Optimal coalition formation and maximum profit allocation for distributed energy resources in smart grids based on cooperative game theory

Abstract

Over the past decades, significant revolutions have occurred on electricity market to reduce the electricity cost and increase profits. In particular, the novel structures facilitate the electricity manufacturers to participate in the market and earn more profit by cooperate with other producers. This paper presents a three-level game-play-based intelligent structure to evaluate individual and collaborative strategies of electricity manufacturers, considering network and physical constraints. At the Level I, the particle swarm optimization (PSO) algorithm is implemented to determine the optimum power of distributed energy resources (DERs) in the power grid, to maximize the profits. Further, the fuzzy logic algorithm is applied to model the intermittent nature of the renewable sources and implement load demand in the power grid. At the Level II, DERs are classified into two different fuzzy logic groups to secure the fairness between every participant. Finally, at the Level III, the DERs in each group are combined each other by cooperative game theory-based algorithms to increase the coalition profits. Thereafter, Shapley, Nucleolus, and merge/split methods are applied to allocate a fair profit allocation by coalition formation. Ultimately, the results verify the proposed model influence electric players to find effective collaborative strategies under different conditions and environments.

Keywords: smart grid, electricity energy market, coalition formation and competition, cooperative game theory, Merge and Split, Nucleolus, profit allocation, Shapley value.

Nomenclature

Acronyms	
CES	Community-level Energy System
CVaR	Conditional Value at Risk
DER	Distributed Energy Resource
DR	Demand Response
ECs	Energy Communities
ESS	Energy Storage System
H-MGs	Home Microgrids
LMP	Local Marginal Price
MCP	Market-clearing Price
MILP	Mixed-integer Linear Programming
OCS	Optimal Coalition Structure
PSO	Particle Swarm Optimization
PV	Photovoltaic
TE	Transactive Energy
WT	Wind turbine

Indices

i	Index for DER

Parameters

v_w	Predicted the speed of the wind
$v_w^{'}$	Actual the speed of the wind
P_L	Demand for the active power of the load
T_c	Total fuel cost of the thermal units
F_i	$i-th$ thermal unit fuel cost
a_i, b_i, c_i, de_i, f_i	Cost function coefficients
P_{gi}	True output power of the thermal unit i
N_g	Number of thermal units
μ_c	Membership function the total fuel cost
μ_l	Membership function of the total load
TC_{min}	Lowest total cost of the fuel
TC	Total cost of units
TL	Total loses of the real power of the network
N_L	Number of transmission lines in the system
P_{Li}	Predicted active power demand
G_{Li}	Predicted reactive power demand
P_{Gi}	Active power output injected into the bus i,
Q_{Gi}	Reactive power output injected into the bus i,
V	Voltage of the bus

σ	Angle of the bus
Y_{ij}, θ_{ij}	Admittance matrix elements of the bus
$P_{gi}^{max}/P_{gi}^{min}$	Maximum/Minimum active output power
$Q_{gi}^{max}/Q_{gi}^{min}$	Maximum/Minimum output reactive power
V_{i}^{max}/V_{i}^{min}	Upper/Lower limits of the voltage on the bus
N_{bus}	Number of buses
S_{li}	Reactive power of the line
S_{li}^{max}	Maximum reactive power of the line $i - th$
$V(i)$	Profit of each DER_i
ρ_i	Sales price to the generator consumer i
P_i	Effective power of each generator
ω_i	Periodic charge rate
$f(i)$	Generator cost function in DER_i
λ	Lagrange coefficient
P_R	total load (MW)
P_i	Effective power of the generator i after the co-operation (MW/h)
m	Number of coalitions
x_i	Benefit of player "i" in independent condition

1. Introduction

1.1. Motivation and Contributions

At present context, numerous research are conducted on distributed energy resources (DERs) by cooperate with other DERs in the network and also with DGs in neighboring networks, to enhance the profits and form a coalition. Further, the profit allocation from a coalition between DERs is an essential measure to observe the improved performance of smart grids. In this study, a bi-level methodology is proposed to maximize the profit in the competitive market and allocate profit from a coalition formation between DERs. Moreover, the different distribution methods such as, Shapley, Nucleolus, and Merge/ Split, are compared with each other in profit allocation analysis. Further,the disconnection of DERs due to the pricing decisions allows to collaborate with aggregated facilities, to achieve higher profits by the excess production and avoid penalties by the production shortages. This concept could apply to all energy suppliers and producers to form a coalition in economic optimizations. The study further investigates that the grids could increase the profit by cooperating with each other instead of individual operation. Hence, the cooperative coalition formation game among the grids is presented at the Level III in the study. Furthermore, different mechanisms for allocating profits in the coalition are observed, and the results confirm that the profit in cooperative operation is higher than the profit in the individual performances in each grid.The consumer feedbacks is also considered in the proposed work to improve the cooperative game performance, when networking with different power suppliers and the consumers. The feasibility of the proposed structure is confirmed by including numerous buyers and manufacturers. This structure illustrates that the cooperation between the producers could significantly increase the profits of the players, and the changes on the coalition between the members would result notable changes in the profits. The groups which based on the game theory are assessed that the distribution of profits among the group members is strongly depending on the way of grouping. Moreover, the efficiency and sustainability of various cooperation schemes are analyzed in this paper. The main contributions of the proposed work could be highlighted as follows:

- Presents a structure which links between cooperative game theory and optimal output of production resources (a combination of optimization theory and the game theory), while delivering the optimal power of production resources and the profit for participating in cooperation with other resources.
- Capable of easily extend to different systems with various characteristic functions. The results show that the large coalition is optimal when the size of the coalition is not restricted.
- Observes the effect of classifying the players in the coalition. Players in the group with a steady profit would form a coalition with each other, while players with higher productivity would prefer to form a coalition with larger players. The results have confirmed the efficiency and capability of the proposed structure on the system.
- Influence electric power players to find attractive cooperation strategies while ensuring sustainable profits under changing conditions and environments.

1.2. Literature review

The private electric power market has been changed from conventional single owner to free market, where the sole owner is responsible from electricity market to customer needs and the free market has many participants such as providers, facilitators and users with individual responsibilities. In fact, the main components of this novel market structure are sources of production, distribution, wholesalers, and retailers, where the number of players are continuously rising, and these players are free to enter or exit the market according to the situation and the economic opportunities.

In many countries, after the free market has been introduced ,the technological progress is increased notably due to the competitive environment. Further, the participation of the main parts of the structure in this market has generally led the market to reduce costs and increase higher reliability, which ultimately provides noticeable benefits to the players [1]. Moreover, the prime goal is to develop an optimal market structure with a strong competition between all players, in which the price decisioning and electrical power exchanging could based on market power. In this structure, all players could bid on the offer and must accept the market-clearing price (MCP) as a market decision. In fact, free market laws are based on existing technical problems such as, system failures, transmission security, and economic decisions including limiting blocking market power to resist unreasonably higher bidding. Therefore, power sellers and buyers are capable of re-evaluating their pricing strategies and economic methods according to environmental conditions. In addition, the modernization of the electrical energy price has transformed the energy sales from a monopoly market to a competitive market. Therefore, the technical and physical constraints in the network could significantly impact on economic decisions. Moreover, in a non-competitive economic system, power vendors could work together in a network to influence the market by changing the value of the bid. This reduces the amount of MCP and thereby decreases the local marginal price (LMP).

In this paper, pricing and collaboration strategies of power vendors in a free market are studied by a heuristic approach called cooperative game theory, and particle swarm optimization (PSO) in an agent-based framework. Despite the conventional economic analysis based on robust and restricted assumptions, the agent-based method provides a flexible framework for simulating and validating the decision-making process of different participants in a free electrical market. Further, each agent represents an independent participant with independent pricing strategies, and could respond to market events with learning from current and previous experience. A non-convex coalition game was proposed for energy communities (ECs) in [2], where the Shapley values do not provide a stabilizing value-sharing mechanism for a grand coalition. Further, K-means algorithm has been applied for classifying the prosumers' profiles to remove several redundant constraints. This research has proved that although the Shapley value could be a fair method, it could lead to a stable coalition if the intended game is convex.

Nucleolus method is preferred by many researchers due to the stabilizing capability [3]. In this regard, a coalition game theory-based energy management problem is presented for local energy communities. The literature has demonstrated that although the objective function is convex, a nucleolus-based solution provides a stable and fair payoff distribution scheme to all players [3]. However, profit-sharing methods such as Shapley value and Nucleolus are associated with several computational complexities. Therefore,these methods are inappropriate for distributed frameworks due to the computation of the profitability of all cooperative coalitions, which increases communication and processing time [4]. Hence, investigation on cooperative game theory strategy is necessary to create a grand coalition and achieve a maximum profit.

Accordingly, using a cooperative game to solve a profit-sharing scheme assures that all competitors are financially rewarded and discourages members from straying from the expected collaboration [5]. This type of game allows the participants the freedom of selecting their partners and reduces distribution losses while improving the generation bidding prices. In literature [6], a cooperative Stackelberg game has developed, where the centralized power system serves as the leader and decides the price during the peak demand to convince prosumers not to seek energy. In that model, an algorithm has proposed for the centralized power station and the prosumers to satisfy the equilibrium. In study [7], a cooperative trading framework was presented for a community-level energy system (CES) including of an energy hub and photovoltaic (PV) prosumers with an automatic demand response (DR). This approach is based on cooperative game theory and considers the stochastic characteristics of PV prosumers with the conditional value at risk (CVaR). Furthermore, the optimization problem has converted into mixed-integer linear programming (MILP) model by adding auxiliary variables. It is also demonstrated that the cooperative game theory model could contribute to local utilization of PV energy, increase the leader's profit, and decrease the costs of prosumers compared to the non-cooperative game theory models.

Another type of cooperative game is the merge and split method. In fact, the merging process assists small microgrid coalitions to form larger coalitions. This is obvious when the greater utility of some microgrids could be obtained without sacrificing any microgrids. Therefore, the splitting process divides large coalitions into small coalitions, if no microgrids lose utility because of the splitting process and some microgrids reach higher individual utility [8]. This technique has a lower complexity compared to the non-cooperative model, especially for a higher number of players in a coalition. Besides that, this cooperative game strategy is suitable for both convex and non-convex problem, which exists in Shapely value [8]. Further, a smart transactive energy (TE) framework is presented in [9], where home microgrids (H-MGs) collaborate with each other in a multiple H-MG systems by forming coalitions to gain competitiveness in the market. Profit allocation due to the coalition between H-MGs is an important issue to ensure the optimal use of installed resources in the multiple H-MG systems. In addition, considering demand fluctuations, energy production based on renewable resources in the multiple H-MG could be accomplished by demand-side management strategies to achieve a flatter demand curve. In this regard, demand shifting is tapped through shifting certain amounts of energy demand from one time period to other time period with lower expected demand, to match prices and to ensure that the existing generation is economically sufficient. In [10], an agent-based model for market realization in the real world has been investigated. In fact, an agent-based model considering a vendor who needs to evaluates a set of contractual conditions is presented in [11]. A market-clearing plan was prepared in [12] for fair distribution of the demand response benefits with different market participants, in which the participants were modeled as smart agents. Literature [13], observed that adaptive Q-learning could be successfully applied to agent-based electricity market modeling. In [14], a multi-processor simulator was proposed for wholesale markets to simulate trading agents in power spot markets. An alternative co-evolutionary method was proposed in [15] with improved strategies of the agents. The implicit collusion occurs when limited information is available from contributors. algorithms based on comparative players were applied in [16], to define the equilibrium point in a complex two-way bidding market in a discriminatory pricing market. Equilibrium models of the feeding function in an oligopolistic power market were analyzed considering both piecewise linear feeding functions in [17], and the results represent a robust convergence towards the equilibrium point.

In the competitive market, both the production factor and the consumption factor continuously adapt their strategies according to the objective functions. Further, an agent-based model could be used to simulate a bilateral auction market. Moreover, optimal pricing strategies for regenerators and consumers in a competitive market have used Monte Carlo sampling to assess rivals' behavior in [18]. The study, [19] has focused on minimizing the LMP of buyers by using various evolutionary algorithms and adding a game-based decision based on game theory. Furthermore, the alliance strategy was studied in [20] and proved that buyers could reduce the costs by the number of members. In [21], different game scenarios are simulated individually or in collaboration and the results indicate that there is a good cooperation between the members.

The game theory offers several methods during the study of the interference of the interests in different agents at the competitive market. In [22], a comprehensive analysis is proposed between different game theory models. Particularly, the competitive game theory provides a tool for solving conflicts resulting from interest interference of different players such as allocating transmission costs [23]. The solution mechanisms of this approach are based on fairness, efficiency, and sustainability in the distribution of benefits between agents. In addition, extensive efforts were carried out to formulate a coalition between members. The method studied in the research is based on the division of agents within the coalitions to maximize the total benefits. In [24], a dynamic programming (DP) with the ability to consider n complexity has been introduced (n is the number of agents). Further, the complexity and implementation time is increased with the growing number of agents. More recently, in [25], the problem of optimal coalition structure (OCS) has been formulated as a hybrid integer programming. Although the use of inappropriate algorithms is not a guarantee of locating the optimal local point, they provide fast and convenient solutions compared to other algorithms. The authors proposed a genetic algorithm for the formation of an optimal coalition in [26], and the results suggest that these algorithms are outstripping the deterministic algorithms. In addition, both coalition structures and the distribution of profits in competitive environments are presented in [27] and [28], where an optimal point could be obtained if the kernel stability criterion is satisfied [28]. Most of the recent studies

[29, 30] have been modeled in a dynamic environment where uncertainties, for example, the amount of coalitions are not constant [31].

Many research have been conducted on scheduling of the microgrid systems which propose a dynamic transactive energy scheme. In these works, the distribution system operator at the upper level optimizes the profit and it is independence of the system. Further, the carbon mechanism of transactive energy in the islanded microgrid systems is investigated in[32].

Computational intelligence approaches play an essential role in the energy scheduling of microgrid systems because of the effective management, faster performance, and higher accuracy. The authors of [33] apply the particle swarm optimization algorithm for coordinated distribution systems with multiple microgrids. In this work, the probabilistic behavior of renewable generation is ignored although the research investigates the impacts of demand response programs. Further, an adaptive particle swarm optimization algorithm is developed in [34] to coordinate vehicle-to-grid in microgrid systems. However, the cooperation among microgrids for profit maximization is not studied in this work. The literature [35] presents a multi-objective optimization framework by the non-dominated genetic algorithm-II to optimize the power losses, efficiency, voltage deviation, and reliability issues in the microgrid systems. However, the roles of demand response programs and non-renewable resources are not investigated.

A chaos sparrow search algorithm is presented in [36] to minimize the operation costs of microgrids considering different demand response programs and energy storage systems. Nevertheless, the coalition formation among microgrids and related uncertainties are not studied. The disadvantages of computational intelligence approaches such as the particle swarm algorithm are easy to fall into local optimum, and have a low convergence in the iterative process. Therefore, presenting an analytic approach is essential to ensure the optimal solution. A coalitional game is proposed in [37] to enable microgrids to form coalitions considering transmission fee, where the Shapley value is utilized to allocate the overall gain of coalition among microgrids.

The authors of [38] suggested optimal energy management sharing systems that the cooperator microgrids can share the surplus power for cost minimization. Although this model allows the microgrids to self-adapt to environmental changes, the uncertainties of demands and renewable generation are not considered. In literature [39], the uncertainties in the microgrids system is managed by the scenario generation and scenario-reduction approaches to determine the probability behavior of renewable generation [39].

In Table 1, a comprehensive comparison is presented between state-of-the-art approaches and the present study. In this table, the main components such as type of coalition, type of optimization, energy resources and presence of energy storage system (ESS) cooperative and non-cooperative game, and the number of DG resources applied in the grand coalition are compared. Furthermore, the number of DGs in forming a coalition is not restricted in the proposed approach. The suggested study achieves following advantages:

1. The Number of DGs to form a coalition is not limited. (the existing studies have not considered more than five DGs and have failed to form a coalition, while this paper simulated more than 5 DGs, and defined that the increasing the players in the grad coalitions is not restricted).
2. The profits of the grand coalition would be increased with the growing number of DGs. Hence, the profits of each of the DGs that participated in the grand coalition is also increased.

In a competitive market, the buyers are not price-takers since the electrical energy is not influenced the market using different pricing strategies and not cooperate with other buyers. Therefore, it is necessary to explore the strategies for cooperation and customizing of electricity buyers. However, since most investigations were not conducted on the demand side,many researchers focused only on the production and transmission of power. In addition, based on the previous authors, the OCS problem in the electricity market has not been discussed. This article presents an important theory, where the distribution of interest in cooperative game theory, and the formation of an optimal coalition in the hybrid optimization theory are interrelated by considering the cooperative behavior of buyers.

This paper discusses the links between the distribution of benefits in cooperative game theory and the formation of an optimal coalition in hybrid optimization, along with the formation of a theoretical basis background for the proposed methodology. Additionally, while the previous articles focused on simplifying the market model by low-level participants (no more than five DGs are considered, and they do not form a coalition), the proposed model could deal with a large number of buyers.

2. The proposed structure

In the proposed electricity market, several DERs in a network could cooperate with each other or with DERs in other networks by adjusting their production capacity and local demand for maximum profit. In Figure 1, a game theory-based on three-level structure is presented to form an optimal coalition between DERs and to allocate profits between them.

At the Level I (DGs classification), the load distribution is first performed on the DGs in the network. Then the load distribution response is optimized by the PSO optimization algorithm, and the amount of active and reactive power of each source is determined. Uncertainty in wind resources is also analyzed at this stage. Thereafter, the power of each resource is categorized based on their power output by fuzzy logic classification, to form a coalition based on their power output relative to their nominal production capacity.

At the Level II (optimum power determination of DGs unit), DGs can increase their profits by competing with others. A coalition should be formed when each player can achieve a higher level of productivity to gain more profits. At this level, all resources (based on the ratio of production capacity to nominal capacity) are divided into two groups. The first group includes the resources which the production capacity is less than 50% of their production capacity. These resources combine with each other in the first group. The second group includes the resources that have a production capacity more than 50% of their production capacity. In this group, resources with more productive capacity form a coalition with each other and finally participate in the formation of a grand coalition. Moreover, this mechanism allows to move from first group to second group by increasing the production capacity, to

Table 1: A comparative summary of this study and previous papers.

Ref. Number	Strategies for Coalition Implementation				Cons	Class	Network				Game Theory		Number of Players in Big Coalition Formation	
	Shapely	Nucleous	Merge/ Split	Other coalition methods			PV	Wind	Other DGs	Energy Storage	Cooperative	Non-Cooperative	Less than 6	More than 6
[2]	✓	✓	✖	✖	✓	✖	✓	✓	✓	✓	✓	✖	✓	✖
[3]	✖	✖	✖	Adaptive ADMM	✓	✖	✖	✓	✓	✓	✖	✖	✓	✖
[4]	✓	✓	✖	✖	✓	✖	✓	✖	✓	✓	✖	✖	✓	✖
[5]	✖	✖	✖	Peer-to-Peer	✓	✖	✖	✖	✓	✖	✓	✖	✖	✖
[6]	✖	✖	✖	Nonlinear Programming Models	✓	✖	✓	✖	✓	✖	✓	✖	✓	✖
[7]	✓	✖	✖	✖	✓	✖	✓	✓	✓	✓	✓	✖	✓	✖
[8]	✓	✖	✖	✖	✓	✖	✓	✓	✓	✓	✖	✖	✓	✖
[9]	✖	✖	✖	Market clearing price	✓	✖	✖	✓	✓	✓	✓	✖	✓	✖
[13]	✖	✖	✖	Demand response exchange	✓	✖	✖	✖	✓	✖	✖	✖	✓	✖
[19]	✖	✖	✖	Monte Carlo	✓	✖	✖	✖	✓	✖	✖	✖	✓	✖
[20]	✓	✖	✖	Co-evolutionary Algorithm	✓	✖	✖	✖	✓	✖	✓	✖	✓	✖
[21]	✖	✖	✖	Locational Marginal Prices (LMPs)	✓	✖	✖	✖	✓	✖	✓	✖	✓	✖
[22]	✖	✖	✖	Co-evolutionary Algorithm	✓	✖	✖	✖	✓	✖	✓	✖	✓	✖
[23]	✖	✖	✖	Cournot Model	✓	✖	✖	✖	✓	✖	✓	✖	✓	✖
[24]	✓	✓	✖	✖	✓	✖	✖	✖	✓	✖	✓	✖	✓	✖
[26]	✖	✖	✖	Partition Function Games (PFGs)	✓	✖	✖	✖	✓	✖	✖	✖	✓	✖
[31]	✖	✖	✖	Dynamic Coalition in Electricity Markets (DYCE)	✓	✖	✖	✖	✓	✖	✖	✖	✓	✖
[40]	✓	✓	✓	✖	✓	✓	✖	✖	✓	✖	✓	✖	✓	✖
[41]	✓	✓	✓	✖	✓	✖	✖	✖	✓	✖	✓	✖	✓	✖
[32]	✖	✖	✖	Stochastic optimization	✓	✖	✓	✓	✓	✓	✖	✖	✓	✖
[33]	✖	✖	✖	Multi-agent system	✓	✖	✓	✓	✓	✓	✖	✖	✓	✖
[34]	✖	✖	✖	Stochastic optimization	✓	✖	✓	✓	✓	✓	✖	✖	✓	✖
[35]	✖	✖	✖	Multi-objective optimization	✓	✖	✓	✓	✓	✓	✖	✖	✓	✖
[36]	✖	✖	✖	Chaos sparrow search algorithm	✓	✖	✓	✓	✓	✓	✖	✖	✓	✖
[37]	✓	✖	✖	✖	✓	✖	✓	✓	✓	✓	✓	✖	✓	✖
[38]	✖	✖	✖	Optimal energy sharing	✓	✖	✓	✓	✓	✓	✖	✖	✓	✖
[39]	✖	✖	✖	Multi-objective optimization	✓	✖	✓	✓	✓	✓	✖	✖	✓	✖
This study	✓	✓	✓	✖	✖	✓	✖	✓	✓	✖	✓	✖	✖	✓

form the grand coalition and gain greater profits.

The Level III (forming a coalition and allocation profits) concerns the allocation of profits and the formation of coalitions between DGs. At this level, the interaction of players is examined based on cooperative game theory to form a group or a coalition. The result of the coalition formation is studied based on the Shapley, Nucleolus, and merge/split methods. The profit-sharing mechanism is essential to motivate each player in the coalition. In the proposed structure, different profit-sharing rules such as Shapley value, and merger/split and Nucleolus will be compared to evaluate the profit of each DG, by joining the coalition. The implementation of each level and the goals pursued are described below.

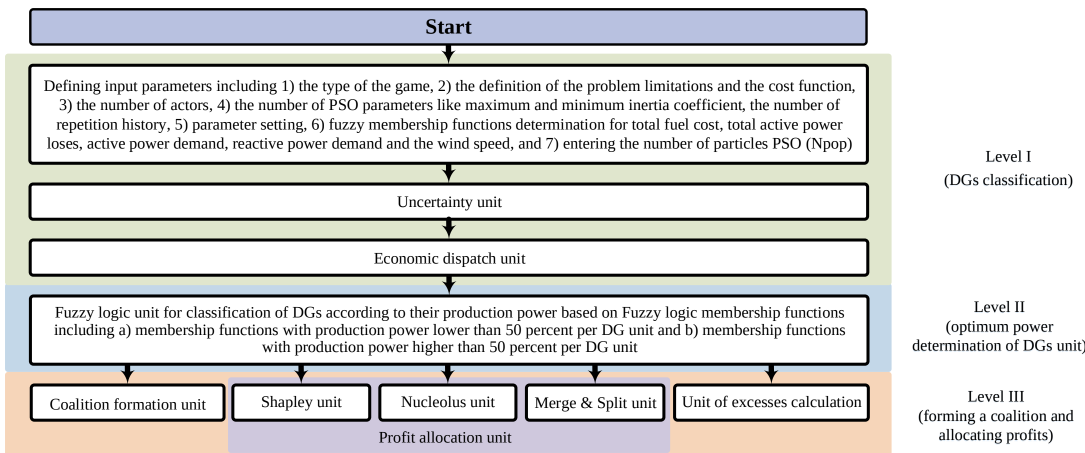

Figure 1: The structure implemented to form a coalition and allocate profits.

2.1. Assumptions

Following assumptions are defined to improve the computation time and the convergence of the optimization:

1. In the proposed structure, the power planned by DERs does not depend on the characteristics of the loads, which means it is possible to active or inactive any number of time.

2. The congestion line is not considered. Line overload does not present when considering the power flow in the network and re-allocating the load in the cooperation between the DGs.

3. Dynamic pricing has been used instead of static pricing.

2.2. *Level I*

2.2.1. *PSO based economic dispatch unit combined with the Fuzzy Logic-based Uncertainty Unit (FLC)*

The prime purpose of the implementation of this unit is to find the active optimal power of distributed generation units by the fuzzy logic combined with PSO method. This minimizes the total fuel cost of the thermal units and the total active power loss with the uncertainty of the wind units. Further, it also considers the network technical constraints such as load distribution constraints, output power limitations in thermal units and voltage restrictions on each bus. Moreover, the load demand errors and predicted wind speed are considered as uncertainties in the proposed PSO algorithm combined with the fuzzy logic set.

2.2.2. *Uncertainty unit*

The random nature of the renewable resources generation and the demand for loads causes errors in the forecasted inputs of these resources. Moreover, the uncertainty unit based on fuzzy logic is used to predict the wind power production and load demand. Further, the formation of fuzzy membership functions is presented for wind speed and load demand.

2.2.3. *Fuzzy membership function for wind speed*

The fuzzy membership function for the predicted wind speed error could be calculated by

$$\mu^{WT} = \begin{cases} \frac{1}{1+\eta^{WT}(\Delta v_w / v_w^{+})^2} & \Delta v_w \geqslant 0 \\ \frac{1}{1+\eta^{WT}(\Delta v_w / v_w^{-})^2} & \Delta v_w < 0 \end{cases} \tag{1}$$

$$\Delta v_w = \frac{v_w' - v_w}{v_w} \times 100\% \tag{2}$$

where v_w^+ and v_w^- are the average percentage error, when the actual wind speed is greater or less than the expected wind speed, η^{WT} is a weighting factor. Δv_W is the difference in speed between the predicted value and its value with regard to uncertainty. Further, v_w' and v_w are the actual and predicted the speed of the wind, respectively.

2.2.4. *Fuzzy membership function for load active power demand*

The membership function can be calculated from equation (2).

$$\mu^n = \begin{cases} \frac{1}{1+\eta^n(\Delta P_L/P_L^+)^2} & \Delta P_L \geqslant 0 \\ \frac{1}{1+\eta^n(\Delta P_L/P_L^-)^2} & \Delta P_L < 0 \end{cases} \tag{3}$$

$$\Delta P_L = \frac{P_L' - P_L}{P_L} \times 100\% \tag{4}$$

where P_L is the demand for the active power of the load for all loads involves in the errors between the predicted and actual load demand. Further, P_L^+ and P_L^- are the average error percentage of the average demand for active power load when its actual value is greater or less than the expected value, while is the weight factor coefficient.

2.2.5. *Economic Dispatch Unit*

The purpose of this unit is to determine the optimal active power of dispersed generation units by the PSO method with the fuzzy logic. This is to minimize the total fuel cost of the thermal units, and the total active power losses considering the uncertainty of the wind units. The objective function is based on the reduction of fuel cost and the active power losses of the network. In the following, the cost function and technical constraints of the network under study are described.

2.2.6. *Objective function*

Fuel cost of thermal units: The cost function for the fuel in thermal units is defined as follows:

$$T_c = \sum_{i=1}^{N_g} F_i(P_{gi}) \tag{5}$$

where T_c is the total fuel cost of the thermal units, F_i is the i^{th} thermal unit fuel cost which could be calculated from the following equation.

$$F_i = a_i P_{gi}^2 + b_i P_{gi} + C_i + |e_i \sin(f_i(P_{gi}^{min} - P_{gi}))| \quad (6)$$

In this relationship, a_i , b_i, c_i, e_i and f_i are the cost function coefficients. P_{gi} is the true output power of the thermal unit i, and N_g is the number of thermal units. The membership function for the fuzzy set is related to the total fuel cost. Hence, a high fuel cost generates a lower membership value. The membership function of the total fuel cost (μ_c) is defined as follows.

$$\mu_c = \exp(-W_1 \Delta C) \quad (7)$$

$$\Delta C = \frac{TC - TC_{min}}{TC_{min}} \quad (8)$$

In equation 7 and 8, TC_{min} is the lowest total cost of the fuel achieved from the optimization of the target function, and W_1 is the weighting factor.

Active network power losses: The cost function associated with reducing the active power losses of a network could be calculated as follows:

$$TL = \sum_{i=1}^{N_l} P_{loss,i} \quad (9)$$

where, TL is the total loses of the real power of the network, while $P_{loss,i}$ is the real power of line i and N_l is the number of transmission lines in the system. Moreover the fuzzy membership function has been defined to limit the true power losses.

$$\mu_L = \exp(-W_3 \Delta L) \quad (10)$$

$$\Delta L = \frac{TL - TL_{min}}{TL_{min}} \quad (11)$$

where, TL_{min} is the lowest actual power loss and W_3 is the weighting factor.

2.2.7. The system constraints understudy

In this section, technical constraints such as, constraints related to loading distribution equations, constraints related to the output power of thermal units, buses' voltage limits, and power transitions constraints is expressed.

Constraints related to load equations

$$P_{G_i} - P_{L_i} = \sum_{j=1}^{n} |V_i||V_j||Y_{ij}| \cos(\theta_{ij} - \delta_i - \delta_j) \tag{12}$$

$$Q_{G_i} - Q_{L_i} = \sum_{j=1}^{n} |V_i||V_j||Y_{ij}| \sin(\theta_{ij} - \delta_i - \delta_j)(13) \tag{13}$$

where, P_{Li} and Q_{Li} are predicted active and reactive power demand, P_{Gi} and Q_{Gi} are the active and reactive power output injected into the bus i, σ and V are the voltage and the angle of the bus, Y_{ij} and θ_{ij} are the admittance matrix elements of the bus.

2.2.8. The limitations on the output power of thermal units

$$\begin{aligned} & P_{g_i}^{\min} \leqslant P_{g_i} \leqslant P_{g_i}^{\max} \\ & i = 1, 2, \cdots, N_g \end{aligned} \tag{14}$$

$$\begin{aligned} & Q_{g_i}^{\min} \leqslant Q_{g_i} \leqslant Q_{g_i}^{\max} \\ & i = 1, 2, \cdots, N_g \end{aligned} \tag{15}$$

P_{gi}^{max} and P_{gi}^{min} are the maximum and minimum output active power for unit i, Q_{gi}^{max} and Q_{gi}^{min} are the maximum and minimum output reactive power for unit i.

2.2.9. Voltage constraints on each bus

$$\begin{aligned} & V_i^{\min} \leqslant V_i \leqslant V_i^{\max} \\ & i = 1, 2, \cdots, N_{bus} \end{aligned} \tag{16}$$

which V_i^{max} and V_i^{min} are the upper and lower limits of the voltage on the bus i, and N_{bus} is the number of the buses.

2.2.10. The Limitations of power transmission per line

$$\begin{aligned} & S_{l_i} \leqslant S_{l_i}^{\max} \\ & i = 1, 2, \cdots, N_l \end{aligned} \tag{17}$$

2.3. *Level II*

Fuzzy logic unit: Since a DER unit supplies 90% of the required load power, it should receive higher profits from resource partnerships than a DER unit, that supplies only 10% of the required power. Hence, fuzzy logic is applied to establish fairness in the competition between the players in the market structure, using the Sugeno method. This method is preferred over the Mamdani method because of the better performance with the linear techniques and the guaranteed continuous output level. In this method, all units were classified into 2 groups such as, group 1 includes the units with production capacity is less than 50%, and group 2 includes the units with production capacity is higher than 50%. Under these conditions, in addition to gaining more profits for members players could also generate more power. Moreover, at this level, players in group 1 could increase their production by participating in the game and integrating with group 2 players.

2.4. *Level III*

The formation of the DER coalition is formulated with respect to the distributed power and the unit cost functions. Further, the profit allocated to each unit is determined by the game theory methods.

2.4.1. *Unit for coalition formation*

In the retail market, distributed energy resources sell electricity directly at contract prices. In particular, the power is transmitted from the generator to the load by transmission lines owned by the distribution company. Therefore DERs must pay a periodic charge to the distribution company for power transferring [25]. Hence, the i^{th} (DER_i) profit per hour ($V(i)$) could be expressed as follows:

$$v(i) = \rho_i P_i - f_i(P_i\ ) - \omega_i P_i \tag{18}$$

$$f(i) = a_i\ {P_i}^2 + b_i P_i + c_i \tag{19}$$

where $v(i)$ is the profit is each DER_i (pound per hour), ρ_i is the sales price to the generator consumer i (pounds per megawatt-hour),P_i the effective power of each generator,ω_i is the periodic charge rate, $f(i)$ is the generator cost function in DER_i,

a_i, b_i, c_i are the coefficients of the generator i. DERs could work together to feed consumers and coalition formation. In this coalition, DERs determine their production according to the law of the expense increase equation to reduce the production costs, as expresses follows: [26].

$$f_i(P_i) = a_i P_i^2 + b_i P_i + c_i \tag{20}$$

$$\frac{df_i}{dP_i} = 2a_i P_i + b_i = \lambda \tag{21}$$

$$P_i = \frac{\lambda - b_i}{2a_i} \tag{22}$$

$$\begin{aligned} & P_1 + P_2 + \cdots + P_n \\ & = \tfrac{\lambda - b_1}{2a_1} + \tfrac{\lambda - b_2}{2a_2} + \cdots + \tfrac{\lambda - b_n}{2a_n} \\ & = \tfrac{\lambda}{2} \textstyle\sum_{i=1}^{n} \tfrac{1}{c_i} - \tfrac{1}{2} \textstyle\sum_{i=1}^{n} \tfrac{b_i}{c_i} = P_R \end{aligned} \tag{23}$$

$$p_i = \frac{1}{2c_i} \frac{\sum_{i=1}^{n} \left({}^{b_i}\!/_{c_i} \right) + 2P_R}{\sum_{i=1}^{n} \left({}^{1}\!/_{c_i} \right)} - \frac{b_i}{2c_i} \tag{24}$$

Here, λ is the Lagrange coefficient, P_R is the total load in megawatt and P_i is the effective power of the generator i after the co-operation (MW/h). Therefore, in a S alliance with a number of DERs equal to m, the profit of each DER in the coalition could be calculated as follows.

$$v(s) = \sum_{i=1}^{m} (\rho_i \ P_i) - \sum_{i=1}^{m} f_i\ (P_i) - \sum_{i=1}^{m} \omega \ P_i \tag{25}$$

2.4.2. Profit allocation unit

In game theory, when DERs collaborate to form coalitions, different DERs would earn different profits in different coalitions. It is possible to any DER to earn their maximum proportion of profit during the same coalition. Therefore, it is important to introduce a balanced strategy for each of them. In the game theory, two issues are considered: the coalition formation and the allocation of profits through collaboration and partnership. Since the coalition participants could gain more profit than independent participants, they would perform the best to form the best coalition. Each participant aim to gain the most out of the coalition, hence providing a satisfactory plan for allocating profits for each one is important.

It is worth mentioning that, the individual rational is that the player can make a profit in a coalition, while the group rational is that all the values obtained in a coalition are distributed among the players. An essential solution to the collaborative game is directly related to the stability of the grand coalition. In this cooperative game, a set of profit allocations that guarantee that players has no incentive to leave the grand coalition.

2.4.3. Shapley Unit

The players could predict the amount of the profit they earn, when they initiate to participate in the game. In fact, an earlier assessment for all players is important in deciding whether to join the game. The value of Shapley is the expected margin for the player in the coalition and it can be calculated by equation (19),according to the concept of "fairness" in the distribution of overall profits in the big coalition [40].

$$\phi_i = \frac{(m-1)!(n-m)!}{n!}\{v(s) - v(s - \{i\})\} \tag{26}$$

In which, m is the number of coalitions, n is the total number of big coalition members, s is the members who participated in the coalition and $s - \{i\}$ is the members who did not participate in the coalition. Furthermore, the profit earned by the player "i" in network with $s - \{i\}$ members is equal to $v(s) - v(s - \{i\})$. The phrase $\frac{(m-1)!(n-m)!}{n!}$ indicates the possibility of the player "i", who will join the coalition "$s - \{i\}$".

2.4.4. Nucleolus Unit

The Nucleolus method is an effective profit allocation approach that minimizes the maximum surplus S than x. The objective function of Nucleolus is formulated as follows [40]:

$$\min_{X \in S} \ \max_{S \subset N} \ e(S, x) \tag{27}$$

where it can be calculated from the following equation:

$$e(s, x) = V(s) - \sum_{i \in S} x_i \tag{28}$$

where x_i is the benefit of player "i" in independent condition.

2.4.5. Merge/ Split Unit

The merge law means that two coalitions or more could merge if the combination leads to a greater profit than the losses in the total coalition. In the split law, the coalitions can be divided into smaller components for a greater profit [41]. To implement this unit, a distributed algorithm has used to form a coalition with an allocation mechanism. For DER_i in coalition "s", profits could be calculated as follows:

$$x_i = \frac{u(s) \times u(\{i\})}{\sum_{j \in s} u(\{j\})} \tag{29}$$

Definition: Consider two sets of separate coalitions $A = \{A_1, A_2, \cdots, A_m\}$ and $B = \{B_1, B_2, \cdots, B_m\}$ that are similar for set of DERs. For set "A", the benefit of player "i" (payoff) in a coalition is, which is determined by equation (32). Set A is preferred to set $B(A \triangleright B)$, if and only if, types of functions can be used as follows:

$$Z = \left\{ \begin{array}{lll} \text{Merge} & \text{if} & \{\cup_{i=1}^{\prime} S_i\} \triangleright \{S_1, S_2, \cdots, S_m\} \\ \text{Split} & \text{if} & \{S_1, S_2, \cdots, S_m\} \triangleright \{\cup_{i=1}^{\prime} S_i\} \end{array} \right\} \tag{30}$$

In this equation, it is stated that, if $\{\cup_{i=1}^{\prime} S_i\}$ is preferred to $S = \{S_1, S_2, \cdots, S_m\}$, which means that its value in the coalition is greater than when they are independent and in this case, the merge is occurred. On the other hand, if $S = \{S_1, S_2, \cdots, S_m\}$ is preferred to $\{\cup_{i=1}^{\prime} S_i\}$, which means the value in the coalition is greater than when they are independent and in this case, the split is occurred.

2.5. Surplus Profit Calculation Unit

Surplus benefit for each coalition is equal to the difference of profits generated by the large coalition and total profits allocated to the units in that coalition. For play "v" with n player, if "S" is the coalition and $(x_1, x_2, \cdots, x_n)$ is a vector of benefit for this coalition, surplus S to x for play "v" with n player, the coalition "S" and the profit vector could be calculated from the following equation:

$$e(s, x) = V(s) - \sum_{i \in S} x_i \tag{31}$$

And

$$\sum_{i \in S} x_i = v(123) \tag{32}$$

"S" is the coalition.

If the benefit vector proposed for x is positive than the surplus of coalition "S", x does not satisfy any proposal and does not produce a surplus profit. Otherwise, S has a surplus profit with respect to x.

3. Grid Under Study

In this study, the modified IEEE 30-Bus version of system has simulated in which one power generator unit located at bus 1 and five non-renewable units are considered in buses 2, 5, 8, 11, and 13, respectively [42]. Further, two wind turbine (WT) units are installed at buses 24 and 27. Moreover, the loads of the studied system, from D1 to D21 are depicted in Figure 2, while the load values and cost function coefficient values are listed in Table .17 and Table .18 of the appendix.

4. Simulation Results

In this section, the simulation results for the coalition are analyzed under following case studies:

Case study 2: It is a grand coalition. In this case study, the arrangement of all DERs (in a group with 7 DERs) within a coalition and the amount of their production capacities have been considered. This is due to each DER is benefited from the amount of production in the final coalition (grand coalition), and each DERs aim to produce more capacities to earn higher profits. As oppose to case study 1 where the DERs could be classified, the case study 2 only contain one group with DERs to form a grand coalition.

Definitions:

Group 1: The prime purpose of creating Group 1 in case study 1 is to form a coalition. Since DERs are mainly focusing to increase the profits when each player can achieve a higher level of productivity by joining a grand coalition. In this article, all resources (based on the ratio of the production capacity to the nominal capacity) are divided into two groups. The first group belongs to resources whose production capacity is less than 50% of their production capacity. These resources combine with each other in the first group.

Group 2: The second group belongs to resources that have a production capacity of more than 50% of their production capacity. In this group, resources with more productive capacity form a coalition with each other and participate in the formation of a grand coalition.

The simulation is run by MATLAB on a personal computer with Dual-Core, CPU E5700 @ 3.00 GHz, 2 GB RAM.

4.1. Case study 1

As shown in Figure 3, in case study 1, seven DERs in the system are divided into two groups, and each group forms a coalition independently, while calculating allocated profit of the coalition. Power generated by each DER is determined using load flow and results are listed in Table .19 in the appendix.

Each DER is classified into three and four groups to form a coalition by the fuzzy logic method (Level II). The specifications of the group 1 is presented in Tables (2) and (3). Table 2 is the result of power flow by PSO algorithm and the Table 3 is the input data for simulation.

Table 2: Power generated by DERs in group 1.

DER	DER 1	DER 2	DER 3
P (MW)	30.3725	45	39.0883

Table 3: Cost function coefficient values of DER in group 1.

	a	b	c	ρ
DER 1	0.0075	10	110	15.28
DER 2	0.0022	10	316	13.46
DER 3	0.005	10	115	15.85

Profit earned by each coalition after coalition formation is shown in Table 4. According to Table 4, that the profit earned by the coalition of two players is greater than the profit earned by individual players. Consequently, profit earned by coalition members 1, 2 and 3 (i.e.$\{1,2,3\}$), is 3.47% , 0.9% and 3.31% higher than that in coalition $\{1\}+\{2\}+\{3\}$, $\{1\}+\{2\}$, and $\{2\}+\{1,3\}$, respectively. In this table, each coalition has satisfied relation $u(N)-u(N-i) \geqslant u(S)-u(S-i), \forall i, S \subset N$, which means that no players tend to exit from the big coalition.

Table 4: Profit earned by each coalition.

Coalition	Profit earned
{1}	6.27
{2}	8.14
{3}	8.38
{1,2}	15.06
{1,3}	14.61
{2,3}	17.28
{1,2,3}	23.57

Table 5 represents the coalition type, gross earning, power generation cost of units, periodic charge, and the net profit of each different coalitions. The results of profits allocation for each DERs using various game theory methods are presented in Table 6.

Table 5: Earning, generation cost, periodic charge, and net profit of each different coalitions.

Coalition	Earning (€/h)	Generation cost (€/h)	Periodic charge (€h)	Net profit (€/h) ×1.00E+04
{1}	0.4641	0.0004	0.0152	6.27
{2}	0.6057	0.0008	0.0225	8.14
{3}	0.6195	0.0005	0.0195	8.38
{1,2}	1.1163	0.0012	0.0377	15.06
{1,3}	1.0807	0.0009	0.0347	14.61
{2,3}	1.2792	0.0013	0.042	17.28
{1,2,3}	1.7446	0.0017	0.0572	23.57

Table 6: Profit allocation for each DERs using different game theory methods.

Generation Unit	DER 1	DER 2	DER 3
Shapely			
Profit (€/h)×1.00E+04	6.3773	8.6472	8.5405
Nucleolus			
Profit (€/h)×1.00E+04	6.2789	8.8275	8.4586
Merge / Split			
Profit (€/h)×1.00E+04	6.4822	8.4181	8.6648

In DER 1, the profit increased by the merge/split method compared to Shapely and Nucleolus methods is 1.7% and 3.12%, respectively, while in DER 2, the profit increased by Nucleolus method compared to Shapley and merge/split methods is 2.1% and 4.63%, respectively. Moreover, in DER 3, with the merge/split method, the profit has escalated by 4.4% and 2.38%, compared to Shapely and Nucleolus methods, accordingly. The surplus profit of each coalition coalition "S" is obtained separately by calculating the profit after different DERs coalition islisted in Table 7. In addition, the allocated profit of each DERs with different game theory methods is calculated, as follows:

Table 7: Surplus profit in group 1.

Coalition	Surplus profit
{1}	-1.0752
{2}	-5.0486
{3}	0.3721
{1,2}	-1.5962
{1,3}	-3.0803
{2,3}	0.8931
{1,2,3}	0

The specifications of the group 2 is presented in Tables (8) and (9). Table 8

Table 8: Power generated by DERs in group 2

DER	DER 1	DER 2	DER 3	DER 4
P (MW)	20.0416	10.6022	18.5	23.9

Table 9: Cost function coefficient values of DER in group 2.

	a	b	c	ρ
DER 1	0.0009	10	420	13.27
DER 2	0.0024	10	156	14.24
DER 3	0	0	0	13.75
DER 4	0	0	0	14.36

shows the power generated by DER in the second group, and Table 9 depicts cost function coefficient values of DER in group 2. Profit earned by each coalition after coalition formation is shown in Table 10. According to Table 5, the profit earned by the coalition of two players is greater than the profit earned by individual players. Table 10 represents the coalition type, generation cost of units, periodic charge, and the net profit of each different coalitions.

Profit allocated in each DERs by different game theory methods is compared in Table 11. In DER 1, profit earned by merge/split method compared to Nucleolus and Shapley methods has increased by 50.68% and 53%, respectively, while in DER 2, the profit earned by Nucleolus method has risen than Shapley and merge/split methods by 2.7% and 1.1%, respectively. Moreover, in DER 3, profit earned by the Shapley method has increased by 1.3% and 1.9% compared to merge/split and Nucleolus methods, respectively, while in DER 4, the profit increment of 1.01% and 31.98% is shown by Nucleolus method than in Shapley and merge/split methods, respectively.

In addition, surplus profit of DERs coalition in group 2 are presented in Table 12.

In group 1, both the profits after a coalition of each unit in all three profit allocation methods and general profit or large coalition has been increased, which was

Table 10: Cost function coefficient values of DER in group 2.

Coalition	Earning (€/h)	Generation cost (€/h)	Periodic charge (€h)	Net profit (€/h) ×1.00E+04
{1}	0.319	0.0007	0.012	4.28
{2}	0.151	0.0003	0.0053	2.03
{3}	0.2544	0.0001	0.0092	3.43
{4}	0.3432	0.0001	0.012	4.63
{1,2}	0.4842	0.0009	0.0173	6.51
{1,3}	0.0585	0.0004	0.0213	7.87
{1,4}	0.6885	0.0004	0.024	9.28
{2,3}	0.4065	0.0002	0.0146	5.39
{2,4}	0.4955	0.0002	0.0173	6.67
{3,4}	0.5959	0.0001	0.0212	8.03
{1,2,3}	0.7371	0.0006	0.0266	9.84
{1,2,4}	0.8407	0.0006	0.0293	11.34
{1,3,4}	0.9338	0.0004	0.0332	1258
{2,3,4}	0.7472	0.0002	0.0265	10.04
{1,2,3,4}	1.0829	0.0006	0.0385	14.59

the main purpose of this paper. In group 2, the profit allocated to each unit by Shapley and Nucleolus methods are different and not fairly divided. Therefore, among four generation units, the profits of DER 1 and DER 2 are higher than before the coalition, while the profit of DER 3 and DER 4 are lower than before the coalition. Nevertheless, the key goal of this paper is to maximize the profit of the grand coalition with the cooperative game. On the other hand, allocated profit by merge/split method is appropriate and the profit of all units has increased compared to before coalition.

In addition, the surplus profit in the big coalition is zero, therefore equations 31 and 32 are satisfied. Further, in other conditions, their profit increases or decreases satisfactorily. Finally, allocated profit to each DERs is significant. Although,

Table 11: Profit allocation for each DERs using different game theory methods.

Generation Unit	DER 1	DER 2	DER 3	DER 4
Shapely				
Profit (€/h)×1.00E+04	2.3468	1.8138	3.5824	6.8491
Nucleolus				
Profit (€/h)×1.00E+04	2.1444	2.2895	3.2499	6.9079
Merge / Split				
Profit (€/h)×1.00E+04	4.3478	2.0637	3.4789	4.7013

Table 12: Surplus profit in group 2.

Coalition	Surplus profit	Coalition	Surplus profit
{1}	1.936	{2,4}	-1.1611
{2}	0.2191	{3,4}	2.5012
{3}	0.4709	{1,2,3}	-1.7338
{4}	1.8063	{1,2,4}	-0.5953
{1,2}	-2.5020	{1,3,4}	-0.2734
{1,3}	1.1186	{2,3,4}	-2.2034
{1,4}	-1.0671	{1,2,3,4}	0
{2,3}	0.9825	-	-

there is less profit in some coalitions, but the allocated profits to each DERs and big coalition's profits is greater than before coalition.

A comparison between profit before coalition and the average earned profit using game theory methods are expressed in tables 13 and 14. In group 1, the profit of DERs 1, 2, and 3 increased by 17.56%, 6.03%, and 2.1%, than before the coalition, respectively. In group 2, the profits of DER 1 is increased by 31.16% compared to before coalition, while the profit of DERs 2, 3, and 4 are increased by 1.26%, 1.8%, and 32.89%, respectively.

In Table 15, the profit allocation of each coalition in group 2 according to Shapley, Nucleolus, and merge/split methods is compared with individual profit of each

Table 13: A comparison between profit before coalition and the average earned profit in group 1.

	DER 1	DER 2	DER 3
Profit before coalition	6.27	8.14	8.38
Average earned profit after coalition	6.3795	8.6309	8.5547
Increase/decrease profit (%)	+17.56	+6.03	+2.1

Table 14: A comparison between profit before coalition and the average earned profit in group 2.

	DER 1	DER 2	DER 3	DER 4
Profit before coalition	4.28	2.03	3.43	4.63
Average earned profit after coalition	2.9463	2.055	3.4369	6.1527
Increase /decrease profit (%)	-31.16	+1.26	+1.8	+32.89

unit. As can be seen, the profit of DER 1 using the merge/split algorithm is 2.51% higher than when the network operates independently, while the earned profit for each network has increased significantly in all units in level III, to coalition formation and allocate profits. However, there is a significant different between the proposed algorithms. For instance, the earned profit after coalition in DER 1 with merge/split algorithm has increased by 46.02% and 50.67% compared to Shapley and Nucleolus algorithms, respectively. And in DERs 2, 3 and 4, the profit reduction rate in Shapley algorithm for DER 1 and DER 2 is 28.68% and 26.26% compared to merge/split algorithm, respectively. Further, the profit reduction rate in Nucleolus algorithm for DER 1 and DER 3 is 49%, 75% and 58.6% compared to merge/split algorithm, respectively.

According to the results, it is proven that the merge/split algorithm in group 2 is more appropriate and fairer for allocating profits between DERs and the allocated profit to this algorithm is higher than the profit before coalition.

Table 15: Profit allocation in each coalition in group 2.

Algorithm	DER #1	DER #2	DER #3	DER #4
Shapley	2.3468	1.8138	3.5821	6.8491
Nucleolus	2.1444	2.2895	3.2499	6.9079
Merge/Split	4.3478	2.0329	3.4268	4.6309
Non-coalition	4.2828	2.0329	3.4268	4.6309

4.2. Case study 2

According to this case, all DERs are considered as one group, and the profit of each unit in this coalition is determined. The general scheme of this case study is depicted in Figure 4.

According to this case, it is observed that by increasing DERs and coalition formation, allocated profit to each DERs is not fair than before coalition, It I is evident in some DERs, where the profit has been increased. On the flip side, it has dropped drastically in some DERs. However, in the first case study, fairer and more reasonable profit could be achieved by classifying units at the middle level.

According to Table 16, the Shapley method has used in case study 1. The allocated profits of units in buses 2, 5, and 8 belong to group 1 are increased by 1.68%, 5.83%, and 1.84% than before coalition, respectively. However, in cast study 2, the allocated profits were decreased by 67.06%, 61.11%, and 36.13%, accordingly. Further, In case study 1, the allocated profits of units in buses 11 and 13 in groups 2 have decreased by 54.2% and 10.77%, and the buses 24 and 27 in the same group have decreased by 4.33% and 32.38%, compared to before coalition. However, in case study 2, the allocated profits of bus 11 has decreased by 2.39% , and increased by 66.12%, 58.98%, and 35.23% for buses 13, 24 and 27 respectively. Further, In case study 1, allocated profits of units in buses 11, 13, 24, and 27 belonging to group 2 decreased by 54.2% and 10.77%, increased by 4.33% and 32.38% compared to before coalition, respectively. However, in case study 2, it decreased by 2.39% and increased by 66.12%, 58.98%, and 35.23%, respectively. Further the obtained values in case study 2 represent the unbalanced profits in DERs. In the

Nucleolus method in case study 1, allocated profits of units located in buses 2, 5, and 8 belong to group 1, has increased by 0.145%, 7.76%, and 0.919% than before coalition, respectively, while in case study 2, they decreased by 14.48%, 77.75%, and 36.13%, respectively.

In addition, in the case study 1, the allocated profits of units have decreased by 49.93% and 5.16% in buses 11 and 24, and have increased by 11.21% and 49.17% in buses 13 and 27, compared to before coalition, respectively. In case study 2, it decreased by 2.39% in bus 11 and increased by 56.45%, 45.35%, and 11.23%, in buses 13,24, and 27, accordingly. Further, the obtained values in case study 2 represent the unbalanced profits in DERs.

In the merge/split method in case study 1, allocated profits of all units located in buses 2, 5, and 8 belong to group 1, have increased by 3.27% than before coalition, while, in case study 2, they have decreased by 3.27%. Moreover, in case study 1, allocated profits of all units in buses 11, 13, 24, and 27 in group 2 were escalated by 1.5% compared to before coalition, and in case study 2, it has dropped by 2.39%.

Table 16: Comparison between DERs profit before and after coalition using case study 1 and 2.

		DER #1	DER #2	DER #3	DER #4	DER #5	DER #6	DER #7
Bus number		2	5	8	11	13	24	27
				Shapley				
Before coalition		62698.19	81423.65	83808.97	42827.77	20328.59	34268.47	46309.31
After	case study 1	63773.41	86472.21	85405.15	23467.58	18137.95	35820.5	68491.14
coalition	case study 2	20652.51	31663.37	53521.93	41826.22	60004.26	83554.79	71503.22
				Nucleolus				
Before coalition		62698.19	81423.65	83808.97	42827.77	29328.59	34268.47	46309.31
After	case study 1	62789.26	88275.24	84586.27	21443.74	22894.64	32499.47	69079.32
coalition	case study 2	73315.91	67103.14	18642.63	41672.13	47114.42	62712.39	52165.67
				Merge/Split				
Before coalition		62698.19	81423.65	83808.97	42827.77	20328.59	34268.47	46309.31
After	case study 1	64821.76	84181.45	86647.55	43478.24	20637.34	34788.94	47012.65
coalition	case study 2	61190.28	79465.39	81793.33	41797.75	19839.68	33444.31	45195.56

5. Conclusion

This paper investigates a novel three level structure for forming optimal coalition and increases the allocated profits of the participants in the market. In the proposed method, physical and technical constraints of the modified IEEE 30-Bus system have considered and the optimal power flow is applied. Further, the PSO optimization method has utilized to determine the optimal generation capacity of all DERs and power supplies, while the fuzzy logic has applied to evaluate the load demand uncertainties, renewable resources, and reservation resources. In addition, the fair profit allocation among players with increased DERs generation is performed by fuzzy logic. Accordingly, the coalition formation and the profit designation are assessed by the cooperative game theory algorithms. The feasibility of the proposed structure has verified by engaging many buyers and power producers. The suggested model further investigated that the cooperation between power producers has increased the profit of players, and restructuring of the coalition between members had a significant impact on the profits. The groups formed by fuzzy logic, represents that the distribution of profits between members in a group is highly depending on the way of grouping. Most importantly, this study presents a structure which links between cooperative game theory and DERs. Thus, the optimization theory and the game theory simultaneously optimize the generation of resources, and earn the maximum profit in collaborating with other resources. Consequently, the main advantage of the proposed methodology is that, it could extend the specific function and effortlessly merge with the current structure. The simulation results and math analysis verify that the big coalition is the optimal coalition when there is no size limitation. Grouping of players in coalition presents that the players in a group with similar interest have more tendency to form a coalition between themselves, while the players with higher power tend to form a coalition with bigger players. Further, the efficiency of the proposed structure has been tested and demonstrated with the modified IEEE-30 bus system. The proposed method facilitates the electricity participants to find attractive collaborative strategies with sustainable benefits under variable conditions and environments. Ultimately, this study closely examined the private electricity market for market operators and policy makers.

6. Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Table .17: Load values in different buses.

Bus number	Load number	Load (MW)	Bus number	Load number	Load (MW)	Bus number	Load number	Load (MW)
2	D1	21.7	10	D7	5.8	18	D13	3.2
3	D2	2.4	12	D8	11.2	19	D14	9.9
4	D3	7.6	14	D9	6.2	20	D15	2.2
5	D4	54.2	15	D10	8.2	21	D16	17.5
7	D5	22.8	16	D11	3.5	23	D17	3.2
8	D6	20	17	D12	9	24	D18	8.7
26	D19	3.5	29	D20	2.4	30	D21	10.6

Table .18: Parameters values in different buses (according to network under study).

Bus number	2	5	8	11	13	24(1)	27(2)
a_i	0.0075	0.0009	0.0022	0.005	0.0024	0	0
b_i	10	10	10	10	10	0	0
c_i	110	420	316	115	156	0	0
ρ_i	15.28	13.27	13.46	15.85	14.24	13.75	14.36

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Table .19: Generated power of each DER after power flow.

Bus number	2	5	8	11	13	24	27
P (MW)	30.3725	24.0416	45	39.0883	10.6022	18.5	23.9

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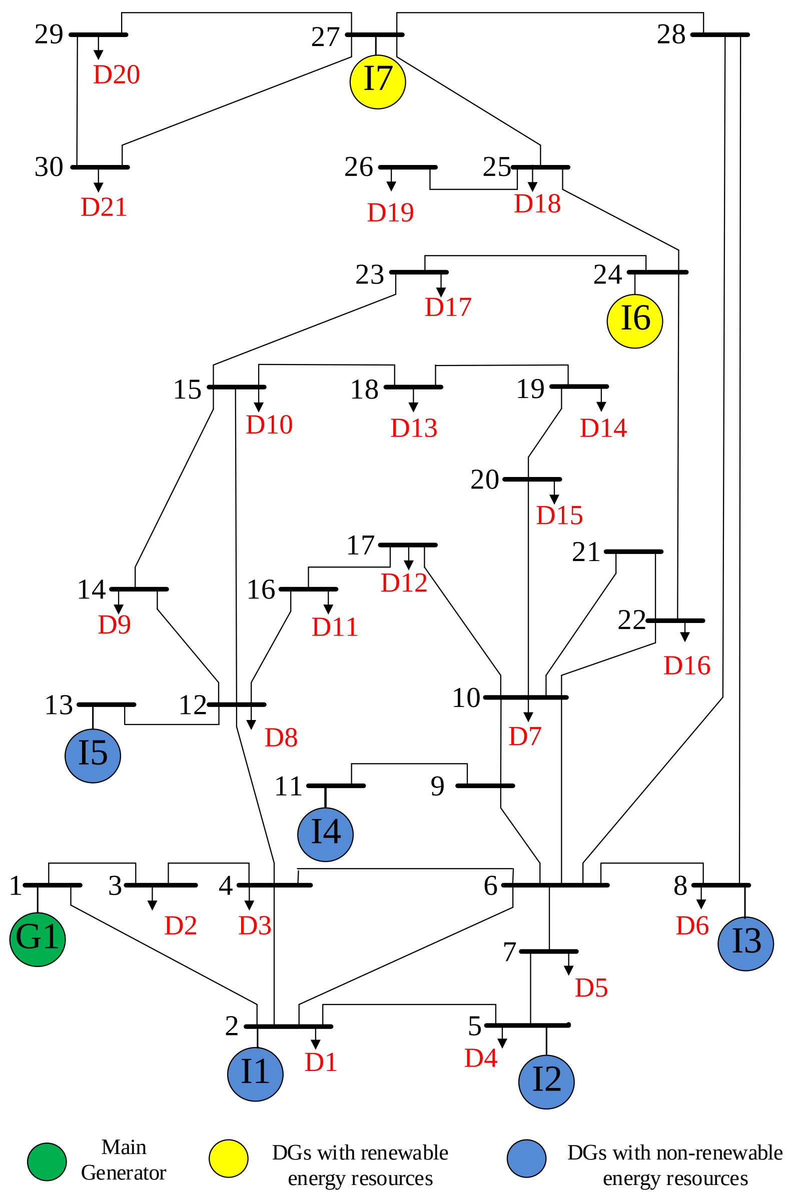

Figure 2: Modified IEEE 30-Bus system under study.

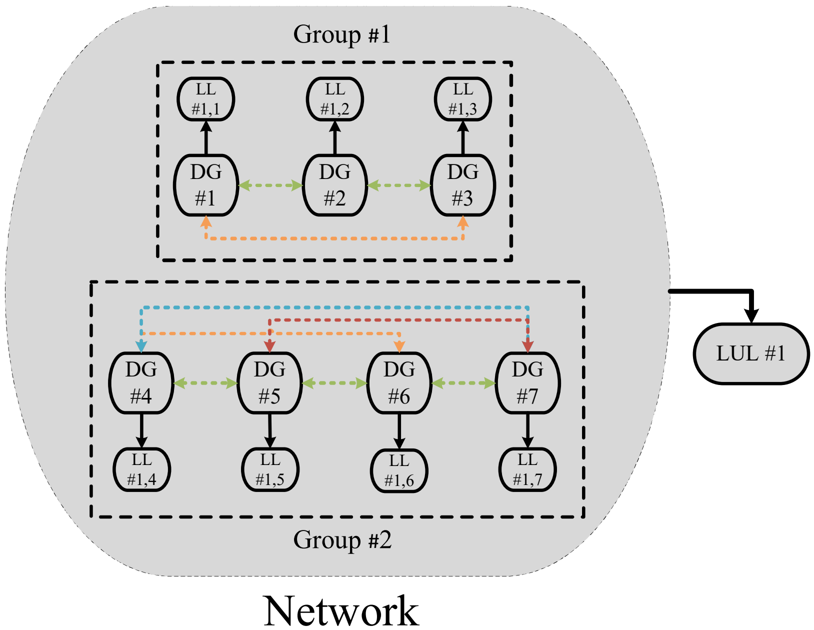

Figure 3: DERs Classification in case study 1.

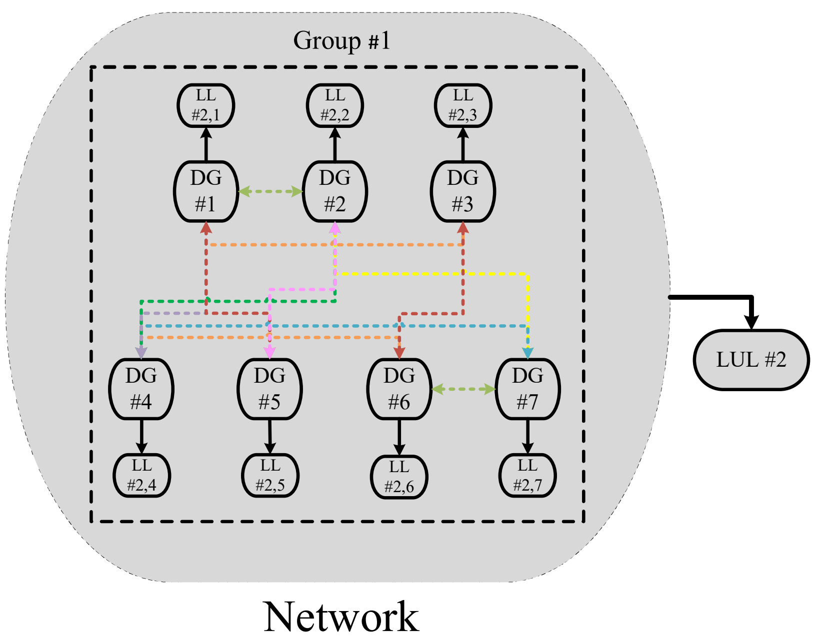

Figure 4: DERs group in case study 2.