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Economic Planning and Comparative Analysis of Market-driven Multi-microgrid system for Peer-to-Peer energy trading

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***Abstract* – This paper focuses on the implementation of peer-to-peer (P2P) energy trading and planning of a grid-connected multi-microgrid system (MMS) based on an advanced optimization approach. The proposed architecture is comprised of three microgrids (MGs) with combinations of distributed energy resources (DERs), including wind turbines, photovoltaic panels, and storage batteries to meet the load requirement. A game theory technique, Nash equilibrium, is used to structure the proposed model for multi-objective optimization, where the main objectives are to determine the correct sizing of DERs and optimum payoff values. Due to the variability of DERs, to maintain lower energy costs, the reliability index (I_R) and levelized cost of energy (LCOE) are the benchmarks considered for optimization. The proposed model is analyzed and rigorous comparison is carried out for both peer-to-grid (P2G) and P2P energy trading schemes considering the Australian profiles for wind speed, solar irradiation, and residential load. The simulation model is built in MATLAB software and the particle swarm optimization (PSO) algorithm is exploited for the optimization. The results illustrate that P2P energy trading reduces payoff value of multi-objective function (MOF) to 36 %. The robustness of MOF is validated and analyzed with different combinations of constant coefficients K_1 and K_2. In the end, the most economical and suitable models with DERs are proposed for each microgrid and the results are verified with sensitivity analysis.**

***Index Terms*—Batteries, microgrids, game theory, particle swarm optimization, photovoltaic cells and wind power generation.**

I. NOMENCLATURE

CO_i	The total cost of the player i
CO_{INV}	Investment cost
$C_{O\&M}$	Operation and maintenance cost
CO_{ENS}	Cost for energy not supplied
CO_{PUR}	Cost of power purchased from the grid
D_r	Discount rate
$DP(t)$	Unbalance power in hour t
$\Delta(t)$	Difference between total generation and load in hour t
ξ_c	Battery charging efficiency
E_{an}	Annual energy supplied from multi-microgrid system
i	Players $i \in \{WT, PP, SB\}$
L_i	Life span of the player i
N	Total number of microgrids
n	Index of a microgrid
P_i	The capacity or size of the player i
$p_i(t)$	The capacity of the player i in hour t
$P_L(t)$	Residential load demand in hour t
$P_g(t)$	Power purchased from the grid in hour t
P_{T_max}	The Maximum transmission line capacity
$P_{ENS}(t)$	Energy not supplied in hour t
P_{SB_min}	The minimum capacity of a storage battery
$R(t)$	Electricity price in hour t
T	Total number of hours
U_{INV}	Per unit investment cost
$U_{O\&M}$	Per unit operation and maintenance cost
$v(t)$	Wind speed in hour t
v_c	Cut-in wind speed
v_o	Cut-out wind speed
v_r	Rated wind speed

II. INTRODUCTION

A. Background

Presently, local distributed energy resources (DERs) – driven by renewable energy – are playing a vital role in fulfilling electricity requirements for more than 31% Australian households [1]. However, due to the intermittent nature of DERs, battery energy storage systems (BESSs) are connected in conjunction to avoid power fluctuation [2]. A multi-microgrid system (MMS) – a combination of different DERs-enabled microgrids (MGs) in either grid-connected or islanded mode – is another promising approach to overcome this issue. Further, it is fruitful in meeting load requirements, minimizing electricity prices, and getting rid of power outages in distribution systems [3]. Within the MMS, it is also important to manage the energy exchange properly so that the economic efficiency of the network can be enhanced [4]. Worldwide, energy supply patterns and technologies are advancing swiftly such that financially attractive peer-to-peer (P2P) energy trading is finding its suitability in the DERs-facilitated energy market [5, 6].

P2P energy trading allows prosumers – electricity consumers who can produce energy locally – to trade energy in a connected network without the direct intervention of a centralized entity [7, 8]. It is opposed to peer-to-grid (P2G) energy trading, which is a traditional unidirectional approach enabling customers to exchange energy via the main grid [9]. As such, P2P energy trading provides multidirectional control to the customers to buy/sell energy not only with the main grid but also with each other within an electricity network [10] as shown in Fig. 1. In addition, P2P energy trading offers better flexibility [11], cost minimization [12], social attributes [13], generation-consumption balance [14], peak demand shaving [15], and reliability [16], which makes it a

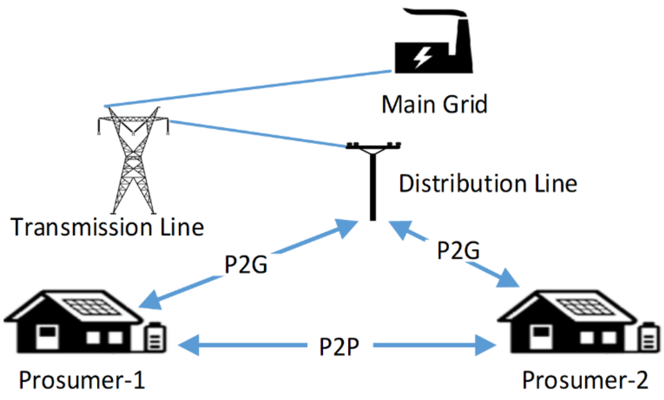

Fig. 1. Peer-to-grid and peer-to-peer energy trading schemes

very promising approach in MMS [17].

B. *Literature Review*

In recent studies, a number of literature devout towards modeling P2P energy trading frameworks in DERs-based electricity networks. In particular, mixed-integer linear programming and alternating direct method of multipliers are adopted in [18] and [19] respectively to model contract-driven decision strategies for P2P energy trading in optimal ways. P2P bidding schemes are also formulated via iterative and double auction theories in [20] and [21], respectively. Moreover, a game theory-based decision-forming strategy is also applied in the area of P2P energy trading research, which designates multiple players to resolve the conflicts and to reach their optimum payoff values within the set space limits [22]. Designing the network based on game theory can be organized either in a cooperative or non-cooperative way for finding the optimum sizes of players [23]. In [24], both cooperative and non-cooperative game theory approaches are compared and analyzed for the purpose of identifying the most economical and efficient method for a stable P2P MG based on single-objective optimization.

A non-cooperative game model is proposed for P2P energy trading in a typical MG in [25], in which a single-objective optimization is used to find out the optimum results. The price competitions of P2P energy trading models – structured by the non-cooperative game theory – are also developed in [26] and [27], where optimal solutions are determined by dint of Nash Equilibrium. The cooperative game theory is also adopted in the existing research studies to incentivise the P2P players' coalition. The authors in [28] exercise this form of game theory to settle optimum energy management in the P2P players' group. Similar game models are also utilized in [29] and [30] to cut down the total electricity cost amount and maintain stable operation in a small MG community. Besides, the applications of cooperative game theory-empowered P2P energy trading methods are noticeable [31] in order to evaluate the optimum sizing of clustered MGs.

Clearly, the aforementioned recent studies have laid the foundation to formulate P2P energy trading in MG domain. However, these works have primarily focused on optimizing the small-scale MGs operation through a single-objective function (SOF). The combination of MGs to form an MMS – with different objectives in mind – constitutes a multi-objective function (MOF), which has not been solved thoroughly for large-scale P2P energy trading in the current literature. Therefore, in this research, an MMS with combinations of three different MGs is proposed, and the MOF is formulated through the cooperative game theory technique and P2P energy trading. This paper also designs an innovative real-world data-based MMS model, and input profiles are fetched from the Australian energy market to perform the analysis. Noted that the analysis conducted in this paper opens up the possibility to implement wide-scale P2P energy trading between existing towns.

C. *Contributions*

In this paper, we extended a previous line of work [32-33] and performed a multi-objective optimization– based on P2P energy trading operation – for planning and cost minimization of the proposed MMS in grid-connected mode. Each studied MG consists of a residential load and different combinations of DERs including wind turbines, photovoltaic panels, and BESS. The technical objectives of multi-objective optimization are levelized cost of energy (LCOE) and reliability index (I_R). The proposed MMS is modelled through the game theory technique named Nash Equilibrium, in which a cooperative game model is optimized to form a single coalition. The real weather data and load profiles of three remote towns of Australia are taken into consideration to carry out the analysis. The simulation model is integrated with particle swarm optimization (PSO) and designed in MATLAB software. The results for both P2G and P2P energy trading schemes are analyzed and compared in terms of set criteria, and the suitable sizes of DERs are proposed. The multi-objective function (MOF) is validated, and sensitivity analysis is then performed to verify the optimized results. The main contributions of this paper are summarized as follows:

- A functioning P2P energy trading mechanism is proposed for an MMS – designed by means of an advanced cooperative game-theoretic model.
- A typical MOF is formulated using set criteria of levelized cost of energy and reliability index to determine the suitable sizes of DERs and reduce the annual cost of the proposed MMS.
- The proposed P2P architecture is optimized for SOF and MOF, and results are validated for different combinations of constant coefficients K_1 and K_2.
- A two-stage P2P and P2G energy trading frameworks are developed, and rigorous comparisons and analysis are carried out to ensure model feasibilities and payoff verifications.
- Accurate results are ascertained by acquiring real data of three towns from an energy supplier in Western Australia.

The remainder of this paper is organized as follows. Section-III illustrates the considered microgrids in Australia. Section-IV designs the proposed MMS. Section-V formulates the multi-objective function based on the set criteria. In Section-VI, the Nash Equilibrium-driven technique is demonstrated for the proposed model. The simulation results and analysis are provided in Section-VII. In the end, Section-VIII contains the concluding remarks.

Fig. 2. Towns of Australia Laverton, Mount Magnet and Wahroonga

III. Market Profiles for the Model

To achieve optimum results and suitable sizing of the DERs, the realistic field data of wind speed, solar radiation, and residential load are considered for three towns named Laverton, Mount Magnet, and Wahroonga located in Western Australia (WA) and New South Wales (NSW) as shown in Fig. 2. Laverton and Mount Magnet are WA's remote towns [34] and are located 957 km and 560 km, respectively, northeast of the state's capital, Perth. Wahroonga is a suburb of NSW and is located 19 km northwest of the state's capital, Sydney. The state of WA has rich solar and wind energy resources that encourage the use of DERs to fulfil residential load

requirements. The state of WA has installed many large and small renewable generation units at different locations to meet the residential demand [35–36]. Australia's best renewable generation locations for wind energy and solar radiations are in NSW. Therefore, Government is encouraging industrial owners to invest in renewable energy-based farms [37–38].

The data profiles of Laverton, Mount Magnet and Wahroonga are considered for MG-1, MG-2 and MG-3, respectively. Fig. 3 illustrates the annual data profiles for wind speed, solar radiations, and residential loads for three towns. The average wind speed of Laverton is between 5-7 m/s, and its mean daily temperature changes from summer 36 °C to winter 17 °C. The Mount Magnet temperature varies from 37.9 °C in summer to 18.8 °C in winter, with an average wind speed between 5-6 m/s. The temperature of the Wahroonga decreases from 27 °C in summer to 11 °C in winter, and its average wind speed changes between 4 to 6 m/s. For each MG, the average and maximum data for wind speed and residential load and the maximum solar radiation are shown in Fig. 3. The data profiles for the Laverton, Mount Magnet, Wahroonga are used for Jul 2014 – Jun 2015, Jun 2015 – May 2016, and Jul 2012 – Jun 2013, respectively [39-43].

IV. The Multi-Microgrid System

The block diagram of the grid-connected MMS based on the P2P energy trading scheme is shown in Fig. 4, where three MGs are connected with their residential loads. Different combinations of wind turbines, photovoltaic panels, and batteries are connected with each MG to meet their residential load requirement. MMS meets both stability and economic requirements more comfortably in the joint presence of DERs. MGs are connected with each other through bidirectional power links to do energy exchange and perform P2P energy trading. It is worth mentioning that the geographical distance between the towns is not considered because the proposed P2P energy trading is the main objective of this paper. P2P energy trading is controlled through a cloud-based platform and smart meters provide household energy readings to perform the energy trading among the prosumers and consumers based on smart trading algorithms. To analyse the power exchange within the system and measure the power consumption, generated and transferred, smart meters are installed at both sides of transmission and distribution lines. Wind turbines and photovoltaic panels are connected with DC-bus through unidirectional AC/DC and DC/DC converters. However,

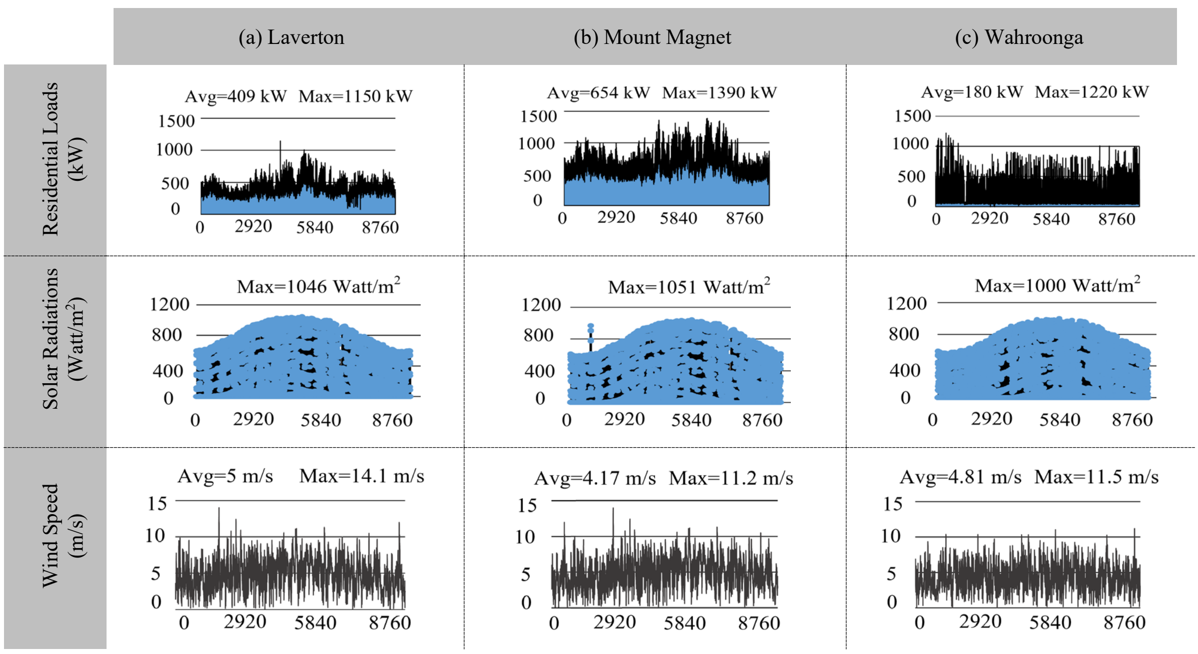

Fig. 3. Data profiles of (a) Laverton, (b) Mount Magnet, and (c) Wahroonga

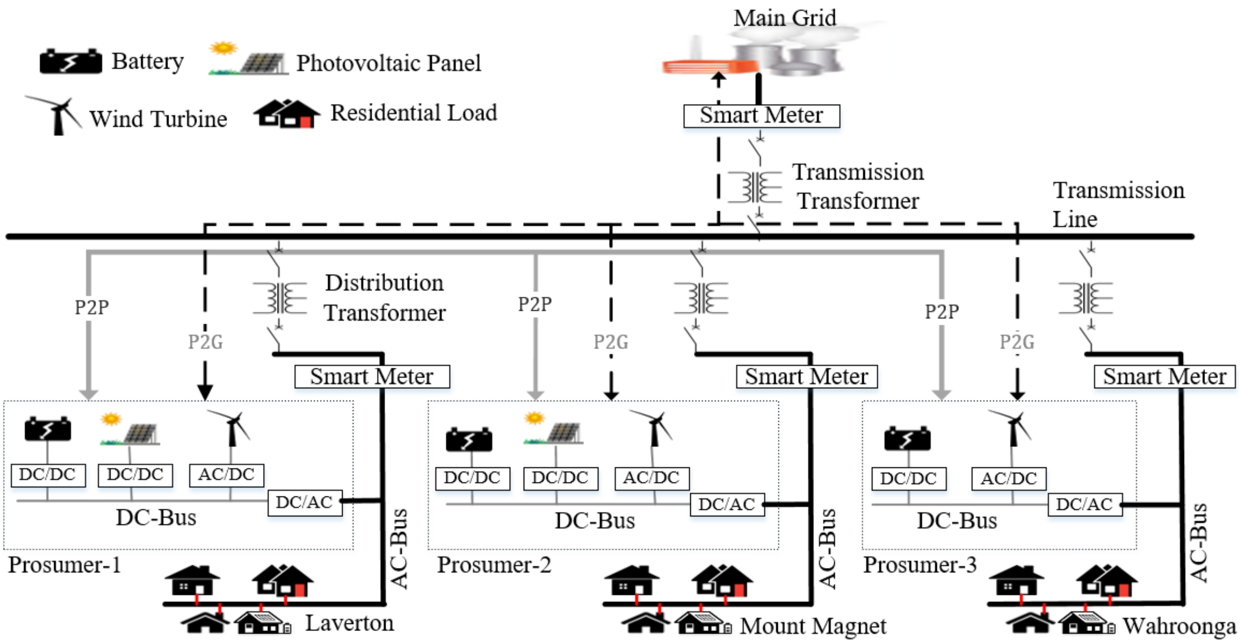

Fig. 4. Market base multi-microgrid system for peer-to-peer energy trading

storage batteries are connected with DC-bus via bidirectional DC/DC converters. Within MGs, a DC/AC converter is placed to connect the DC-bus with AC-bus. All grid-connected MGs are integrated together in the system and complement each other to serve the loads while meeting specific economic and reliability standards.

To design the proposed MMS, both P2G and P2P energy trading schemes are considered simultaneously to propose the most economical and efficient option. The main priority of each MG is to first meet their residential load requirements through their DERs. MGs are connected with each other and have the ability to operate as prosumers. At any stage, if generated and stored power is insufficient for the load, MGs can perform P2P energy exchange to buy power shortage from networked MGs or sell excess power to the neighbours. The proposed framework has the capability to perform P2G and P2P energy trading simultaneously. Therefore, MGs are capable for P2G trading with the main grid, if they have either excess power or shortage of power after P2P trading. In the MMS, for both energy trading schemes, the cash flow will be in the opposite direction of the energy flow. The cash flow talks about the annual profit gained from the energy trading schemes and the energy flow talks about the power flow.

V. Problem Formulation

To achieve the objective of this study, a MOF is formulated, including the criteria of LCOE and I_R based on a P2G and P2P energy trading schemes. To design a proposed MMS a cooperative game theory technique is used, players are defined, and the strategic spaces are set to find the optimum payoff values and for suitable sizing. Wind turbines (WT), photovoltaic panels (PP), and storage batteries (SB) are the players i for each microgrid. The sizes or capacities of players are P_{WT}, P_{SP} and P_{SB}, and the strategic spaces are set as $(P_{WT}^{min}, P_{WT}^{max})$, $(P_{PP}^{min}, P_{PP}^{max})$, and $(P_{SB}^{min}, P_{SB}^{max})$ for wind turbines, photovoltaic panels, and storage batteries, respectively.

A. *The economic model based on LCOE concept*

An optimum model of MMS should satisfy the requirements of reliability and economics. On the commercial and residential levels, more priority is given to lowering the energy cost of the overall system. Therefore, the concept of LCOE is selected in this study as a criterion for the best benchmark of cost analysis. For the selected model, the LCOE is defined as the sum of the total cost of the MMS divided by the total annual energy to minimize the electricity bills. Therefore, in this study, the first supplied E_{an} [44]. In the architecture, the LCOE for MG-1 is expressed as follow:

$$LCOE_1 = \sum_1^3 (CO_i / E_{an}) \quad i \in \{WT, PP, SB\} \tag{1}$$

The total cost CO_i for each player i, is the sum of its annual investment cost CO_{i_INV} and operation and maintenance cos $C_{i\_O\&M}$.

Annual Investment Cost: If the U_{i_INV} is the per-unit investment cost of the player i, then the annual investment cost for each player is found as follow:

$$CO_{i.INV} = U_{i\_INV} * P_i * D_r (1 + D_r)^{L_i} / ((1 + D_r)^{L_i} - 1) \tag{2}$$

Annual Operation and Maintenance Cost: If the $U_{i\_O\&M}$ is the per-unit operation and maintenance (O&M) cost of the player i, then the O&M cost for each player $CO_{i.O\&M}$ is found by multiplying the capacity of a player P_i by the $U_{i\_O\&M}$.

The LCOE for the MMS under P2G energy trading scheme where MGs can only sell or purchase power with the main grid is written as follow:

$$f(LCOE_{MMG_{P2G}}) = min\,(\sum_1^N(LCOE_n)) \tag{3}$$

The calculation of LCOE depends upon the annual investment cost and O&M cost, and these criteria did not have any kind of power exchange; therefore, payoff values of LCOE will be similar for P2G and P2P energy trading schemes and can be expressed as follow:

$$f\left(LCOE_{MMG_{P2P}}\right) = min\,(\sum_1^N(LCOE_n)) \tag{4}$$

B. Reliability Index

The second criterion to design a MMS is I_R [23], which aims to minimize the cost of power loss. The output of I_R depends upon two parameters, including the cost of energy not supplied CO_{ENS} and cost of power purchased from the grid CO_{PUR}. For MG-1, I_R is expressed as follow:

$$I_{R\_1} = \sum_1^3(CO_{i\_ENS} + C_{i\_PUR}) \quad i \in \{WT, PP, SB\} \tag{5}$$

In the MMS, three players WT, PP, and SB are considered. The generated power through a wind turbine $p_{WT}(t)$ is found as:

$$p_{WT}(t) = \begin{cases} 0 & v(t) < v_c \text{ or } v(t) \geq v_o \\ \frac{P_{WT}*(v(t)-v_c)}{v_r - v_c} & v_c \leq v(t) < v_r \\ P_{WT} & v_r \leq v(t) < v_o \end{cases} \tag{6}$$

The power generated by the storage battery $p_{SB}(t)$ is shown as follow:

$$p_{SB}(t) = \begin{cases} p_{SB}(t-1) + \xi_c * \Delta(t-1) & \Delta(t-1) \geq 0 \\ p_{SB}(t-1) + \Delta(t-1) & \Delta(t-1) < 0 \end{cases} \tag{7}$$

$$\Delta(t-1) = p_{WT}(t-1) + p_{PP}(t-1) - P_L(t-1) \tag{8}$$

In the study, the detailed design of photovoltaic panels are not calculated, but its solar power $p_{SB}(t)$ is represented by the sunlight radiations.

Annual Cost for Energy not Supplied: In order to calculate the cost of energy not supplied for the player i, the unbalance power $DP(t)$ in the MMS during hour t is first calculated by:

$$DP(t) = P_L(t) - p_{WT}(t) - p_{PP}(t) - p_{SB}(t) \tag{9}$$

where $p_{SB}(t)$ is the difference between the battery charge level $p_{SB\_SOC}(t)$ in hour t and the P_{SB_min}. The power purchased from the main grid $P_g(t)$ is found as:

$$P_g(t) = \begin{cases} 0 & DP(t) \leq 0 \\ DP(t) & 0 < DP(t) \leq P_{T\_max} \\ P_{T\_max} & DP(t) > P_{T\_max} \end{cases} \tag{10}$$

The energy not supplied ENS in hour t is then written as:

$$P_{ENS}(t) = U(t) * (DP(t) - P_g(t)) \tag{11}$$

where $U(t)$ is the step function, which is zero when the $DP(t)$ is smaller than $P_g(t)$, and equals to one if the $DP(t)$ is larger that $P_g(t)$. The total annual cost of ENS for player i will be:

$$CO_{i\_ENS} = \sum_{t=1}^T k(t) * P_{ENS}(t) \tag{12}$$

where $k(t) = 1.5 * \mathbb{E}(t)$ and $T = 8760$ hours.

Annual Cost for Purchasing Power from the Grid: The total cost of purchasing power from the main grid C_{i_PUR} for the player i is found by multiplying the grid power price $\mathbb{E}(t)$ by the power purchased from grid $P_g(t)$ in hout t.

If three MGs are operating in the MMS with respect to P2G energy trading, the value of I_R is obtained as follow:

$$f(I_{R_{MMG_{P2G}}}) = Min\,(\sum_1^N(I_{R_n})) \tag{13}$$

In the case of P2P energy trading, MGs operate as prosumers that are allowed to exchange in both prosumer-grid and prosumer-prosumer scenarios. The P2P energy trading encourages the prosumers to trade power among each other and also with the main grid. In P2P energy trading, the priority is selling the generated power to the connected load; the second priority is to sell the remaining power to the nearest prosumer in the loop on agreed P2P price $\mathbb{E}_P$; and the last, the remaining power will be sold to the main grid on P2G price $\mathbb{E}_{SG}$. However, if generated power is not sufficient for the load requirement, then first, power will be purchased from the nearest prosumer at agreed $\mathbb{E}_P$. Second, if still there is a shortage, it will be purchased from any other prosumer; and last, the power will be purchased from the main grid at P2G price $\mathbb{E}_{PG}$. If the grid-connected MMS is designed based on P2P energy trading, the value of I_R is calculated as follows:

$$f(I_{R_{MMG_{P2P}}}) = Min\,(\sum_1^N(I_{R_n})) \tag{14}$$

C. Multi-objective function

In the MOF, several criteria can be considered to meet the requirements of optimization [6], [17]. The LCOE and I_R are the criteria to formulate the MOF in this paper. The designed MOF is a minimizing function as both criteria are minimizing. If three MGs are connected in a MMS, the value of MOF based on P2G energy trading is obtained as:

$$f(MOF_{P2G}) = Min\,(K_1 \sum_1^N LCOE_n + K_2 \sum_1^N I_{R_n}) \tag{15}$$

In the MMS, the value of MOF-based on P2P energy trading
is obtained as:

$$f(MOF_{P2P}) = Min\,(K_1 \sum_1^N LCOE_n + K_2 \sum_1^N I_{R_n}) \tag{16}$$

where K_1 and K_2 are the constant coefficients for the LCOE and the I_R, respectively. The ranges of K_1 and K_2 are set $0 < K_1 < 1$ and $0 < K_2 < 1$, respectively. The constant values for both coefficients are the weighting values that classify the preferred objective function in this MOF. In the analysis, both objective functions have equal importance; therefore,

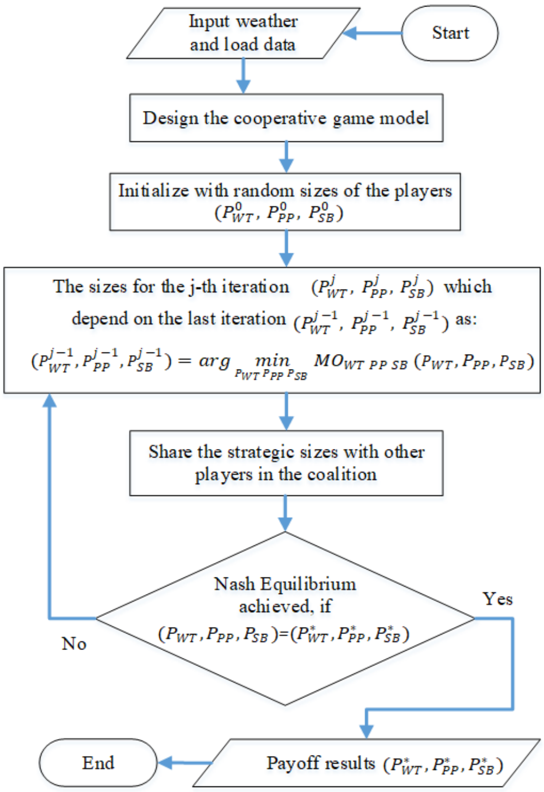

Fig. 5. Game theory-based flowchart.

values for constant coefficients are considered the same equal 0.5.

VI. Nash Equilibrium

To study the cooperation and conflict among rational decision-makers a game theory is used. Following theorem is developed for the existence of Nash equilibrium.

Theorem 1 [45]: Suppose a strategic game has strategic space as a nonempty tight convex set in Euclidean space. The game has the pure strategic Nash equilibrium if the payoff functions are quasi-concave and continuous.

In order to optimize the payoff values the players in a game can cooperate or compete with each other, and cooperative and noncooperative game models will be built for the optimal planning of MMS. If three players, WT, PP, and SB are used to make decisions in their own way, the noncooperative model can have payoff values I as follows:

$$I_{WT}(I_{WT}, I_{PP}, I_{SB}), I_{PP}(I_{WT}, I_{PP}, I_{SB}), I_{SB}(I_{WT}, I_{PP}, I_{SB})$$

At the Nash equilibrium point $(P_{WT}^*, P_{PP}^*, P_{SB}^*)$ the noncooperative game must satisfy the following conditions:

$$P_{WT}^* = \underset{P_{WT}}{\arg\min}\ I_{WT}(P_{WT}, P_{PP}^*, P_{SB}^*) \qquad (17)$$

$$P_{PP}^* = \underset{P_{PP}}{\arg\min}\ I_{PP}(P_{WT}^*, P_{PP}, P_{SB}^*) \qquad (18)$$

$$P_{SB}^* = \underset{P_{SB}}{\arg\min}\ I_{SB}(P_{WT}^*, P_{PP}^*, P_{SB}) \qquad (19)$$

The above equations illustrates that the strategy of each player is optimum when the other players choose the strategies in the Nash equilibrium $(P_{WT}^*, P_{PP}^*, P_{SB}^*)$.

In a cooperative game model, one player may cooperate with other players through coalitions to optimize the payoff values. For three players game problem, four possible coalition forms like cooperation between two players with third one self-sufficient (three ways could occur), and the complete cooperation between all the three players. If three players are cooperating with each other $\{WT, PP, SB\}$ the payoff value will be $I_{WT\_PP\_SB}(I_{WT}, I_{PP}, I_{SB})$ and at the Nash equilibrium $(P_{WT}^*, P_{PP}^*, P_{SB}^*)$ the cooperative game must satisfy the following condition:

$$(P_{WT}^*, P_{PP}^*, P_{SB}^*) = \underset{P_{WT}\ P_{PP}\ P_{SB}}{\arg\min}\ I_{WT\_PP\_SB}(P_{WT}, P_{PP}, P_{SB}) \qquad (20)$$

The cooperative game forms for the other three cases will be in similar way.

A. *Existance of Nash Equilibrium*

According to Theorem-1 , as the strategic space of MMS is a nonempty tight convex set in Euclidean space, the existence of Nash equilibrium is equal to the continuity and quasi-concavity of the payoff functions.

The payoff values of the players can be divided into linear and nonlinear parts, represented by F_L and F_{NL}, respectively. The part F_L includes annual investment cost and annual operation and maintenance cost, and shown as follows:

$$F_L = CO_{i.INV} + CO_{i.O\&M} \qquad (21)$$

A nonlinear function F_{NL} includes annual purchasing cost and annual energy not supplied as follows:

$$F_{NL} = CO_{i\_ENS} + C_{i\_PUR} \qquad (22)$$

CO_{i_ENS} and C_{i_PUR} are nonincreasing functions, so will be concave function of player i. The payoff value I_i of player i is:

$$I_i = F_L + F_{NL} \qquad (23)$$

The concavity of linear part and nonlinear part can be verified for all the players WT, PP and SB. Therefore, for a cooperative game $I_{WT\_PP\_SB}$ is a concave function of P_{WT}, P_{PP} and P_{SB}. The payoff values under cooperative and noncooperative game forms continue and concave functions, the existence of the Nash equilibriums can be guaranteed according to Theorem 1.

B. *Solving Algorithm*

Reference to literature review, different advanced methods have been proposed to perform the optimization. The game theory method is frequently being used to perform the single-objective and multi-objective optimization to solve various decision-making problems [23]. In the case of a cooperative game, the players are arranged in multiple set of coalitions with each other to achieve their optimum payoff values [46]. However, in the case of a non-cooperative game, all the players work independently and decide their own way to optimize the payoff values. It is confirmed through recent research that cooperative-based game models are more profitable and efficient than non-cooperative models [23, 31]. Therefore, in this study, one of cooperative game techniques Nash equilibrium, is considered for designing the proposed MMS based on P2G and P2P energy trading.

In the cooperative game model, WT, PP, and SB are used as players. Therefore, the game model has three players for the MG-1, three players for the MG-2, and two players for MG-3. As a result, among the three players, four ways of coalitions are possible. The game model gives the optimum payoff values when all the players cooperate with each other in a single coalition. For MG-1 and MG-2, one type of coalition is considered where all three players $\{(WT, PP, SB)\}$ are cooperating with each other. Similarly, for the MG-3, WT, and SB are used as the players; therefore, it has one-way of coalition $\{(WT, SB)\}$ where both players are cooperating with each other. To illustrate the Nash equilibrium technique, one coalition $\{(WT, PP, SB)\}$ is considered, and mathematical flow is explained in Fig. 5 for the sizing of the players and to get optimum payoff values.

Step 1. Input data and parameters for MG-1, MG-2 and MG-3.

Step 2. Design and formulate the cooperative game model.

Step 3. Initialize the random sizes of the players $(P_{WT}^0, P_{PP}^0, P_{SB}^0)$ which are chosen from the strategic set.

Step 4. Every player or coalition makes decisions and a cooperative game model is considered where all three players in cooperation to explain the decision-making process. The strategy of the j[th] iteration $(P_{WT}^j, P_{PP}^j, P_{SB}^j)$ is based on previous iteration $(P_{WT}^{j-1}, P_{PP}^{j-1}, P_{SB}^{j-1})$, and shown as:

$$(P_{WT}^*, P_{PP}^*, P_{SB}^*) = \underset{P_{WT}\ P_{PP}\ P_{SB}}{\arg\max}\ I_{WT\_PP\_SB}(P_{WT}, P_{PP}, P_{SB})$$

The proposed model is simulated in MATLAB software, and the PSO algorithm with 100 population is used to perform the optimization. Nowadays, the PSO algorithm is used in various research areas, and different optimization problems are solved [47-48]. In order to reach the suitable sizes of the players, and optimum payoff values, the simulation model is run for 120 iterations.

Step 5. Inform strategies of each player made in Step-4.

Step 6. Check if Nash equilibrium is achieved go to Step 7 and no player change its capacity for one entire round, the process terminates as:

$$(P_{WT}^j, P_{PP}^j, P_{SB}^j) = (P_{WT}^{j-1}, P_{PP}^{j-1}, P_{SB}^{j-1}) = (P_{WT}^*, P_{PP}^*, P_{SB}^*)$$

Otherwise, go to Step 4 to reoptimize the payoff values.

Step 7. Result of the Nash equilibrium of the MMS for cooperative game model $(P_{WT}^*, P_{PP}^*, P_{SB}^*)$.

VII. Results and Analysis

To analyse the feasibility of the MMS, the realistic weather data and residential load profiles of three towns of Australia are considered. The simulation model is designed in MATLAB software using a PSO algorithm with technical parameters summarized in Table-I [49]. In order to achieve the optimum results from MOF, the proposed MMS is first analyzed with SOF where LCOE and I_R are optimized individually. The results of SOF I_R is compared with one of research work [23] for SOF annual profit for cooperative game models and most optimum results are proposed. In the next step, both objective functions are optimized simultaneously in a MOF. The results of both optimizations are further analyzed and compared for P2G and P2P energy trading schemes.

TABLE I.
List of Technical Parameters

Parameters	Values (Units)	Parameters	Values (Units)
$\mathbb{E}$	0.12 \$/kWh	U_{WT}	770 \$/kW
D_r	12 %	$CO_{O\&M}$ of WT	20 \$/(kW. year)
v_c	3 m/s	U_{PP}	1,890 \$/kW
v_o	20 m/s	L_{PP}	20 Years
v_r	12 m/s	$CO_{O\&M}$ of PP	20 \$/(kW. year)
$\mathbb{E}_P$ [50]	0.15 \$/kWh	L_{SB}	10 Years
$\mathbb{E}_{SG}$ [51]	0.10 \$/kWh	U_{SB}	100 \$/kW
$\mathbb{E}_{PG}$ [52]	0.28 \$/kWh	$CO_{O\$M}$ of SB	1 \$/(kW. year)
L_{WT}	20 Years	P_{SB_min}	50 W

A. *Single-objective Optimization for P2G and P2P*

To perform the single-object optimization first benchmark I_R is considered. For MG-1 and MG-2, three players (WT, PP, SB) and for MG-3 two players (WT, SB) are selected in a single coalition, respectively. MMS is programmed in MATLAB software and simulated until the results reached Nash equilibrium point to get optimum payoff values and correct sizes of the players. Fig. 6 illustrates the sizes of the players for the three MGs at the Nash equilibrium point $(P^*_{WT}, P^*_{PP}, P^*_{SB})$ when the I_R is optimized. The objective function I_R is minimized in a way that its minimum values are converged after the 90[th] iteration, and at that points its optimized payoff value is around 1.3826e+6 \$. Table-II illustrates the optimized sizes of the players at the Nash

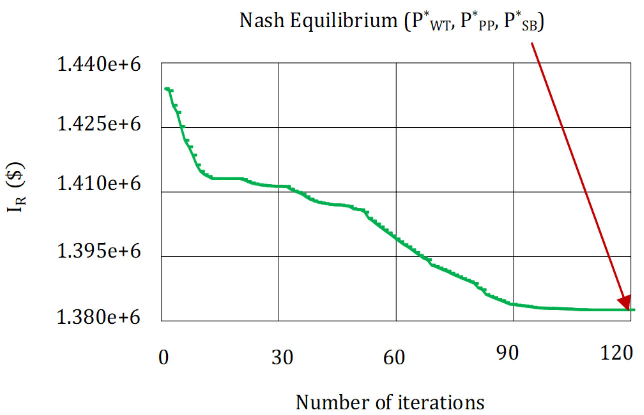

Fig. 6. Sizes of the players for the optimization I_R.

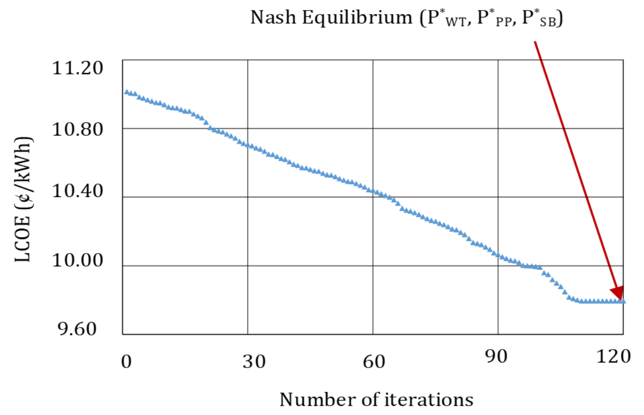

Fig. 7. Sizes of the players for the optimization of LCOE.

equilibrium point when the I_R is optimized. The payoff values of both objective functions are shown for P2G and P2P energy trading. It is evident from the results that the value of LCOE is found at 11.261 ¢/kWh for both energy trading schemes. However, for P2G the value of the objective function I_R is 1.3826e+6 and decreased about 47 % to 7.2103e+5 for P2P energy trading.

Secondly, SOF is performed with respect to LCOE to find the sizes of the players and obtain the optimum payoff values of the objective functions in both P2G and P2P energy trading schemes. Fig. 7 shows the LCOE values that are converged after the 110th iteration and reached 9.794 ¢/kWh for P2G and P2P energy trading schemes. Table-III illustrates the sizes of the players for all three MGs at their Nash equilibrium points. At the optimized sizes of the players, the value of I_R is 1.4520e+6 $ for P2G energy trading and its value decreased 48 % for P2P energy trading to 7.3308e+5 $. It is evident from the results of SOF that only one objective function reaches its optimum values at one time; however, the second one does not touch its optimum value.

TABLE II.
SINGLE-OBJECTIVE OPTIMIZATION (I_{R_MMS}) AT NASH EQUILIBRIUM

Players Sizes (kW)	Laverton			Mount Magnet			Wahroonga	
	P^*_{WT}	P^*_{PP}	P^*_{SB}	P^*_{WT}	P^*_{PP}	P^*_{SB}	P^*_{WT}	P^*_{SB}
	844	570	221	958	614	380	1180	262

Energy Trading Schemes	Payoff values of Single-objective Optimization	
	I_{R_MMS} ($)	$LCOE_{MMS}$ (¢/kWh)
P2G	1.3826e+6	11.26
P2P	7.2103e+5	11.26

TABLE III.
SINGLE-OBJECTIVE OPTIMIZATION ($LCOE_{MMS}$) AT NASH EQUILIBRIUM

Players Sizes (kW)	Laverton			Mount Magnet			Wahroonga	
	P^*_{WT}	P^*_{PP}	P^*_{SB}	P^*_{WT}	P^*_{PP}	P^*_{SB}	P^*_{WT}	P^*_{SB}
	703	395	204	812	466	209	1004	221

Energy Trading Schemes	Payoff values of Single-objective Optimization	
	I_{R_MMS} ($)	$LCOE_{MMS}$ (¢/kWh)
P2G	1.4520e+6	9.794
P2P	7.3308e+5	9.794

TABLE IV.
COMPARISION OF PAYOFF VALUES

SI#	Coalition forms	Results of SOF I_R ($/Year)	Results of SOF Annual Profit [23] ($/Year)
1	{WT, PP, SB}	1.3826e+6	2.4174e+7
2	{WT, PP}. {SB}	1.4405e+6	2.4129e+7
3	{WT, SB}, {PP}	1.4808e+6	2.3064e+7
4	{WT}, {PP, SB}	1.5155e+6	2.2977e+7

B. Comparsion of Results with existing model [23]

In order to verify the results of SOF of I_R for MMS are compared with a similar cooperative game model [23] where SOF is annual profit for a microgrid. In both game models players are wind turbines, solar panels and batteries. In the proposed game model, I_R is a minimizing SOF and in the game model [23] annual profit is a maximizing SOF. The maximum load requirement for both game models is 10 MW but load distribution is different within the year. The results are compared for four possible cooperative game models for P2G energy trading.

The results of the proposed MMS and of game model [23] are listed in TABLE IV. If we compare both results, there is a similarity among all four types of coalitions and results are optimum when all three players are cooperating in a single coalition {WT, PP, SB}. In Fig. 8 per-unit payoff values of both game models are shown, and results illustrate that SOF I_R has minimum optimum value in coalition {WT, PP, SB} and SOF annual profit also have maximum optimum values in coalition {WT, PP, SB}. The trend of payoff values for different coalitions verifies the results and for both game models, payoff values are worst for coalition {WT}, {PP, SB} and best for coalition {WT, PP, SB}.

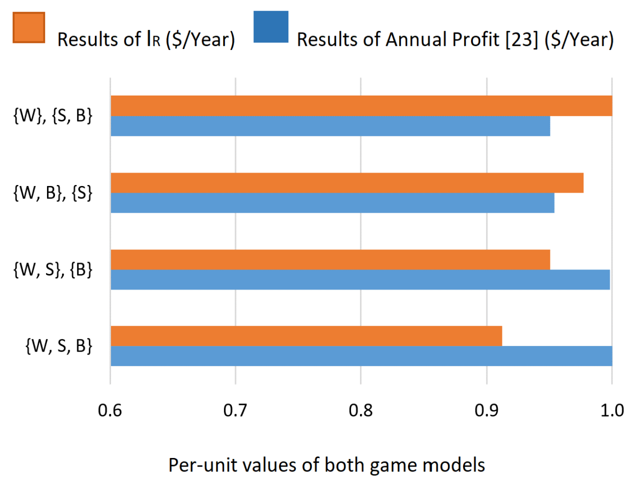

Fig. 8. Comparison of per-unit values of I_R and annual profit.

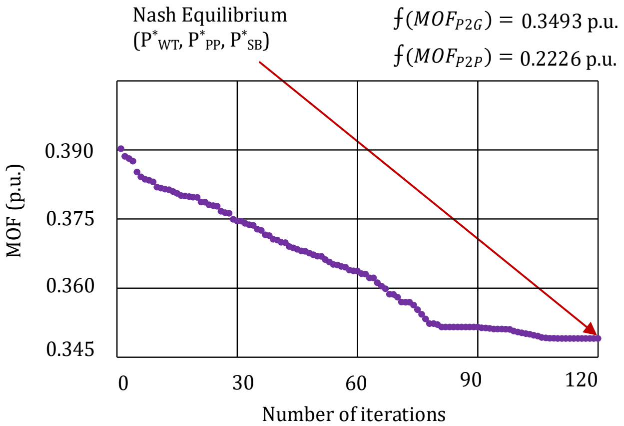

Fig. 9. Payoff values of MOF.

C. Multi-objective Optimization for P2G and P2P

In this section, both objective functions LCOE and I_R are optimized simultaneously to reach their optimum values for P2G and P2P energy trading schemes. Fig. 9 shows the values of the MOF, where both criteria LCOE and I_R are optimized simultaneously to reach their optimum values. The values of the MOF is converged after the 100 iterations and reach their minimum value of 0.3493 p.u. The optimum sizes of the players and payoff values of the objective functions LCOE, and I_R are shown in Table-V. For P2G energy trading, it can be seen that the payoff values for LCOE and I_R are 9.928 ¢/kWh and 1.3962e+6 $, respectively. For P2P energy trading scheme, the LCOE value stays the same while the values of I_R decrease 50 % to 6.9201e+5 $ and the value of MOF decreases 36 % to 0.2226 p.u. Since both objective functions are optimized simultaneously, the payoff values are minimum, and therefore, the sizes of the players will be correct and suitable for the MMS.

The results are sensible for MOF considering the distribution of the player's size within the MGs. Since Mount Magnet has the largest residential load, therefore, the total size of the players is 1,631 kW. Laverton has a second larger residential load and the total size of the players is 1,420 kW. Wahroonga has the smallest residential load compared to other towns, and its total size of the players is 1,399 kW. The sizes of the players are further verified as both SOF and MOF follow the same trend for the players' sizes so that $P^*_{WT} > P^*_{PP} > P^*_{SB}$ [23], which means the wind turbines have the major contribution of generated power and storage batteries have minimum contribution in the proposed MMS.

TABLE V.
MULTI-OBJECTIVE OPTIMIZATION (MOF_{MMS}) AT NASH EQUILIBRIUM

players Sizes (kW)	Laverton			Mount Magnet			Wahroonga	
	P^*_{WT}	P^*_{PP}	P^*_{SB}	P^*_{WT}	P^*_{PP}	P^*_{SB}	P^*_{WT}	P^*_{SB}
	812	380	228	946	448	237	1083	316

Energy Trading Schemes	Payoff values of Multi-objective Optimization		
	MOF_{MMS} (p.u.)	I_{R_MMS} ($)	$LCOE_{MMS}$ (¢/kWh)
P2G	0.3493	1.3970e+6	9.928
P2P	0.2226	7.2706e+5	9.928

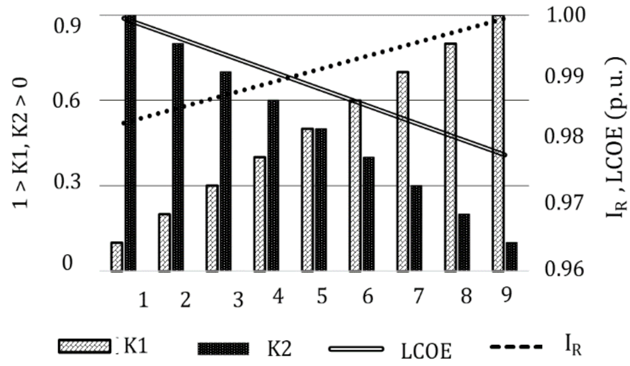

Fig. 10. Comparison of payoff values of SOF.

D. Validation of MOF

In order to analyse the robustness of MMS, the proposed MOF is validated with different values of its constant coefficients K_1 and K_2 for both energy trading schemes P2G and P2P. Table-VI illustrates the results of MOF and SOF for P2G and P2P energy trading schemes with different values of constant coefficients between 0.1 to 0.9. To perform the analysis nine different combinations of K_1 and K_2 ($K_1+K_2=1$) are considered. Since MOF is a minimizing function, therefore, higher weightage of one of constant coefficient results its smaller output value. Figure 10 compared the payoff values of SOFs and it can be seen that at first combination K_1 has a minimum and K_2 has maximum value 0.1 and 0.9, respectively, therefore, $I_{R_{MMG}}$ is prioritized and found minimum payoff value compared to $LCOE_{MMG}$, and vise versa.

The result shows that both objective functions are changing their payoff values with respect to their constant coefficient weightage, and at fifth combination where both K_1 and K_2 have similar values 0.5, they collide with each other and both $LCOE_{MMG}$ and $I_{R_{MMG}}$ have minimum payoffs. Therefore, in the proposed model to optimize the MOF the values of both K_1 and K_2 are considered as 0.5.

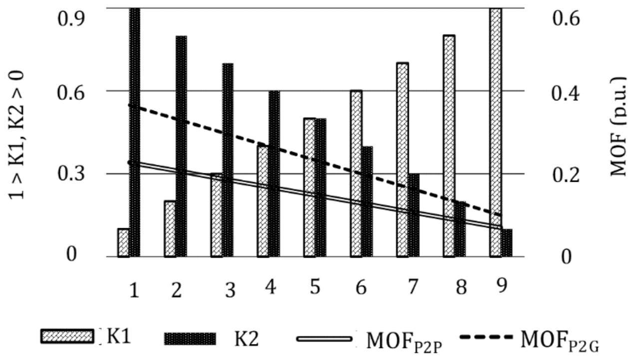

Fig. 11. Optimization results of MOF for the multi-microgrid system.

TABLE VI.
RESULT FOR VALIDATION OF MULTI-OBJECTIVE FUNCTION

Constant Coefficients		P2G Energy Trading			P2P Energy Trading		
K1	K2	MOF_{MMS} $(p.u.)$	$LCOE_{MMS}$ (¢/kWh)	$I_{R_{MMS}}$ ($)	MOF_{MMS} $(p.u.)$	$LCOE_{MMS}$ (¢/kWh)	$I_{R_{MMS}}$ ($)
0.1	0.9	0.549	10.035	1.386e+6	0.341	10.035	7.222e+5
0.2	0.8	0.499	10.008	1.388e+6	0.311	10.008	7.234e+5
0.3	0.7	0.450	9.982	1.391 e+6	0.282	9.982	7.247e+5
0.4	0.6	0.399	9.955	1.394 e+6	0.252	9.955	7.259e+5
0.5	0.5	0.349	9.928	1.397 e+6	0.223	9.928	7.271e+5
0.6	0.4	0.299	9.901	1.399 e+6	0.193	9.901	7.283e+5
0.7	0.3	0.250	9.874	1.403 e+6	0.164	9.874	7.295e+5
0.8	0.2	0.199	9.848	1.406 e+6	0.134	9.848	7.307e+5
0.9	0.1	0.150	9.821	1.409 e+6	0.105	9.821	7.319e+5

Figure 11 shows the comparison of MOF payoff values for different combinations of constant coefficients K_1 and K_2. The payoff values of MOF changes as we increase or decrease values of constant coefficients, and it can be seen that for P2P energy trading payoff values of MOF is always lower than P2G energy trading. The trend in values of SOF and MOF with respect to the constant coefficients K_1 and K_2 justify the effectiveness proposed MMS and validates the MOF.

E. *Sensitivity Analysis*

To verify the feasibility of a MMS and payoff value of MOF for P2G and P2P energy trading, a sensitivity analysis is performed. Different electricity prices ($\mathbb{E}$) and discount rates (D_r) are applied to analyse the proposed MMS. Fig. 12 (a) illustrates the variation in the MOF with respect to $\mathbb{E}$ for both energy trading schemes, and the trend shows that as $\mathbb{E}$ increases, consequently the payoff value of MOF is increased. Because it increases the system cost as a cost C_{PUR} and CO_{ENS} will increase from the main grid and neighboring prosumers. Fig. 12 (b) shows that as D_r is increased, the payoff value of MOF is increased as well. Because more D_r to customers will decrease profit margins to power generation and subsequently, the whole system cost will increase. Therefore, changes in the values of MOF with respect to sensitivity analysis are sensible, and as a result, the multi-objective optimization results are validated.

VIII. CONCLUSION

In this research, multi-objective optimization based on a game theory is proposed for the optimum sizing of the DERs to achieve the optimum payoff values of a MMS. The two benchmarks, LCOE and the I_R are defined to formulate a MOF in MATLAB software based on a PSO algorithm. The optimization is performed for both SOF and MOF. The proposed architecture is modelled with respect to P2G and P2P energy trading schemes to optimize the reliability and system's cost.

The results successfully revealed that the MOF gives the optimum payoff values and the most suitable sizing of DERs when both objective functions are optimizing simultaneously. MMS is analyzed and compared with existing model for P2G and P2P energy trading schemes. The results show that P2P energy trading reduces per-unit value of MOF to 36 % compared to P2G. The proposed model is more reliable and profitable when a P2P energy trading scheme is performed. The sizing of the DERs justify that the total contribution of the players in each microgrid is compatible with their residential load requirements. The capacity allocation of the players is further verified with the symmetrical trend [23] for both types of optimization $P^*_{WT} > P^*_{PP} > P^*_{SB}$, whereas WT shows the major contribution of generated power and SB has minimum contribution in the proposed MMS. The feasibility of the MMS is verified with a sensitivity analysis that proved that variation in the per-unit values of MOF is pragmatic based on different $\mathbb{E}$ and D_r. Finally, the suitable sizes of the DERs are proposed for P2G and P2P energy trading schemes, and accordingly optimum values of I_R and $LCOE$ are suggested.

In the future, the typical MMS and practical networks will

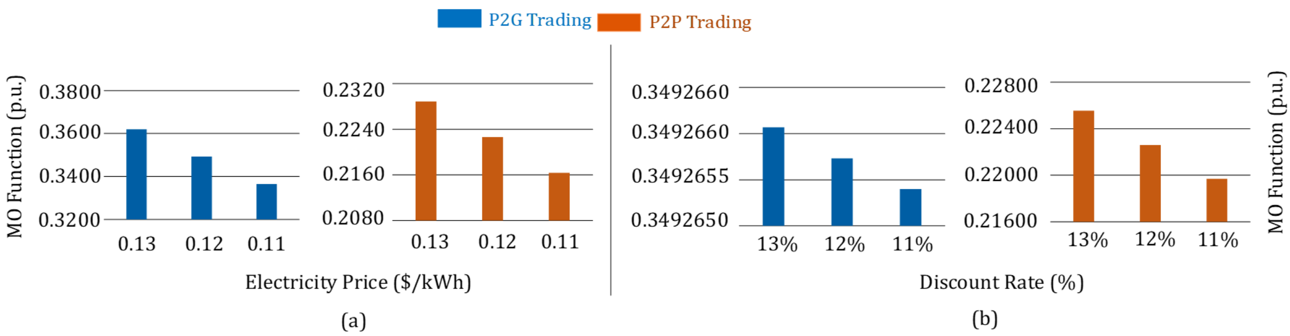

Fig. 12. Sensitivity analysis for MOF based on peer-to-grid and peer-to-peer energy trading

be optimized based on an approach of a transactive energy management system where multiple players will control the energy trading. The structure will be modelled and formulated based on i-framework and Monte-Carlo principle for their validation. Blockchain technology will be adopted for contractual bidding between the energy sells and buyers.

IX. Acknowledgement

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