P2P as a Smarter Way of Energy Trading: A Game Theoretic Case Study for Multi-microgrids

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Abstract— **This paper focuses on performing peer-to-peer (P2P) energy trading in a grid-tied multi-microgrid system (MMS). To do so, three microgrids, each consisting of distributed energy resources (DERs) such as wind turbines (WTs), solar photovoltaic (PV) systems, and battery storage systems, are considered. A game theory-based structure, supported by the Nash equilibrium, is then formulated to derive, and solve the multi-objective function (MoF) with the intention of allocating the correct sizing of each DER and finding out the optimum payoff values. The proposed optimisation model is also integrated with reliability index (I_R) and levelised cost of energy (LCOE) in order to cut down the energy costs during intermittent periods of DERs. The developed framework is analysed and compared with other benchmark techniques on particle swarm optimisation (PSO) algorithm-facilitated MATLAB environment to conduct both P2P and peer-to-grid (P2G) energy trading. The simulation results: 1) verify the proposed MOF against various constant coefficients' combination, and 2) determine the most financially viable model for each DER through sensitivity analysis.**

Keywords— P2P trading, P2G trading, multi-microgrids, cooperative game, Nash equilibrium.

I. INTRODUCTION

The patterns and technologies are advancing swiftly throughout the world to guarantee adequate energy supply in line with the increased amount of demand [1-2]. Peer-to-peer (P2P) energy trading is one of such technologies that is supported by the distributed energy resources (DERs) and facilitates the clean energy supply into the electricity grid through mutual negotiations [3-4]. It is characteristically different from the peer-to-grid (P2G) mechanism as participants receive unprecedented flexibility to integrate their preference while managing their energy [5] using a sustainable technology such as blockchain [6]. This has demonstrated its suitability both in local energy markets (LEMs) [7] and multi-microgrid systems (MMSs) [8]. In [9], feasibility study is performed to design and optimise DERs on real word-based scenarios.

Game theory-driven decision-making strategies have extensively been exploited to construct P2P energy trading in recent years. In short, P2P research studies adopt two types of game theoretic approaches, namely cooperative and non-cooperative game theories [10]. For instance, the non-cooperative game theory is used, in which the Nash equilibrium determines the optimal solutions, to capture the price competitions in community and hierarchical microgrids (MGs) in [11] and [12] respectively. This game model is also employed in [13] to conduct P2P energy trading formulated by a single objective function (SoF) [14]. The authors in [13], [15-17], and [18] model appropriate designs to carry out bilateral bidding, study the social behaviour of the participants, trade energy in different sharing regions, and fix equilibrium trading prices respectively with the help of non-cooperative game frameworks [19].

The cooperative/coalition game theory is also utilised in the available research studies to benefit the participants collaboratively. In particular, canonical coalition games are structured in [20-22] to incentivise the grand group first and then payoffs are allocated fairly between the participating members. The utilisation of this type of cooperative game is also noticeable in [23] to manage congestion under P2P trading among MGs. Furthermore, coalition formation games are applied in [24] and [25] to design optimal coalitions and increase financial benefits respectively [26]. Moreover, the coalition graph game is exercised in [27] to maintain the network management.

These research studies primarily focus on SoF as small-scale MGs' P2P operations are considered. However, several microgrids constitute an MMS — that has a number of objectives in mind while settling P2P transactions and thus forms a multi-objective function (MoF), which needs to be analysed thoroughly for wide-scale P2P trading. To this end, this paper proposes a game-empowered structure to solve an MoF for an MMS model, using levelised cost of energy (LCOE) and reliability index (I_R), to evaluate the correct sizing of each DER, wind turbines (WTs), solar photovoltaic (PV) systems, and battery storage systems) of each MG and reduce the annual cost of the network. The robustness of the proposed approach validated by rigorous analytical analysis and simulation results, in which real data of three Western Australian suburbs are taken into account.

The remainder of this paper is organised as follows. Section II illustrates the structure of a market model. Problem formulation is described in Section III. Simulation results and analysis are given in Section IV. Lastly, the conclusion and future work are outlined in Section V.

II. ARCHITECTURE OF PROPOSED MODEL

To structure the MMS, three different microgrids based on Australian data are considered for P2P energy trading. Fig. 1 exhibits the flow of energy of traditional P2G and P2P energy trading within a simple network consisting of these microgrids. This case study considers load profile; solar PV

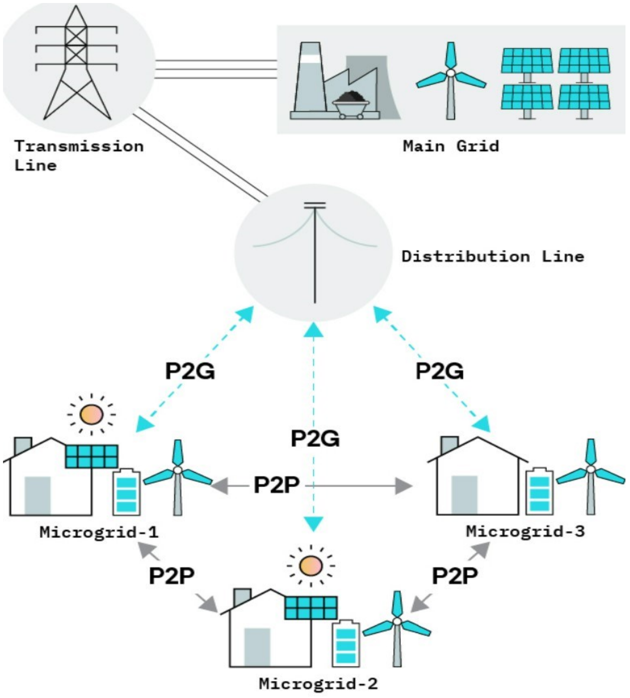

Fig. 1. Energy flow for P2P and P2G trading.

radiation; and wind speed data of Laverton, Mount Magnet and Wahroonga and assumes them as MG-1, MG-2 and MG-3, respectively. Laverton has a wind speed between 5 and 7 m/s on average, and everyday temperature varies between 17 °C (winter) and 36 °C (summer) [28-29]. On the other hand, the Mount Magnet temperature changes from 18.8 °C (winter) to 37.9 °C (summer) while the variation in the average wind speed stays between 5 and 6 m/s [30-31]. Similar trend is also noticeable in Wahroonga, its average wind speed fluctuates between 4 and 6 m/s on average, and the average summer temperature drops from 27 °C to 11 °C in winter [32].

The proposed model takes a set of three MGs into account, and eight assets each of variable size in total. They comprise one or more WTs, solar PVs, and battery units in total to supply an average load of 1 MW as shown in Fig. 2. In particular, this case study is conducted on three Australian townships that are operating as interconnected microgrids and accommodates local energy markets to perform traditional P2G and P2P energy trading. The residential data are assumed to be LEM data at this stage, and small-scale DERs are considered to be connected with the main grid through modern smart meters to monitor and track the energy flow [33].

III. Methodology

The intention of this work is to create a theoretical framework and the main objective is to determine optimal sizing of solar, wind, and battery assets and minimise the cost of energy and power loss. A cooperative game-driven MMS structure is developed; wherein WTs, solar PVs, and battery storages are considered as three defined players for each MG and they are symbolised by W, S, and B respectively. Further, optimum payoff values and correct sizing of players are determined through setting up strategic spaces.. In this study, government subsidies are not considered that can increase FiT values. The case study is effective if FiT values are closer to wholesale or retail energy price and not artificially inflated through subsidies and premiums.

To achieve optimum payoff values, an MoF is formulated based on the benchmarks of $LCOE$ and I_R [35-36]. The MoF for microgrid $n, \forall n \in N$, is:

$$MoF = Min(K_1 * LCOE + K_2 * I_R) \quad (1)$$

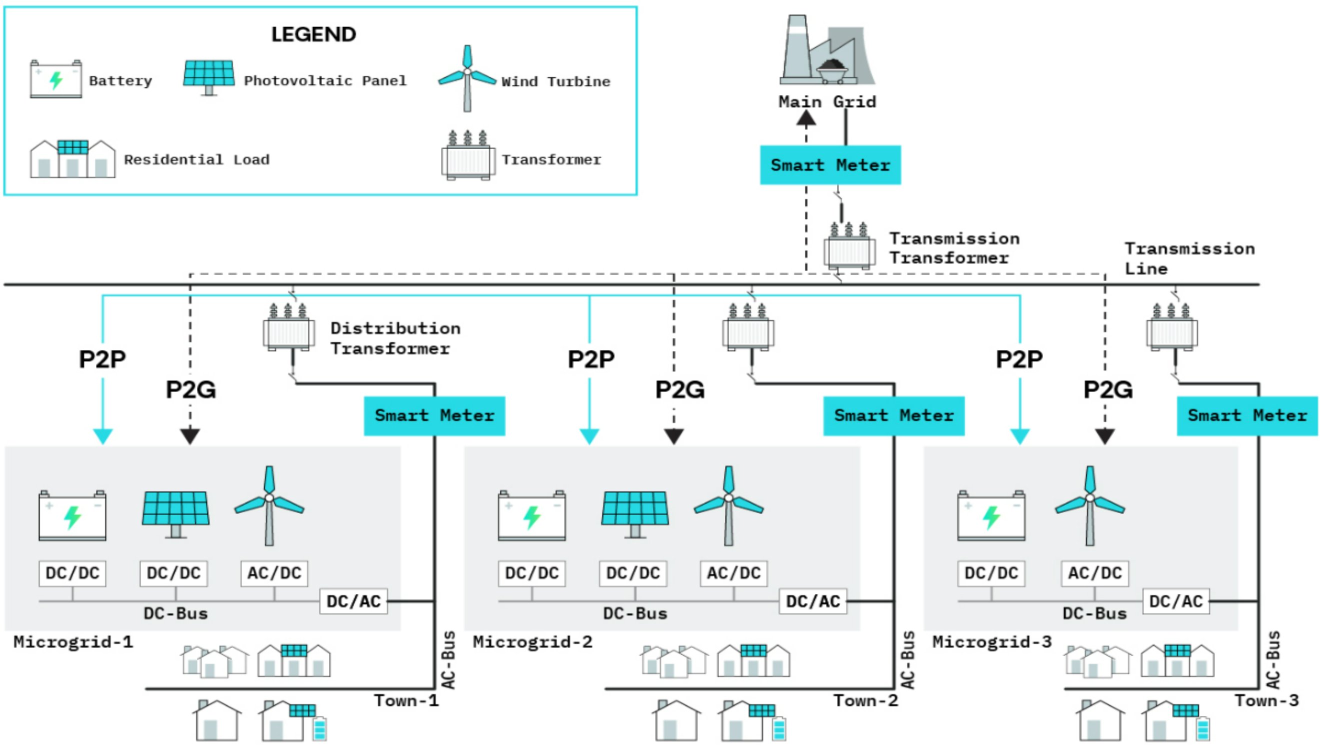

Fig. 2. The architecture of the proposed multi-microgrids system.

where K_1 and K_2 are the constant coefficients for the LCOE and the I_R, respectively, with ranges are set as $0< K_1, K_2 <1$. In this paper, both objective functions are considered as equally important; therefore, values for their constant coefficients are equally divided.

The levelised cost of energy ($LCOE$) is:

$$LCOE = \sum_{n=1}^{N} (Cost^n / E_{an}{}^n) \quad (2)$$

where $Cost$ and E_{an} are total cost and annual energy supplied. The total cost is the sum of the annual investment cost and operation and maintenance cost.

The index of reliability I_R for proposed model is:

$$I_R = \sum_{n=1}^{N} (C_{ens}{}^n / C_{pur}{}^n) \quad (3)$$

where C_{ens} and C_{pur} are the annual cost of energy not supplied and power purchased from the superior grid.

A game theory solution method called Nash equilibrium is adopted to size the player's capacity including batteries P_B, WTs P_W and solar PVs P_S. To achieve the optimum payoff values, the players participating in the game model are allowed to compete/collaborate among themselves, based on their cooperation, different coalitions can be formulated for the payoff values' optimisation. For the modelled three player game structure, four coalitions could be formed. For example, collaboration between two players with the third one playing as a self-sufficient or independent player. There are three permutations of this. A number of recent research findings, such as [37-38] demonstrate that more efficient and profitable models can be developed with the help of cooperative games in comparison with non-cooperative games. Thus, this paper concentrates on the cooperative model with a purpose of exploring all four types of coalition. Each coalition focuses on sharing capacity allocation (kW size) and payoff value.

IV. Case Study and Results

In the simulation model, MATLAB is used for modelling the architecture and input parameters [37] for this study are shown in Table-1. Each asset is treated as a player who is opting for optimising its outcome or payoff. To do optimisation for P2P trading-based LEM, the game model is built using a modified particle swarm optimisation (PSO) algorithm. PSO is essentially a computational technique to optimise different iteration problems so that the desired outcomes are improved. This study sets the population size (selected) and maximum number of iterations as 100 and 250 respectively in order to select the size of the defined players optimally while payoff values are also found out.

TABLE-I Input parameters

Parameters	Values (Units)	Parameters	Values (Units)
Price of electricity	0.28 $/kWh	Rated wind speed	12 m/s
Feed-in-tariff	0.10 $/kWh	Wind turbine price	770 $/kW
P2P trading price	0.15 $/kWh	Life of solar panels	20 Years
Life of wind turbine	20 Years	Solar panel price	1,890 $/kW
Cut-in wind speed	3 m/s	Life of battery	10 Years
Cut-out wind speed	20 m/s	Battery price	100 $/kW

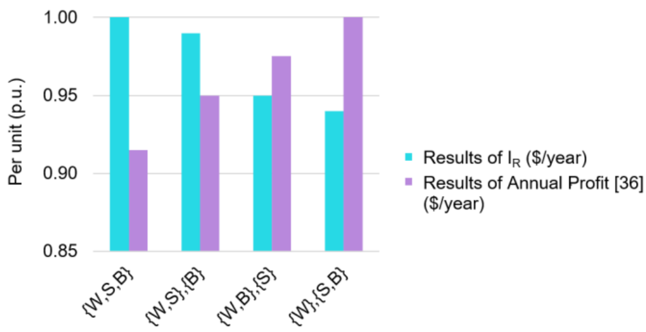

Fig. 3. Comparison among the four possible coalitions in a cooperative game where W, S and B are three parties in the game where {W}, {S,B} represents W is self-sufficient and, S and B are in single coalition, and {W,S,B} is a their joint coalition.

In Fig. 3, the payoff values of the I_R for MG-1 with four different types of coalitions are compared with payoff values of annual profit demonstrated in [36]. I_R is a minimising function for the cost of power loss; however, annual profit is a maximising function. If this analysis is compared with [36], all four coalitions show some sort of similarity, but a single coalition {W, S, B} provides the optimum results. The per-unit values of objective functions of both I_R and annual profit are shown in Fig. 4, and results verify that I_R and annual profit have their optimum minimum and maximum values in case of coalition {W, S, B}. The trend of their payoff values also shows that results are the worst for the coalition {W}, {S, B}.

In other words, the larger the gap is seen between I_R (blue) and annual profit (purple), the better is the the payoff. Every player is controlling two variables in their renewable asset. The first variable is capacity allocation, P, that determines how the sizes of battery, wind turbine and solar panel should be. The second variable is an MoF that comprises LCOE ($/kWh) and I_R ($). This illustrates how much the cost of electricity and the cost of power loss. These two variables have placed every player or asset somewhere in a two-dimensional space. This two-dimensional space is repeated for all three assets, giving a 6-dimensional (D) game space. The overall game consists of playing with the data given by the Australian meteorological data office for those townships. A guestimate point is found to start with, and computes a nearby point that produces more optimal results, and then feeds that result in and iterates the process again. This is repeated until some kind of stationary point, the Nash equilibrium, in the 6-D space is reached.

Fig. 4 depicts the simplest model with capacity allocations and payoff values of the proposed objective functions for the considered MMS. In this research, two objective functions LCOE and I_R are minimised as a single MoF to attain their optimum values. The payoff values of the proposed

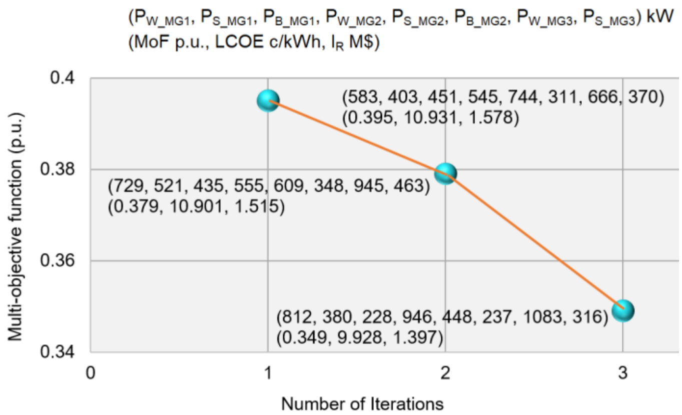

Fig. 4. Capacity allocations of the players and payoff values as result of multi-objective function.

objective functions and capacity allocation of the players P_W, P_S and P_B, where LCOE and I_R are optimised simultaneously to attain their optimum results. The outcomes of the MoF are converged after multiple iterations on the PSO algorithm and three iterations are shown in this diagram. The results illustrate that the payoff values of MoF, LCOE, and I_R are minimum at the third iteration, and optimum sizes of the defined players for each MG. MG-2 contains the largest residential load profile, resulting in greater value of total players' size that is 1,631 kW On the contrary, the smallest load profile is possessed by the MG-3, reducing its total players' size to 1,399 kW. Further validation of the total players' size is carried out as the trend is $P^*_W > P^*_S > P^*_B$ [36]. This demonstrates the maximum and minimum contributions come from WTs and batteries respectively in the formulated MMS model.

Figure 5 shows the per-unit payoff values of objective function including I_R, LCOE and MoF for three different iterations. The trend is very clear that payoff values for each objective function are minimum in iteration 3. Since the costs at this point are minimum (the payoffs are maximum); therefore, the sizes of the players P_W, P_S and P_B in iteration 3 are an optimum.

Further, figure 6 reveals that when the values of I_R (representative of cost of power loss) are compared in a P2P vs P2G scenario, P2P performs better. The results highlight that the 1.397 M$ cost of power loss in P2G decreases to almost 48 % if P2P trading is performed. That proves that modern P2P energy trading is a smarter way to reduce the cost of power loss.

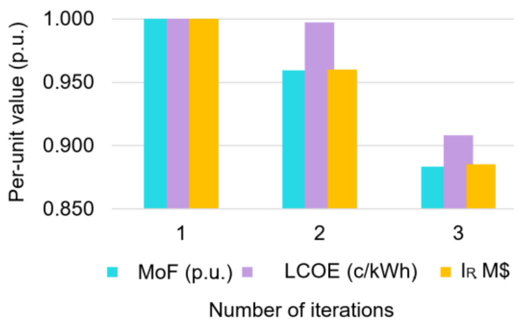

Fig. 5 The simplest model for studying payoff values for three iterations, MoF is the multi-objective function, LCOE is the levelized cost and I_R is the power loss function.

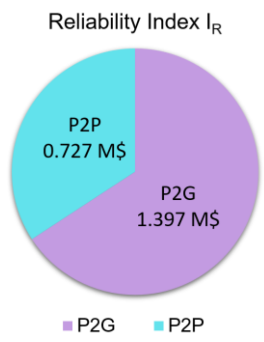

Fig. 6 Comparison of I_R payoff values P2P vs P2G.

V. Conclusion

In this paper, a mechanism has been proposed and analysed to carry out P2P energy trading between three microgrids equipped with DERs, that include WTs; solar PVs; and battery storages. The determination of the accurate size of each DER and payoff values optimally has been considered as the proposed MoF, and it has been solved by the Nash equilibrium in a coalition game theoretic format. The I_R and LCOE have been integrated with the proposed approach to guarantee lower energy costs during intermittent periods of DERs. Finally, an Australian case study, considering real world wind speed; solar irradiation; and residential load profiles, has been demonstrated to validate the proposed MoF and economic feasibility of each DER.

The outcome of this study could allow us to have greater confidence when designing P2P-empowered energy systems and allocating budget in the coming days. A larger number of players with complex permutations could contribute to the present energy sector in transitioning to the energy grid of the future.

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