoff is higher after splitting. Hence, the final coalitions

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can be formed either by merging or splitting. It should be noted that a final coalition will not be provided with an incentive or payoff if it performs merge and split in the middle of the game for a better payoff. A coalition is stable if no player performs merge and split operation to form a new coalition for better payoff at a selected timeslot t. The objective of using FHG is to consider each player's preference in the game, as other games in the literature do not consider preference relations. The minimum (Price of stability), maximum (Price of Anarchy), and sum (Social welfare) operators are used in the literature for hedonic games considering worst agents [9] and best agents [10]. Another class of hedonic games is modified FHG, where a player's utility is the average weight of other players, excluding the player [9]. Additively separable hedonic games introduced in [11] are similar to FHG, with the difference that the utility is the sum of all utilities. Bidding strategies to increase the payoff of an individual user rather than the entire market are shown in [12] by a single auction market. Therefore, the difference between our work and literature is that we focus intensely on using fractional hedonic game theory for forming coalitions at each timeslot for P2P energy trading (not used earlier).

The literature review discussed above is a pressing priority to identify the peer's objectives and recommend a motivational game-theoretic energy trading model that increases participation rate and provides a high payoff to all peers. The main contributions of this paper are as follows: -

- A model to increase the participation rate and provide a high payoff to the system's peers is introduced. A bipartite directed graph is formed in work after calculating the trading price of the coalition created.
- To calculate the valuation function of the arc between two peers, a matrix is generated for the coalition. A pair having the highest payoff is selected from the coalition matrix.
- A coalition formation algorithm is proposed using FHG to prepare multiple optimal coalitions. The algorithm tries to look into all potential coalitions that can be formed and select the stable and optimal one.
- To examine the social efficiency of P2P energy trading, we compared the social welfare of FHG and the grand coalition.

II. Fractional Hedonic Game Formulation

Bakers and Miler's problem inspired by [13] is a famous economic problem of FHG. This problem is implemented when players of category A are competitors participating in trade with category B players. We have considered bakers and Miler's example and model it for consumers and prosumers for this study's energy trading. Let us take two kinds of categories, consumers, and prosumers, where all players of category A are competitors, trading energy with players of the category B. Both categories (consumers and prosumers) are free to make pairs and coalitions for P2P energy trading. In this game, prosumers always tend to be in a coalition with as many consumers ready to trade since it will lead to a high price for the surplus energy (Selling price). However, consumers seek a high ratio of the number of prosumers to the number of consumers to achieve a low energy price (Buying price) and gain more utility (saving in the bill). Thus, each consumer prefers a coalition having a significant fraction of prosumers and each prosumer prefers a coalition having a substantial fraction of consumers.

An FHG is denoted by (N, $\succsim$) where N is a player, $\succsim$ is a set of preference relations of the players in a coalition, and i be a finite set of players. A coalition structure π is a partition of i where $\pi(N)$ denotes the coalition of player $N \in i$. Let us assume that all the players i = {1,2…N} are ready to make groups in a coalition act as a single entity S. A FHG is effectively expressed by a weighted directed graph where N represents players; weight is defined by $w(\{m,n\})$ where m and n are set of players, and E is the edge of players in $G = (N,E,w)$. If the edge between two players is 0, it means there will be no benefit by making pair and thus, $w(\{m,n\}) = 0$. The coalition's utility is denoted by$u_i(C)$, which quantifies the coalition's worth C_x and describes the type and form of the same. A player's utility in a coalition is the average value it assigns to other players in the same coalition.

$$u_i(C) = \sum_{n \in C_x} \frac{w_{m,n}}{C_m} \qquad (1)$$

When a consumer m and a prosumer n choose to trade energy through the FHG approach, both peers expect payoff/utility out of $u_i(C)$. The coalition is in Nash equilibrium if a consumer m chooses to stay in the coalition with a prosumer n when coalition C's expected utility is equal or greater than any other coalition. The proposed game remains strictly in Nash equilibrium when making a coalition for both the peers' betterment. Hence, in the proposed algorithm, all coalitions are strictly in the Nash equilibrium. Any other deviation from strict Nash equilibrium will lead to zero payoff for both peers. Social Welfare of C, i.e. a coalitional structure, is defined as the sum of all the player utilities.

$$SW(C) = \sum_{i \in N} u_i(C) \qquad (2)$$

A. Energy trading

While trading energy, basic consumer-prosumer objectives motivate peers to take part in P2P energy trading. A consumer first objective is the availability of surplus energy and a motivational trading mechanism to provide interminable energy. Secondly, the trading price also plays a vital role in the trading mechanism as it should be less than the consumption tariff. Third, a consumer should have the freedom to choose from available sources of energy. Similarly, a prosumer first objective is an opportunity to sell its surplus energy in the market with a motivational trading mechanism that provides security and privacy. Secondly, the trading price should be higher than the feed-in tariff. Third, a prosumer should also have a degree of freedom to select from available energy consumer. Furthermore, this type of trading network allows new peer to be added to the network and previous peer to be removed from the network. Here, we focus on step 1 of the algorithm where each consumer extracts demand data $d_i(t)$ by smart meters for each timeslot t where t = 30 minutes, and each prosumer extracts demand $d_i(t)$ and generation by solar rooftop $g_i(t)$ for timeslot t where t = 30 minutes. A timeslot can be 1 second or 15 minutes, or half an hour, depending on the data needed. Next, energy demand and solar generation data are used to calculate surplus/deficit energy $e_i\,(t) = \ g_i(t) - d_i(t)$ of each peer and are assigned in one of the categories according to positive or negative energy calculated. The positive value of the energy $(e_i\ + (t))$ denotes the peer is a prosumer, and the negative value $(e_i\ - (t))$ denotes the peer to be a consumer that requires energy from outside. Each prosumer and consumer of both categoriesπ_1 and π_2 submits updated energy data in the system for trading. In this way, each prosumer is informing all consumers in the network about surplus energy and trading price. Similarly, each consumer is informing all prosumers about deficit energy with the price offered. In the algorithm proposed, we assume trading price lies between buying price (BPg(t)) and selling price (SPg(t)), such that profit obtained from trading can be fairly distributed among peers based on their contributions. The TP should satisfy the condition: BPg(t) >> TP(t) > SPg(t).

Step 1 of the algorithm: To calculate the price of surplus/deficit energy of each peer after satisfying its local need and forming a bipartite directed graph.

1. **For** T=30 minutes
2. for i$\in N$ do
3. If $d_i(t) > 0$ then
4. If $g_i(t) > d_i(t)$ then
5. $e_i\,(t) \leftarrow [g_i(t) - d_i(t)]$
6. $e_i\ + (t) \leftarrow [g_i(t) - d_i(t)]^+$
7. else $e_i\ - (t) \leftarrow [g_i(t) - d_i(t)]^-$ end if
8. end for
9. $\pi_1 = \sum_{i=1}^{m} e_i - (t)$
10. $\pi_2 = \sum_{i=1}^{n} e_i + (t)$
11. Enter Buying price *BPg(t)*
12. Enter selling price *SPg(t)*
13. Calculate trading price *TP(t)*
14. $TP(t) = 0.5[BPg(t) + SPg(t)]$
15. end if
16. **End procedure**

B. Valuation function

Step 2 of the algorithm is used to calculate all pairs' valuation function and select the pair having maximum payoff. We study evaluating valuation function by forming a matrix of *m x n* size where m is the number of peers in category one and n is the number of peers in category 2. π_1 and π_2 are the sets for m number of consumers and n number of prosumers. To make a matrix, prosumer n_y interacts with m_x consumers with trading price TP and energy requirement at each timeslot of 30 minutes each. Based on these two inputs valuation function VF_i is calculated for each prosumer n_y interacting with m_x, as illustrated in Table 1. For each timeslot, each pair's valuation function is estimated when the trading price is multiplied by the minimum energy required by the consumer (Line 5). According to the valuation function calculated, peak hours (Line 9) and non peak hours (Line 11) will have different matching criteria. When demand is higher than supply in peak hours, consumers will choose to have a settlement with the prosumer having the highest valuation function. That means C1 will first select the highest valuation function available from the given m prosumers. Once C1 determines the desired prosumer to do trading, all values in the selected column will turn zero so that other prosumers shall get a chance to do trading with left consumers. This process is repeated until all the consumers have chosen their prosumer to trade. In non peak hours, prosumers will decide to have a settlement with the consumer having the highest valuation function as supply is higher than demand. Let us take an example, P1 selects consumer m having the highest valuation function and thus, the algorithm deletes the row of that specific consumer. We can say that the higher the valuation function of a pair higher is the chances of its selection. Therefore, the payoff depends directly on the valuation function, indirectly on the energy available to trade and trading price. Here, we assume that all the peers are next to each other and energy loss while trading is 0.

Table 1. Matrix to evaluate valuation function

	P1	**--**	**Pn**
C1	$TP * e(t)_{min}(C1, P1)$		$TP * e(t)_{min}(C1, Pn)$
--			
Cm	$TP * e(t)_{min}(Cm, P1)$		$TP * e(t)_{min}(Cm, Pn)$

Step 2 of the algorithm: To calculate the valuation function of all the pairs possible and select the pair that maximizes each coalition's payoff.

1. **For** T = 30 minutes
2. Make a matrix of m x n peers
3. for π_1 from $T_1 \ldots . T_m$ do
4. for π_2 from $T_1 \ldots . T_n$ do
5. $VF_i = TP(t) *\ e_i(t) * 100$ end for
6. end for
7. for i$\in N$
8. While peak hours
9. Peer i in a coalition π_1 investigates highest VF_i from $\pi_2 \rightarrow\ VF(\pi_1)$
10. Selects max(VF_i)
11. Delete column from the matrix
12. end while
13. While non peak hours
14. Peer i in a coalition π_2 investigates highest VF_i from $\pi_1 \rightarrow\ VF(\pi_2)$
15. Selects max(VF_i)
16. Delete row from the matrix
17. end while
18. end for
19. **End procedure**

C. Coalition formation

We adopt the FHG coalition mechanism to model P2P energy trading in step 3 of the algorithm. We propose a coalition formation approach that creates clusters from the peers available to trade and forms all possible combinations of consumers and prosumer in each cluster. The algorithm is used to find the optimal cluster, i.e., one consumer and one prosumer according to the valuation function and form *n* number of FHG coalition [C_1, C_2…. C_x]. We can say that for n number of peers in a coalition, the number of possible coalitions is $2^n - 1$. According to their weights, the selected cluster's valuation functions will be rearranged in descending order (Line 1). It is effective to distinguish between each pair's value function (VFi) and the utility/payoff of each coalition ($u_i(C)$). All the clusters formed are joined together to form a possible coalition (Cx) to fulfil the MG demand with minimum surplus energy and profitable trading price. The optimal coalition is the best combination for all possible outcomes found from the algorithm using FHG. With step 3, each peer with an energy surplus/deficit will find their optimal coalitions position to trade energy and receive a better payoff. Note that while evaluating clusters from a set of consumers and prosumers, a peer always tries to pair up with the peer having the highest utility and shortest distance. Multiple coalitions are formed, and if all the players agree on the selected coalition and the utility calculated for each pair, they will create a stable coalition for a specific time. By agreeing to form a coalition according to FHG coalition formation, the peers are supposed to share the utility calculated from their respective coalitions. $FHG = (N, E, w)$ can be expressed as N to be the peers, i.e. prosumer or a consumer, E is the demand and generation profile of peer, and W is the revenue peer will get from the game (line 13). The algorithm calculates the average of the total utility in the coalition and distributes it fairly. Interval. Therefore, we can say that for each pair of peers {T_m, T_n}and weight ($u_{m,n} = u_{n,m}$), peer m and n social welfare belongs to the same coalition. The algorithm further is used to examine the social efficiency of P2P energy trading, we calculated the Price of Anarchy, PoA (G (N, $\succsim$)) (Line 15), i.e., the worst-case scenario of the stable coalition and social optimum, and Price of Stability PoS (G (N, $\succsim$)) (Line 16), i.e., the best-case scenario of stable coalitions and social optimum.

Step 3 of the algorithm: Fractional hedonic coalition formation

1. Arrange u_i in descending order of their weights, i.e. VF
2. if VF>0
3. For T = 30 minutes
4. C= [C_1, C_2…. C_x] with $C_x \neq 0$ for i$\in N$
5.   for each $u_i \in VF$ do
6. C_1= First coalition formation
7. C_n= n coalition formation
8.   else C_x=S
9.   end for
10. end if
11. end for
12. $FHG = (N, E, w)$
13. Calculate social welfare → SW
14. $SW(S) = \sum_{i=1}^{n} u_i(S)$ for grand coalition
15. For each coalition C
16. $SW(C_x) = \sum_{i=1}^{n} u_i(C_x)$
17. Calculate Social Optimum → C^*
18. PoA(G(N, $\succsim$)) = max $SW(C^*)/SW(C)$
19. PoS(G(N, $\succsim$)) = min $SW(C^*)/SW(C)$
20. **End procedure**

III. Simulation and Discussion

In this section, the results of the experiments performed in section II are presented and discussed. The simulations are performed in Matlab_R2020a. The available generation and demand for peers are extracted from the home energy management system. We implemented the data on a timeslot of 30 minutes, each spread over 24 hours in a day because the algorithm presented in this paper form coalitions every 30 minutes based on energy surplus/deficit. This simulation assumes that the MG doesn't have any storage equipment due to the high price of energy storage batteries, long payback period and high degradation cost. This study aims to increase the social welfare of the MG, fulfil the energy demand of consumers, and distribute higher payoff to the peers. Fig 1 presents the surplus/deficit energy profile for peers in a MG for every 30 minutes in a day of 10 peers available for trading. There are five consumers and five prosumers in a MG. The energy shown in positive means the peers' surplus energy, while the energy shown in the negative axis is the deficit energy. From timeslot 0 to 10, we can see that no generation from the solar rooftop was experienced, and hence the MG was in deficit energy. Similarly, from timeslot 39 to 48, no P2P energy trading was experienced. Therefore, we will implement the above-described algorithm from timeslot 10 to 40 for better results. The results illustrate that most of the peer has surplus energy above 5 kW during the daytime to fulfil MG demand.

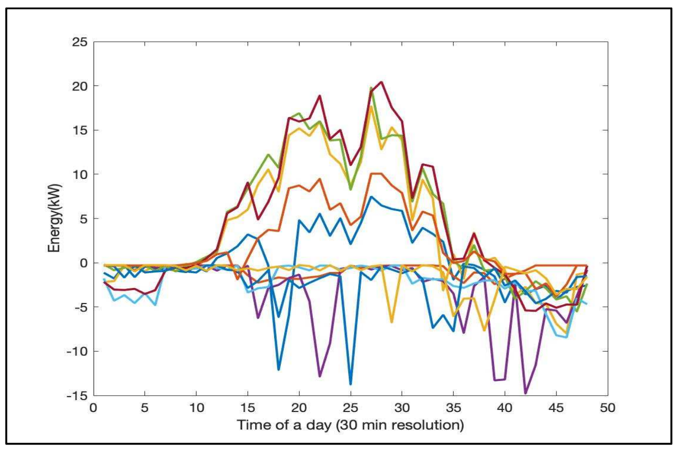

Figure 1. Surplus/deficit energy of 10 peers in an MG

Fig 2 shows 24 hours demand and generation profile of 10 peers with the P2P index. P2P index is the ratio between distributed generation from solar rooftop to the aggregated system load (without losses). To simplify the simulations, power losses are unattended in the MG since the peers are within the same community. Fig 3 shows the utility calculated for a typical day under three different scenarios as per step 1 of the algorithm. If the trading price is too high, the maximum profit will be given to the provider, and if the same is too low, the maximum profit will be given to the receiver. The trading price will be set as two extreme points in a condition where the MG's energy demand does not match with the surplus energy provided. The consumption tariff and feed-in tariff for each timeslot are assumed to be \$0.20/kWh and \$0.10/kWh.

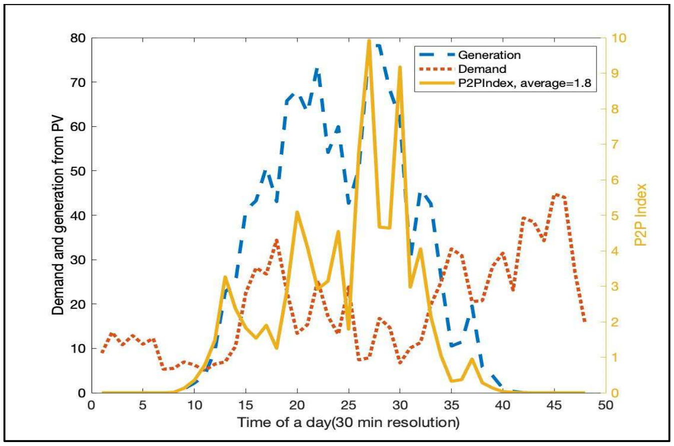

Figure 2. The energy demand of MG and generation from PV with P2P index of average 1.8

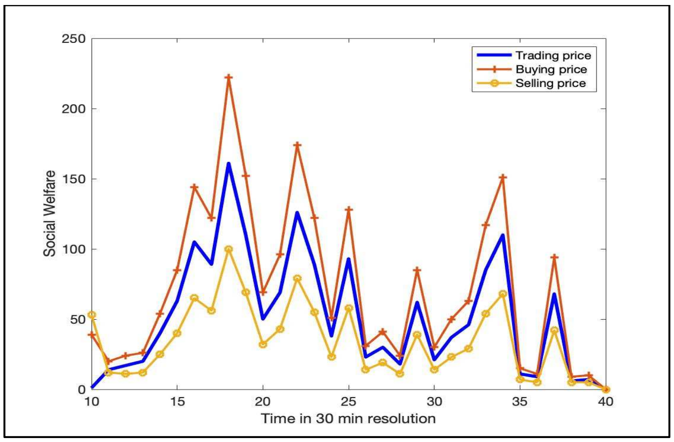

Figure 3. Effect of change in price on a utility

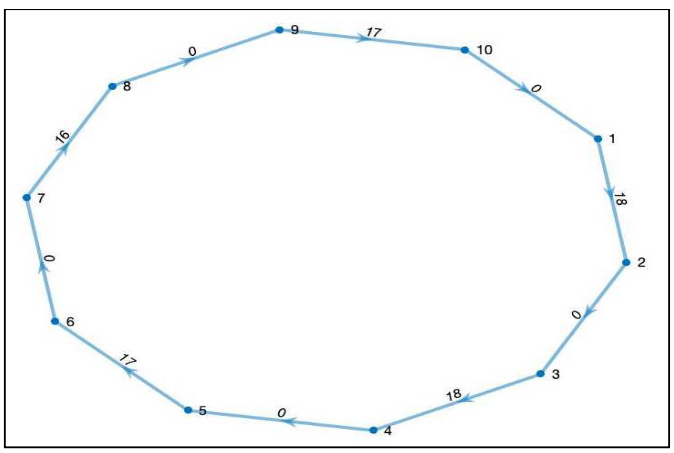

Figure 4. Bipartite directed graph for t = 23 (1100 hrs)

Fig 4 is the bipartite directed graph for a selected timeslot (t = 23). The graph shows the direction of energy delivered from prosumers to consumers, where the nodes represent the household number of the microgrid. At this specific timeslot, all the peers are taking energy from the nearest household possible as all prosumers can generate energy. However, this is not the scenario at every timeslot. If the generation is low, then the consumer tends to take energy from the highest valuation function. The arc of the graph is the FHG weight that illustrates the weightage of P2P energy trading revenue. Fig 5 displays the social welfare of the MG when using FHG. The Social Welfare (SW) of a coalitional structure is the sum of all the player's utilities in a game. The blue area is the SW of the MG when using FHG. The SW is directly proportional to the energy generation by the prosumers and P2P index. The peers' highest SW is 160 at timeslot 19, and lowest SW is 8 at timeslot 39. Fig 6 shows the utility of all the coalitions formed by using the algorithm described in section II. Due to smaller number of peers in a MG, a maximum of 2 coalitions and a minimum of 1 coalition can be created by the algorithm. A coalition will be formed only and only if the utility of the pairs in the coalition is always greater than 1. If the utility is less than 1, that coalition is not considered a stable coalition, and the pair tends to make new coalitions by the merge and split method. It should be noted that a single pair cannot form a coalition, i.e. at least two pairs (4 peers) are required to create a coalition for doing energy trading to increase the social welfare among the peers. If a pair is in an isolated coalition, its payoff will always be zero in any feasible outcome. Coalition 1 and Coalition 2 formed at each time interval are in perfect state equilibrium, i.e. all the peers choose an optimal action after each game's history. The blue bar shows coalition one, and the red indicates the utility of coalition 2.

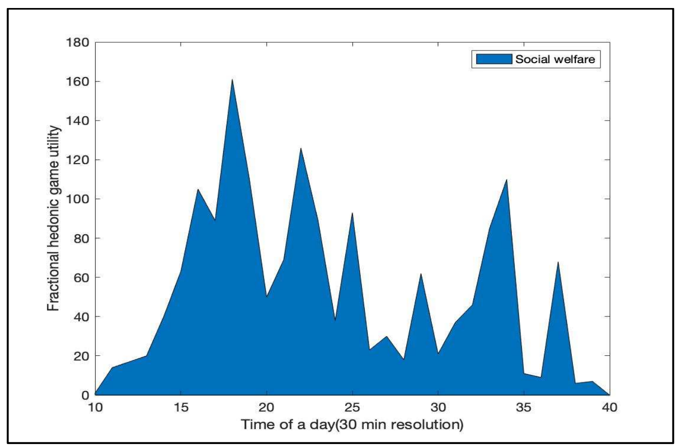

Figure 5. Social Welfare using FHG coalition mechanism

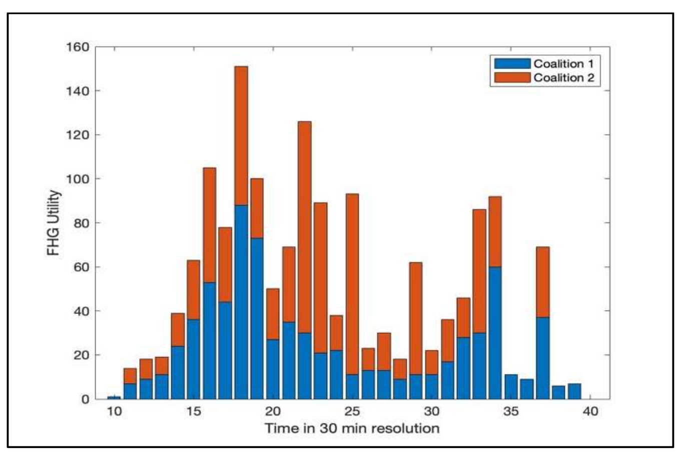

Figure 6. FHG utility of coalitions formed while doing P2P energy trading

In Fig 7, we compared the FHG coalition mechanism with the cooperative game grand coalition mechanism by calculating both cases' utility. We observed that FHG based coalition algorithm has a higher success rate than the grand coalition throughout P2P energy trading. We note that utility is mostly higher when using multiple coalitions and finding utility, according to FHG. Even for a smaller MG having ten peers where network loss is not so significant, all peers are still incentivized to form multiple coalitions because of the reasonable profit calculated from the algorithm used.

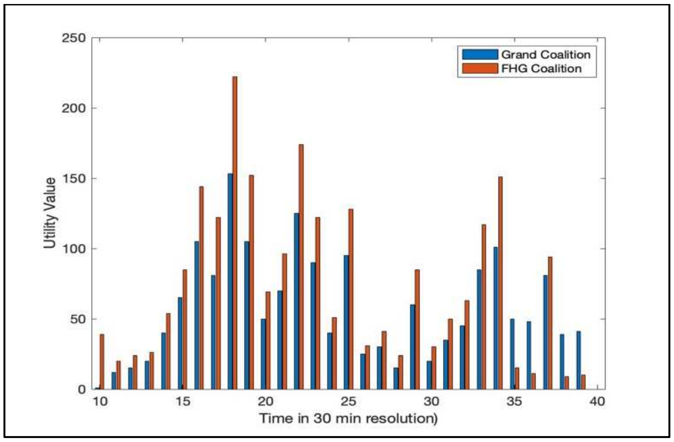

Figure 7. Utility value for peers by forming a grand coalition and FHG coalition mechanism

IV. Conclusion

In this paper, a system model, the effect of price on trade, revenue generation by trading, algorithms based on FHG and coalition formation are presented. Simulations for a MG have verified that FHG usage for energy trading increases the payoff of the users in the network compared to basic cooperative energy trading. It is more profitable for consumers and prosumers to trade energy with each other by forming coalitions than trading with the main grid or in a cooperative model. Coalitions in this game theory are constructed by calculating the valuation function of each and every pair possible in the network. These group of pairs are thus formed into coalitions using matrix formation. The payoff is calculated by an optimized energy transfer matrix of peer resultant from the product of energy demand and the trading price at each timeslot. It is economically better to trade using the price calculated by the algorithm above as a closer bidding range always increases the revenue in a P2P energy market. Moreover, our work also considered every pair's preference relation and form coalitions based on weight. The work presented is scalable as it is possible to use the same algorithm with hundreds of peers in the network. By this mechanism, peers will get monetary benefits that will be fairly divided among all the peers in a coalition. We compared social welfare resultant from our proposed algorithm with a grand coalition in a cooperative game theory. The simulations performed proves that our algorithm's social welfare is higher than a grand coalition. In the future, the study could be extended to incorporate a more significant number of peers considering network losses.

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References

[1] C. Zhang, J. Wu, Y. Zhou, M. Cheng, and C. Long, "Peer-to-Peer energy trading in a Microgrid ☆," *Appl. Energy*, vol. 220, no. February, pp. 1–12, 2018.

[2] S. Malik, S. Vyas, A. Datta, and A. Ahl, "P2P Trading using DERs : A Holistic View of Global Practices and Pioneering Efforts in India," pp. 4–9, 2019.

[3] V. Harish, N. Anwer, and A. Kumar, "Development of a Peer to peer electricity exchange model in micro grids for rural electrification," pp. 259–263, 2019.

[4] G. C. Lazaroiu, V. Dumbrava, M. Roscia, and D. Zaninelli, "Energy trading optimization of a virtual power plant on electricity market," *2015 9th Int. Symp. Adv. Top. Electr. Eng. ATEE 2015*, pp. 911–916, 2015.

[5] V. Dumbrava, G. C. Lazaroiu, S. Leva, G. Balaban, M. Teliceanu, and M. Tîrşu, "Photovoltaic production management in stochastic optimized microgrids," *UPB Sci. Bull. Ser. C Electr. Eng. Comput. Sci.*, vol. 79, no. 1, pp. 225–244, 2017.

[6] S. Thakur and J. G. Breslin, "Peer to Peer Energy Trade Among Microgrids Using Blockchain Based Distributed Coalition Formation Method," 2018.

[7] A. W. M. Gorman, "Hedonic Coalitions- Optimality and Stability," vol. 21, no. 1, pp. 63–80, 2016.

[8] H. Aziz, F. Brandl, F. Brandt, P. Harrenstein, M. Olsen, and D. Peters, "Fractional hedonic games," *ACM Trans. Econ. Comput.*, vol. 7, no. 2, 2019.

[9] K. Cechlárová and A. Romero-Medina, "Stability in coalition formation games," *Int. J. Game Theory*, vol. 29, no. 4, pp. 487–494, 2000.

[10] J. Hajduková and others, "Computational complexity of stable partitions," *Int. J. Game Theory*, vol. 31, no. 3, pp. 353–364, 2003.

[11] H. Aziz, F. Brandt, and H. G. Seedig, "Computing desirable partitions in additively separable hedonic games," *Artif. Intell.*, vol. 195, pp. 316–334, 2013.

[12] G. C. Lazaroiu, V. Dumbrava, M. Costoiu, and M. Roscia, "Game theory and competitive aspects in electricity markets," *Conf. Proc. - 2017 17th IEEE Int. Conf. Environ. Electr. Eng. 2017 1st IEEE Ind. Commer. Power Syst. Eur. EEEIC / I CPS Eur. 2017*, pp. 1–6, 2017.

[13] T. C. Schelling, "Dynamics Model of Segregation," *J. Math. Sociol.*, vol. 1, no. May 1969, pp. 143–186, 1971.