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Comparative Study on Game-Theoretic Optimum Sizing and Economical Analysis of a Networked Microgrid

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Abstract: In this paper, two techniques of game theory are considered for sizing and comparative analysis of a grid-connected networked microgrid, based on a multi-objective imperialistic competition algorithm (ICA) for system optimization. The selected networked microgrid, which consists of two different grid-connected microgrids with common electrical load and main grid, might have different combinations of generation resources including wind turbine, photovoltaic panels, and batteries. The game theory technique of Nash equilibrium is developed to perform the effective sizing of the networked microgrid in which capacities of the generation resources and batteries are considered as players and annual profit as payoff. In order to meet the equilibrium point and the optimum sizes of generation resources, all possible coalitions between the players are considered; ICA, which is frequently used in optimization applications, is implemented using MATLAB software. Both techniques of game theory, Shapley values and Nash equilibrium, are used to find the annual profit of each microgrid, and results are compared based on optimum sizing, and maximum values of annual profit are identified. Finally, in order to validate the results of the networked microgrid, the sensitivity analysis is studied to examine the impact of electricity price and discount rates on maximum values of profit for both game theory techniques.

Keywords: game theory; Nash equilibrium; solar panels; Shapley values; batteries; wind turbines

1. Introduction

In recent years, to control the increasing requirements of electricity price and demand, different renewable methods of energy generation have been of great interest. Novel research studies have shown that generation through renewable energy is the modern way and that environmental concerns are another reason to increase the rapid use of such methods [1,2]. However, the generation from renewable resources like wind and sunlight depend on weather conditions, and consequently it is very hard to achieve high precision or to get the most reliable generation. The solution to control the intermittent type of generation is the addition of different kinds of energy storage systems [3,4].

In fact, generation through renewable resources is not the only reliable, safe, and economical way, but it is a most encouraging and leading way to develop a modern form of power generation. In order to get the most optimum results from the microgrid, the performance needs to be improved by proper planning and minimizing the expenses within the system limitations [5,6]. Minimum investment, maximum utilization of generation resources, and efficient performance of a generation system is guaranteed by considering the right optimization method [7]. In [8], a new strategy using evaluation and interrelation matrixes method was introduced for optimization using a software, TechOptimizer, to perform QDF and TRIZ analyses and to validate a design method for direct open molds. In the past, a number of studies about the sizing and optimization of microgrids used different approaches to achieve desired outcomes; for example, fuzzification mechanism [9] was used to design a grid-connected hybrid generation system consisting of wind turbine generators, photovoltaic panels, and storage batteries. In [10], the loss of power supply probability method was adopted to design a stand-alone photovoltaic system and a relationship was employed between the amount of energy storage and the loss of power supply probability. The trade-off method was used in [11,12], to design a methodology for the sizing of different system components.

A networked microgrid is an architecture, where different connected microgrids are controlled in certain range of space. The concept of a networked microgrid was proposed in [13], with interconnected microgrids being able support each other to meet load requirements and also in the situation of emergencies. Microgrid networking has many other benefits over single microgrids, including economic benefits and also the ability to minimize power outage problems [14]. In a microgrid, generation resources like wind turbines, photovoltaic panels, and batteries may belong to different owners, but for the optimum sizing of each component, it is preferred to maximize their profit. In this regard, when various components are involved in microgrid to maximize the profit, game theory is an advanced type of multi-objective optimization to solve the decision-making problem [15]. An approach of Nash equilibrium was adopted for a non-cooperative game model in paper [16] to model the interaction between the power system components. It was also evident in [17] that in comparison with non-cooperative game models, cooperative game models gave more optimum results and maximum profit. In [17,18], different combinations of cooperative and non-cooperative game theory models were analyzed, and most feasible one was proposed using different game theory techniques, such as Nash equilibrium and Pareto frontier. A game theory approach of dynamic population was proposed in [19] to maximize the payoff and to optimize the sizes of generation resources. The operation strategy and optimization scheme were developed using a game theory technique called Pareto optimal solution in [20]. Consumer-based demand response programs were developed in [21] to minimize the energy cost incurred by the consumer, and optimal scheduling of the game model was achieved using a Nash equilibrium. In [22] a Stackelberg game-based solution was used to maximize the satisfaction level with multi-class appliance control in a microgrid. Cooperative model-based approaches, e.g., namely Shapely values, Auman Shapley, Nucleolus, and T-value were considered in [23] to compare and assess the suitability of selected power system applications; sensitivity analysis was further used to illustrate the results. A cooperative game theory method, the Shapley value, was used in [24] to distribute the economic benefits of the cooperation between the provinces and calculate the optimal quantities of electricity consumption.

In the game theory models, different algorithms are used to perform the optimization, like in [5] where particle swarm optimization algorithm was used to design a grid-connected system, and in [6,14,25] where approaches for hybrid power system planning were proposed. A comprehensive correction algorithm was used in [26] to estimate the thermal power seller's income which enhances the stability of the alliance. A novel approach was presented in [16] to the application of game theory for the distributed control with help of micro-genetic algorithm. A two-level distributed heuristic algorithm was introduced in [27] to solve the energy management problem for the PV-assisted charging station. In [28] a colonial competition algorithm was used for maintaining the frequency stability in a microgrid, and in [29] multi-objective imperialistic competition algorithm ICA was used for the problems of microgrid optimization. It has to be noticed that, in most research papers ICA was used for optimization of a single microgrid, however, in this paper it is applied for a networked microgrid.

This study aims to design the capacity allocation of generation resources and find the maximum value of payoff for a networked microgrid in the planning stage using two game-theoretic approaches. In the networked microgrid, each microgrid consists of different combinations of generation resources and batteries. The game-theoretic technique called Nash equilibrium is used for the optimization purpose through iterative search procedure. To meet the load requirements, generation resources like wind turbines, photovoltaic panels, and batteries are considered as players. In order to find the maximum annual profit of a networked microgrid, two different techniques of game theory, i.e., Nash equilibrium and Shapely value, are used, and most efficient one will be identified by comparing the results. To keep the selected networked microgrid simple, two different microgrids are considered for this study. An imperialistic competition algorithm is used to design the model for the networked microgrid in MATLAB to get most suitable sizing of generation resources and maximum annual profit. Moreover, to ensure the effectiveness of the networked microgrid, a sensitivity analysis will be performed for electricity price and discount rate. The realistic data of load profile, wind speed, and solar radiation are considered for a town of Western Australia named Mount Magnet to achieve optimum sizing of generation resources and maximum profit of the selected architecture. As shown in Figure 1, the location of Mount Magnet is 560 km north-east of the Western Australian capital, Perth.

Figure 1. Mount Magnet in Western Australia.

This paper is organized as follows. Section 2 describes the design of the networked microgrid. Section 3 explains game theory techniques and algorithms to implement the selected architecture. Simulation results and analysis are carried out in Section 4. Section 5 presents the conclusion.

2. Design of Networked Microgrid

The design of a networked microgrid is based upon some input variables such as the weather forecast, solar radiation, and electrical load. In this paper, the feasibility of the proposed game model will be checked for a remote town of Western Australia, Mount Magnet. The annual data for wind speed, solar radiation, and electrical load were considered to conduct the analysis for a networked microgrid for the period from June 2015 to May 2016 [30]. Figure 2a illustrates that the peak electricity demand for Mount Magnet is approximately 1390 kW in the months of summer and the minimum load is about 312 kW in the months of winter. The wind speed data are shown in Figure 2b, for an hourly base, and the annual average and maximum speeds are approximately 4.16 m/s and 11.22 m/s, respectively. The selected town has a very good profile for solar radiation, it can be seen from Figure 2c that the value reaches a maximum of about 1058 W/m^2 in the months of summer; however, it trends down in the winter.

The networked microgrid can be a combination of *m* number of microgrids, however, the selected system consists of two microgrids with different combinations of generation resources and batteries. The block diagram of the proposed networked microgrid is shown in Figure 3, for a remote town, which consists of generation resources, batteries, electrical load, and the main grid. Wind turbines, photovoltaic panels, and storage batteries are considered as the sources of power generation depending upon the weather forecast. For the proposed power system, both microgrids are connected with the main grid and share a common electrical load, therefore, if they fail to meet the load requirements, they have option to purchase power from the main grid and in case of large generation, they can sell the excessive power to the main grid. The goal of this research is to find the optimum sizes of generation resources and battery to meet the load requirements, and achieve maximum annual profit for networked microgrid.

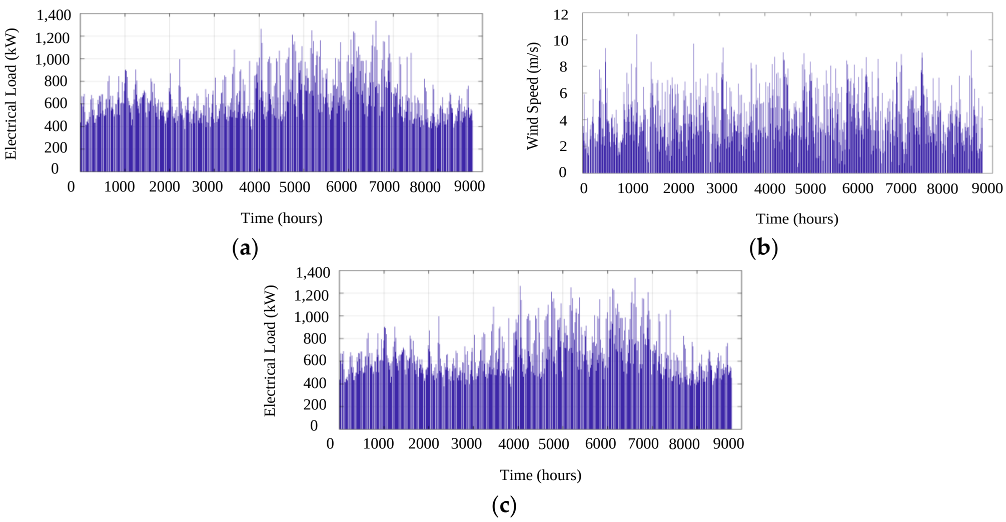

Figure 2. Hourly profiles: (**a**) electrical load; (**b**) wind speed; (**c**) solar radiation.

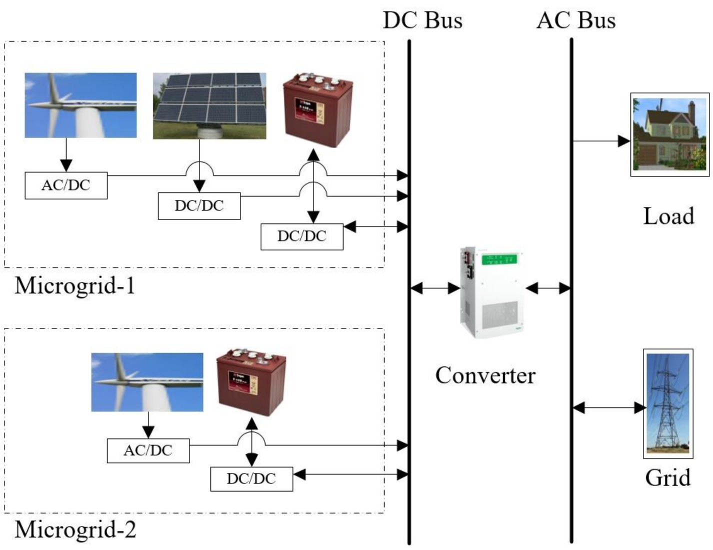

Figure 3. Block diagram of a networked microgrid.

2.1. Game Theory

Game theory is a scientific field dealing with the study and analysis of the strategic, rational decision-making process of individuals and their interactions in the environment. In other words, it is a decision-making process that can resolve different kinds of conflicts between the decision makers and find the maximum payoff [31]. A model of game theory is the combination of autonomous decision-makers known as players, who should be two or more in quantity to play a game. Besides this, every player should have more than one choice to achieve a payoff from a game, otherwise, it is not able to adopt a strategy. This means that a model of game theory is the combination of different players, strategies, and payoff functions [32,33]. Game theory is a wonderful way to deal with various decision-making problems in microgrids, where different renewable resources and batteries are used for generation purpose. For many years, game theory techniques have been used in different research areas to solve various technical problems [15,28,34], which confirms the solid basis for the market contributions to get their optimum payoff.

The main element of any game model are the decision variables known as the players, and each of the players must have more than one option to make their strategies to find the required payoff. In the networked architecture m, n, i, P_i, and I_i represent the number of microgrids, number of decision variables or players, generation resources, decision variables, and payoff or annual profit, respectively. The maximum and minimum power values of the players are the constraints in a selected game model and are represented as strategic space $SS_i = \left[P_i^{min},\ P_i^{max}\right]$. The total annual profit for a single microgrid MG is given as:

$$I_{MG\_m} = \sum_{1}^{n} I_i \tag{1}$$

Similarly, the annual profit for a networked microgrid NMG that is the combination of m number of microgrids can be found as:

$$I_{NMG} = I_{MG\_1} + I_{MG\_2} \ldots\ldots\ldots\ldots + I_{MG\_m} = \sum\nolimits_1^m \left(\sum\nolimits_1^n I_i\right). \tag{2}$$

2.2. Payoff of Microgrid-1

In the microgrid-1, three generation resources i, namely wind turbines WT, solar panels SP, and batteries BT are considered, and their decision variables or players are represented by P_{WT}, P_{SP}, and P_{BT}, respectively. Similarly, the maximum payoff or profit for the WT, SP and BT are I_{WT}, I_{SP}, and I_{BT}, respectively. The total annual profit for the microgrid-1 is:

$$I_{MG\_1} = \sum\nolimits_1^{n=3} I_i. \tag{3}$$

In grid-connected mode, to get the maximum annual profit for the generation resource i different parameters are considered, like power selling income I_{i_SE}, salvage value I_{i_SV}, income from ancillary services I_{i_AS}, initial investment cost C_{i_IN}, compensation cost from energy which cannot be supplied C_{i_ES}, purchasing power from the grid C_{i_PR}, and operation and maintenance cost C_{i_OM}. The annual profit for each of the generation resource can be found using the equation below:

$$I_i = I_{i\_SE} + I_{i\_SV} + I_{i\_AS} - C_{i\_IN} - C_{i\_OM} - C_{i\_ES} - C_{i\_PR}. \tag{4}$$

In comparison with wind turbines and solar panels, batteries normally do the activities of smoothing power generation, filling valleys, and reducing peaks, so their payoff mainly comes from ancillary services. For simplicity, in this analysis only I_{i_AS} of batteries is considered, however, for wind turbine and the solar panel this value is taken as zero. Moreover, when the storage batteries are out of service their I_{i_SV} will be zero. C_{i_OM} for the i is calculated by multiplying the per-unit operation and maintenance costs of the player by the generation capacity of the decision variable. I_{i_SV}, C_{i_IN}, and C_{i_PR} for each player i can be calculated as follows:

$$I_{i\_SV} = P_i \times S_{i\_pu} \times D_r / \left((1 + D_r)^{L_i} - 1\right), \tag{5}$$

$$C_{i\_IN} = U_i \times P_i \times D_r (1 + D_r)^{L_i} / \left((1 + D_r)^{L_i} - 1\right), \tag{6}$$

$$C_{i\_PR} = \frac{C_{GR} * P_i}{\left(\sum_1^{n=3} P_i\right)}, \tag{7}$$

where S_{i_pu}, L_i, and U_i are per-unit salvage value, life span, and per-unit cost for each player i. D_r and C_{GR} are discount rate and annual cost of each player for purchasing power from the large grid, respectively. C_{GR} can be found by multiplying the per-hour result of power purchased from grid $P_{GR}(t)$ and the grid power price, for a year.

The annual compensation cost for energy not supplied C_{i_ES} in a networked microgrid is:

$$C_{i\_ES} = C_{ES} \times P_i / \left(\sum\nolimits_1^{n=3} P_i\right), \tag{8}$$

$$C_{ES} = \sum\nolimits_{t=1}^{8784} \times 1.5 \times R(t) \times \{DP(t) - P_{GR}(t)\}, \tag{9}$$

$$DP(t) = P_L(t) - p_{WT}(t) - p_{SP}(t) - (p_{BT}(t) - P_{BT\_min}), \tag{10}$$

$$P_{GR}(t) = \begin{cases} 0 & DP(t) \leq 0 \\ DP(t) & 0 < DP(t) \leq P_{TL}^{max} \\ P_{TL}^{max} & DP(t) > P_{TL}^{max} \end{cases} \tag{11}$$

where C_{ES}, $R(t)$, $DP(t)$, $P_L(t)$, and P_{TL}^{max} are the total annual cost of energy not supplied, electricity price, unbalance power in microgrid, load demand, and transmission capacity of tie-line between networked microgrid and main grid, in hour t, respectively.

The output power of the wind turbine $p_{WT}(t)$ and storage battery $p_{BT}(t)$ can be found as:

$$p_{WT}(t) = \begin{cases} 0 & V(t) < V_{ci} \text{ or } V(t) \geq V_{co} \\ \frac{P_{WT} * (V(t) - V_{ci})}{V_r - V_{ci}} & V_{ci} \leq V(t) < V_r \\ P_{WT} & V_r \leq V(t) < V_{co} \end{cases}, \tag{12}$$

$$p_{BT}(t) = \begin{cases} p_{BT}(t-1) + \varepsilon_c * \Delta(t-1) & \Delta(t-1) \geq 0 \\ p_{BT}(t-1) + \Delta(t-1) & \Delta(t-1) < 0 \end{cases}, \tag{13}$$

$$\Delta(t-1) = p_{WT}(t-1) + p_{SP}(t-1) - p_L(t-1), \tag{14}$$

where V_{ci}, V_{co}, V_r, and ε_c, are cut-in wind speed, cut-out wind speed, rated wind speed, and battery charging efficiency, respectively. The batteries are charged with respect to the power difference $\Delta(t)$ between the electrical load and the total generation capacities in hour t.

The annual income from power selling I_{i_SE} can be calculated from the following:

$$I_{i\_SE}(t) = \sum\nolimits_{t=1}^{8784} (1 + \propto_s) * R(t) * P_{i\_SE}(t), \tag{15}$$

$$P_{i\_SE}(t) = \begin{cases} p_i(t) & P_{SU}(t) \leq 0 \\ \frac{p_i(t) * P_{mx}(t)}{(\sum_1^{n=2} P_i)} & P_{SU}(t) > 0 \end{cases}, \tag{16}$$

$$P_{mx}(t) = P_L(t) + P_{TL}^{max} + (P_{BT} - p_{BT}(t)), \tag{17}$$

$$P_{SU}(t) = p_{WT}(t) + p_{SP}(t) - P_{mx}(t), \tag{18}$$

where $\propto_s$, $P_{i\_SE}(t)$, $P_{SU}(t)$, and $P_{mx}(t)$ are the subsidy coefficient, power selling, surplus power, and maximum power that can be consumed, respectively.

The annual selling power $P_{BT\_SE}(t)$ and ancillary income for storage battery I_{BT_AS} can be found as:

$$P_{BT\_SE}(t) = \begin{cases} Dp_{BT}(t) & Dp_{BT}(t) > 0 \\ 0 & Dp_{BT}(t) \leq 0 \end{cases}, \tag{19}$$

$$Dp_{BT}(t) = p_{BT}(t) - p_{BT}(t+1), \tag{20}$$

$$I_{BT\_AS} = I_{pu\_RP} \times \sum\nolimits_{t=1}^{8760} (p_{BT}(t) - P_{BT\_SE}(t) - P_{B\_min}), \tag{21}$$

where $Dp_{BT}(t)$ and I_{pu_RP} represent the change in battery capacity in hour t and per-unit income from reserve power, respectively.

2.3. Payoff of Microgrid-2

In microgrid-2, two generation resources i wind turbine WT and batteries BT are considered to design a model, and their decision variables are P_{WT} and P_{BT}, respectively. I_{WT} and I_{BT} represents the annual profit for each of the player. The total annual profit for the microgrid-2 is:

$$I_{MG\_2} = \sum\nolimits_{1}^{n=2} I_i. \tag{22}$$

To get the maximum annual profit for microgrid-2, the technical parameters and Equation (4) will be used for wind turbine WT and batteries BT. Lastly, the total annual profit of the networked architecture including microgrid-1 and microgrid-2 will be calculated as follows:

$$I_{NMG} = \sum\nolimits_{1}^{m=2}\left(\sum\nolimits_{1}^{n} I_i\right) = I_{MG\_1} + I_{MG\_2}. \tag{23}$$

3. Game Theory Techniques and Algorithm

Game theory is an advanced type of multi-objective optimization that has been applied for many years to solve different decision-making problems. To design cooperative and non-cooperative game models, various kinds of solution concept or techniques are used, such as Nash equilibrium, Pareto optimality, Shapley values, and Nash bargaining solutions. In game theory, Nash equilibrium is a fundamental concept and the most widely used technique for cooperative and non-cooperative game models to find the sizing and outcome of decision variables [35]. Shapley values is a technique mostly used for cooperative game models to fairly allocate the benefits among the independent power producers for the success of cooperation [24,36]. In this research, cooperative game models are designed using a technique of Nash equilibrium for optimum sizing of the capacities of generation resources and batteries. The maximum profit from networked microgrid is obtained based upon the optimum sizes of the players, and also a technique incorporating Shapley values is used to fairly allocate the profit among the players based upon their contribution in the game model.

In order to explain the Nash equilibrium, consider microgrid-1 which consists of three players as generation resources: wind turbines WT, solar panels SP, and batteries BT. Therefore, the cooperative game model can have four different possible coalitions for the planning problem of a three-player game. The optimum values of decision variables are found through Nash equilibrium using iterative procedure, and illustrated bellow when WT and SP are cooperating with each other and BT is working as self-sufficient:

1. Input the parameters such as wind speed, solar radiation, electricity price, and discount rate.
2. For the selected microgrid, randomly choose initial values of decision variables (P^0_{WT}, P^0_{SP}, P^0_{BT}) from strategic space.
3. In the case of generation resources, WT and SP are cooperating with each other and BT is self-sufficient. To explain this, consider a j^{th} iteration (P^j_{WT}, P^j_{SP}) (P^j_{BT}), which depends upon previous iteration $(P^{j-1}_{WT}, P^{j-1}_{SP})$ (P^{j-1}_{BT}), as:

$$(P^{j-1}_{WT}, P^{j-1}_{SP}) = arg \max_{P_{WT}P_{SP}} I_{WT\ SP}\left(P_{WT}, P_{SP},\ P^{j-1}_{BT}\right)$$

$$P^{j-1}_{BT} = arg \max_{P_{BT}} I_{BT}\left(P^{j-1}_{WT},\ P^{j-1}_{SP}, P_{BT}\right)$$

4. In this step, share with every player in the coalition regarding strategic values of third step.
5. Check the condition of Nash equilibrium, if none of the players changes its value during whole round of iteration, this means $(P_{WT}, P_{SP}) = \left(P^*_{WT},\ P^*_{SP}\right)$, and $P_{BT} = P^*_{BT}$, the Nash equilibrium is found. In case, results are not achieved, move back to Step 3.

To find the maximum value of annual profit from networked microgrid, a cooperative game theory technique, i.e., Shapely values, is introduced based upon the optimum sizing of generation resources and batteries. This is most widely used solution concept in coalition-type games, and its main advantage is the fair distribution of profit among the players depending upon their marginal contribution in the architecture [30,37,38]. Shapely value is a very simple and straightforward to distribute the payoff or profit among the players of a game model in collaborative way [31]. Shapley values are represented by Φ_i for each of the players; the game model is defined by $(n,\ f)$ for each of the player $n \in N$ and expressed as:

$$\Phi_i = \sum_{S \in N} [f(S) - f(S-i)] \times \frac{(|S|-1)!(n-|S|)!}{n!}, \quad (24)$$

where N is the total number of players in coalition, $|S|$ is the number of player in set S, $v(S)$ is the payoff or profit when all players of set S in coalition, and $v(S-i)$ is the profit when all players except i are in coalition. Through this game technique, the players who contribute the most in networked microgrid will be rewarded most, and the one who contribute the least will be rewarded least as well.

To design and simulate the proposed networked architecture in MATLAB, an imperialistic competition algorithm is used. The main operators of this algorithm are assimilation, revolution, and imperialistic competition, as shown in Figure 4. It is a modern population-based algorithm and used in various research areas to solve many optimization problems [39,40]. In this research work, to find the most feasible sizes of decision variables, 50 populations or countries, 5 imperials, and 50 maximum decades, are considered. Besides this, one-year realistic input data of residential load, wind speed, and solar radiation of a remote town in Western Australia are considered in designing and simulation to find optimum sizes of generation resources and maximum profit of the networked microgrid.

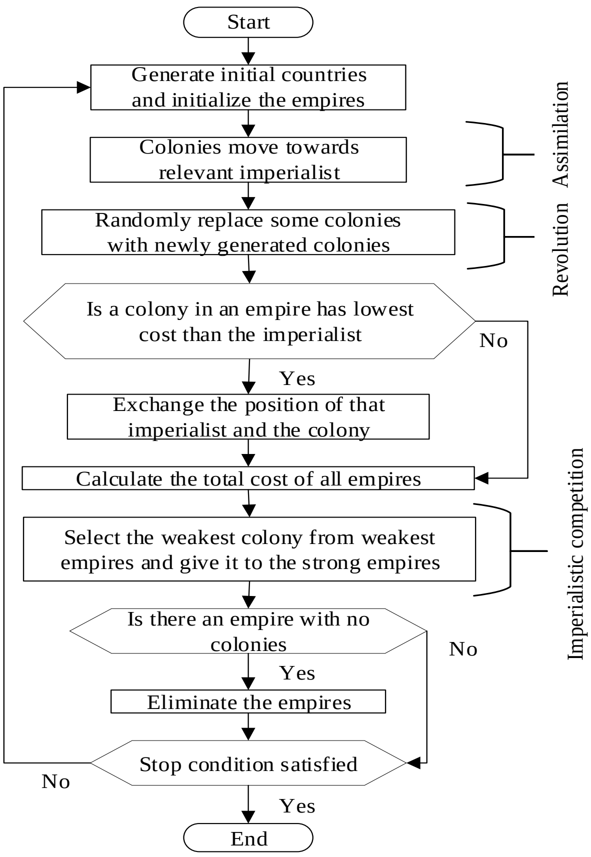

Figure 4. Imperialistic competition algorithm.

4. Results and Analysis

The optimum sizing of the networked microgrid was carried out with the help of game-theoretic technique of Nash equilibrium and all possible combinations of cooperative game model were considered. The annual profit of the each microgrid was found using Nash equilibrium and Shapely values, and a comparative analysis was carried out among the game-theoretic techniques to identify the maximum profit of the networked microgrid. A simulation model was made in MATLAB software and used a population-based imperialistic competition algorithm. In order to optimize the objective function and to find suitable sizes of decision variables, input parameters as listed in Table 1 [18] were considered for each of the generation resources and batteries.

Table 1. Input parameters for networked microgrid.

Parameters	Values	Parameters	Values
Electricity price (R)	0.12 $/kWh	WT salvage value (SV_{WT})	77 $/kW
Discount rate (Dr)	12%	PV panel price (U_{SP})	1890 $/kW
Cut-in wind speed (v_{ci})	3 m/s	Life span of PV (L_{SP})	20 Years
Cut-out wind speed (v_{co})	20 m/s	OM cost of PV (OM_{SP})	20 $/(kW·year)
Rated wind speed (v_r)	12 m/s	PV panels salvage vale (SV_{SP})	189 $/kW
Life span of WT (L_{WT})	20 Years	Life span of batteries (L_{BT})	10 Years
WT price (U_{WT})	770 $/kW	Battery price (U_{BT})	100 $/kW
OM cost of WT (OM_{WT})	20 $/(kW·year)	OM cost of battery (OM_{BT})	1 $/(kW·year)

In case of microgrid-1, three generation resources, i.e., wind turbines WT, solar panels SP, and batteries BT, were considered as players, and therefore, for the cooperative game model four different kinds of coalitions are possible. However, microgrid-2 consists of two players, i.e., wind turbines WT and batteries BT, and therefore, only one coalition is possible among them. To find the cooperative game model with maximum profit and most suitable generation sizes, all possible coalitions were considered and simulated. The optimum sizes of decision variables and maximum annual profit were found using the Nash equilibrium technique for each combination and are listed in Table 2 for both microgrids. It is evident from the results that the power capacity of WT is higher than SP and BT, however, SP capacity is smaller than BT in all of the cases except case-3.

Table 2. Nash equilibrium results for the networked microgrid.

	Game Model		Capacity Allocation of the Players (kW)			Total Profit ($/year)
	Case#	**Coalition**	P_{WT}	P_{SP}	P_{BT}	I_{MG_1}
MG-1	1	{WT, SP, BT}	44,876	8007	9294	2.48×10^7
	2	{WT, SP}, {BT}	44,979	8541	9999	2.47×10^7
	3	{WT, BT}, {SP}	44,952	15,020	9304	2.29×10^7
	4	{WT}, {SP, BT}	32,482	8032	9756	2.06×10^7
MG-2	**Case#**	**Coalition**	P_{WT}	P_{BT}		I_{MG_1}
	5	{WT, BT}	44,903	8752		2.50×10^7

Table 2 illustrates that annual profit is higher when wind turbines WT form a coalition with any of other players, and it reaches maximum values when all other players (solar panels SP and batteries BT) are in coalition with wind turbines WT. Therefore, case-1 is the most suitable coalition for microgrid-1 with sizes of 44,876 kW, 8007 kW, and 9294 kW for WT, SP, and BT, respectively, and maximum profit is 2.48×10^7 $/year using Nash equilibrium. Besides this, for microgrid-2 maximum profit is 2.50×10^7 $/year and optimum sizes of WT and BT are 44,903 kW and 8952 kW, respectively. The cooperative game models also show that if larger sizes of generation resources are considered in a microgrid, the value of annual profit increases. As the microgrid gets the opportunity to sell additional power to the main grid, and it is easier for networked architecture to meet load requirements in any emergency situation.

In this analysis, to get the maximum value of annual profit from the networked microgrid, two different game theory techniques, i.e., Nash equilibrium and Shapley values, were used and the results were compared to identify most feasible solution. The annual profits of Nash equilibrium and Shapley values are shown in Tables 2 and 3, respectively, for each microgrid. If the annual profits for each possible coalition are compared between both game-theoretic techniques, it is found that results are higher for Shapley value than for Nash equilibrium. It is also illustrated in Table 3 that the distribution of the annual profit among the players is fair in each coalition with respect to the player's contribution. Therefore, the technique of Shapley value is proposed for the maximization of the annual profit of the networked microgrid, and the optimum sizing of generation resources and batteries is found through Nash equilibrium.

Table 3. Shapley values result for networked microgrid.

Game Model			Profit Using Shapley Values ($/year)			
	Case#	**Coalition**	Φ_{WT}	Φ_{SP}	Φ_{BT}	Φ_{MG_1}
MG-1	1	$\{WT, SP, BT\}$	1.63×10^7	8.24×10^6	1.09×10^7	3.54×10^7
	2	$\{WT, SP\}, \{BT\}$	1.60×10^7	8.11×10^6	1.09×10^7	3.50×10^7
	3	$\{WT, BT\}, \{SP\}$	1.47×10^7	7.59×10^6	1.00×10^7	3.23×10^7
	4	$\{WT\}, \{SP, BT\}$	1.19×10^7	6.12×10^6	8.80×10^6	2.68×10^7
MG-2	**Case#**	**Coalition**	Φ_{WT}	Φ_{BT}		Φ_{MG_2}
	5	$\{WT, BT\}$	1.74×10^7	1.25×10^7		2.99×10^7

In the end, sensitivity analysis was performed for both techniques of game theory to analyze the impact of changing the values of electricity price R and discount rate Dr for the proposed networked architecture. These parameters are considered to validate the results and observe the variations in the value of annual profit from microgrid-1 and microgrid-2. The influences in changing the electricity price and discount rate are shown in Figure 5a,b and Table 4.

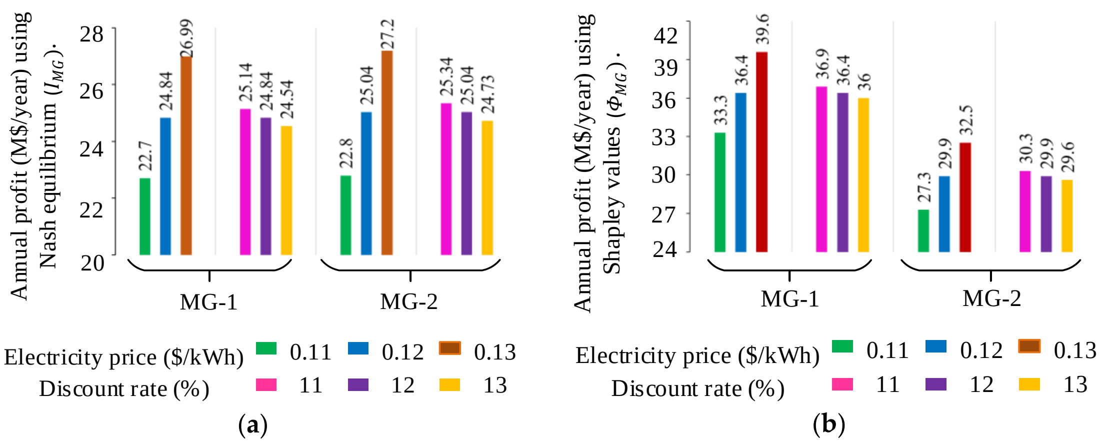

Figure 5. Sensitivity analysis for game theory techniques: (**a**) Nash equilibrium; (**b**) Shapley values.

Table 4. Sensitivity analysis of networked microgrid for game theory techniques.

Game Model		Profit (M$/year) Using Nash Equilibrium (I_{MG})						Profit (M$/year) Using Shapley Values (Φ_{MG})					
		Electricity Price ($/kWh)			Discount Rat (%)			Electricity Price ($/kWh)			Discount Rate (%)		
		0.11	0.12	0.13	11	12	13	0.11	0.12	0.13	11	12	13
MG-1	$\{WT, SP, BT\}$	22.7	24.8	26.9	25.1	24.8	24.5	33.3	36.4	39.6	36.9	36.4	36.0
MG-2	$\{WT, BT\}$	22.8	25.0	27.2	25.3	25.0	24.7	27.3	29.9	32.5	30.3	29.9	29.6

In case of high electricity prices, generation resources earn more profit by selling power to the load and main grid. On the other side, as the value of discount rate increases, the value of profit increases sequentially, and vice versa. Moreover, it is also evident that both parameters are more sensitive to the influence of electricity price compare to discount rate. Therefore, a small increase in electricity price brings a quick increase in profit value.

5. Conclusions

Nash equilibrium and Shapley values game theory techniques are used and compared in this paper to model a networked microgrid, and optimization is performed in MATLAB software using ICA. The main achievement of this research is making a suitable capacity allocation of generation resources and batteries using Nash equilibrium for each microgrid. Another game-theoretic technique, Shapely values, is considered with Nash equilibrium to find the annual profit of the networked microgrid; comparative analysis is performed between the game theory techniques and maximum profits of each microgrid are identified. In this analysis, a cooperative game model is considered where all the players are in coalition through different combinations, therefore, the results for all possible coalitions are calculated. It is clear from the results (Table 2) of Nash equilibrium that the value of annual profit is higher when all the players of game model are in coalition with each other. Therefore, the sizes of generation resources and batteries are optimum in case-1 for microgrid-1, and in case-5 for microgrid-2. The results of Nash equilibrium are further compared with another game theory technique, Shapley values (Table 3). Shapley values found higher annual profits for each microgrid. It is also illustrated for Shapley values that the distribution of the annual profit among the generation resources and batteries is fair for every possible coalition with respect to the player's contribution. Therefore, annual profit of each microgrid is maximum and feasible when cooperative game theory Shapely values are used. In the end, the sensitivity analysis validated the results of networked microgrid and checked the influence on decision variables of generation resources and batteries for both game theory techniques.

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Nomenclature

BT	Batteries
C_i	Cost of the player i
C_{IN}	Investment cost
C_{OM}	Operation and maintenance cost
C_{ES}	Cost of energy not served
C_{GR}	Total cost of purchasing power from grid
C_{i_PR}	Cost of purchasing power from grid by player i
D_r	Discount rate
$R(t)$	Electricity price in hour t
ε_c	Battery charging efficiency
i	Generation resources $i \in \{WT,\ SP,\ BT\}$
I_i	Income of the player i
I_{SE}	Income from power selling
I_{SV}	Salvage value
I_{AS}	Annual ancillary service benefits
n	Number of players
L_i	Life span of the player

m	Number of microgrid
MG	Microgrid
NMG	Networked microgrid
P_i	Decision variable of the player i
$\Delta(t)$	Difference between generation and load in hour t
$P_{mx}(t)$	Maximum power consumed in hour t
I	Payoff of the player or microgrid
$P_L(t)$	Electrical Load demand in hour t
P_{TL}^{max}	Maximum transmission capacity of tie line
$P_{SU}(t)$	Surplus power in hour t
$p_i(t)$	Output power the player in hour t
$P_{GR}(t)$	Power purchased from grid in hour t
$DP(t)$	Unbalance power in hour t
P_{BT_min}	Minimum capacity of batteries
I_{pu_RP}	Per unit income from reserve power
SP	Solar panels
SS_i	Strategic space of the player i
U_i	Per unit cost of the player i
S_{i_pu}	Per unit salvage value
$V(t)$	Wind speed in hour t
V_{ci}	Cut in wind speed
V_{co}	Cut out wind speed
V_r	Rated wind speed
WT	Wind turbines
Φ	Shapley values

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