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

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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 gameplay-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.

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

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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	ith 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 ith
$V(i)$	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

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 game's 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 multiprocessor 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 co-operation 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 their surplus power for cost minimization. Although the proposed model allows the microgrids to self-adapt to environmental changes, the uncertainties of demands and renewable generation are not considered. To consider the probability behavior of renewable generation, the scenario-generation and scenario-reduction approaches are employed to handle the uncertainty in the microgrids system [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 used in the grand coalition are compared. It is also shown that in this study, the proposed method has no limit on the number of DGs in forming a coalition. This case has the following advantages:

1. No limitation on the number of DGs in forming a coalition.
2. With more DGs involved, the profits from the grand coalition will increase. Hence, the profits of each of the DGs that participated in the grand coalition will be increased.

In a competitive market, the buyers are not price-takers since the electrical energy is not influence the market using different pricing strategies as well as not cooperate with other buyers. Therefore, it is necessary to explore the strategies for cooperation and customizing of electricity buyers. However, as mentioned before, since most investigations were not conducted on the demand side, most of the researchers focused on the production and transmission of power. In addition, based on the best-informed 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 and gain maximum profit.

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 articles focus on simplifying the market model by focusing on only a few low-level participants. This has considered all the technical and physical constraints and extension to other market models.

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 Fig. 1, a game theory-based with 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 on 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. Next, the power of each resource is categorized based on their power output using fuzzy logic classification to be different groups 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 competitively competing with others. Since energy sources are mainly looking for a way to increase their profits, forming a coalition should be implemented when each player can achieve a higher level of productivity by joining a large coalition. At this level, all resources (based on the ratio of their production capacity to their 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 ally with each other in the first group. 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 can finally participate in the formation of a grand coalition. Also, this mechanism allows any resource that has increased its production capacity and was previously in the first group to be present in the second group and contribute to the grand coalition and the greater profit.

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 ways in which some players may interact with each other and work together to form a group or coalition are examined. The proposed methods at this level are based on cooperative game theory. The result of the coalition formation process has been studied based on the Shapley, Nucleolus, and merge/split methods. The profit-sharing mechanism is essential in order to motivate each actor to participate 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 that can be obtained by joining the coalition. The implementation of each level and the goals pursued by them are described in detail below.

2.1. Assumptions

The simplifications are performed in this paper based on the following assumptions to improve the computation time and the convergence of the optimization:

1. In the proposed structure, the power planned by DER resources does not depend on the characteristics of the loads. It simply means that it does not matter if you are active or inactive many times.

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	Nucleolus	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	✓	✓	✓	✖	✖	✓	✖	✓	✓	✖	✓	✖	✖	✓

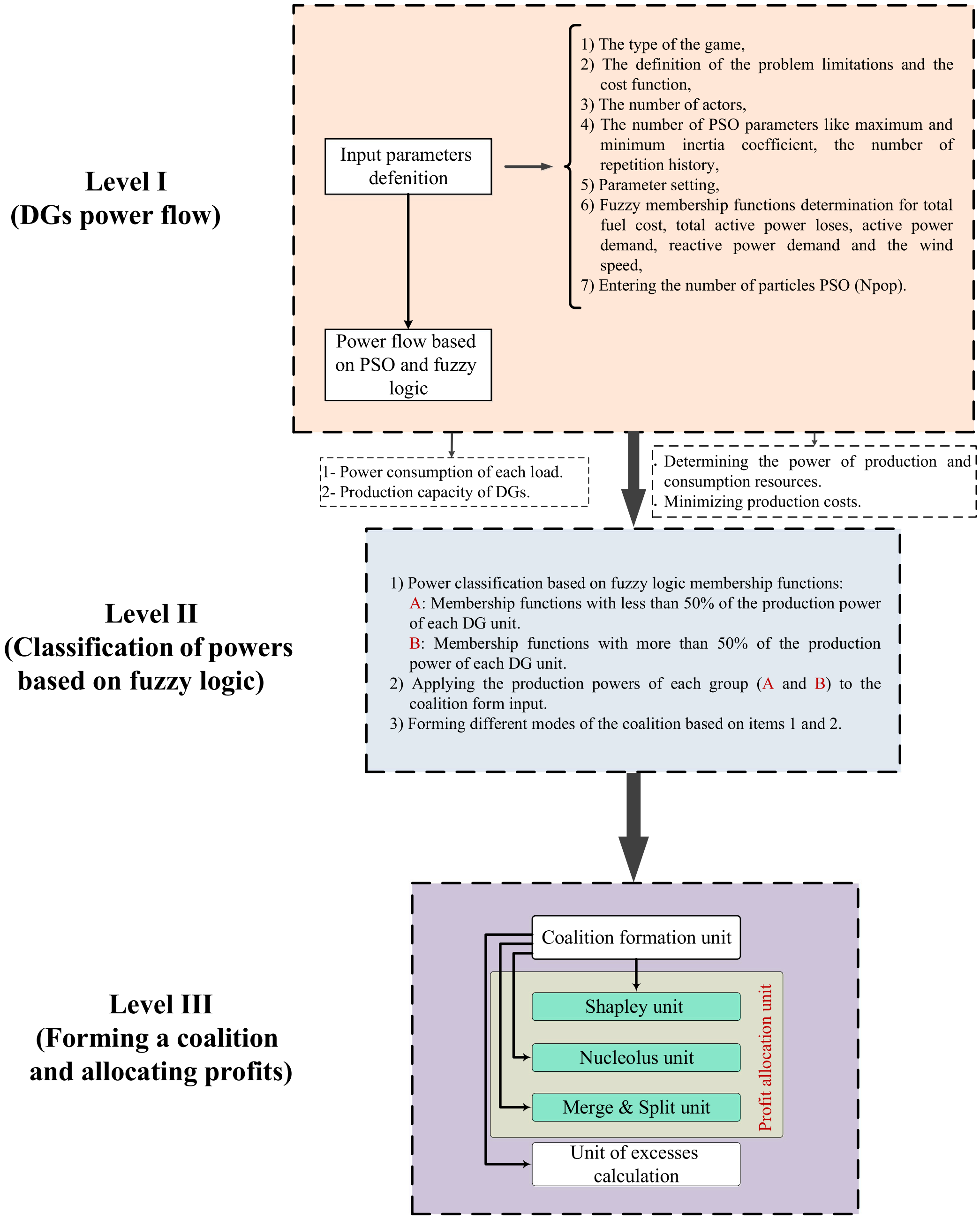

Fig. 1. The structure implemented to form a coalition and allocate profits.

2. The congestion line is not considered. When considering the power flow in the network and re-allocating the load in the cooperation between the DGs, there is no possibility of overload in the lines.
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 PSO method while minimizing the total fuel cost of the thermal units, the total active power loss with the uncertainty of the wind units, and considering the understudied network technical constraints, including load distribution constraints, output power limitations in thermal units and voltage restrictions on each bus. Further, the load demand errors and predicted wind speed are considered as uncertainties in the proposed PSO algorithm with the fuzzy logic set.

2.2.2. Uncertainty unit

The random nature of the renewable resources generation and the demand for consumables loads causes errors in the forecasted inputs of these resources. Moreover, the uncertainty unit based on fuzzy logic has implemented to use uncertainty regarding the prediction of 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

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

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

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 respectively the actual and predicted the speed of the wind.

2.2.4. Fuzzy membership function for load active power demand

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

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

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

where P_L is the demand for the active power of the load for all loads involves the errors between the predicted and actual load demand. Further, P_L^+ and P_L^- are respectively 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 the implementation of this unit is to find the optimal active power of dispersed generation units by the PSO method with the fuzzy logic to minimize the total fuel cost of the thermal units, the total active power losses, considering the uncertainty of the wind units. The defined 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 in detail.

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 ith thermal unit fuel cost which could be calculated from the following equation.

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

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.

$$\mu_c = \exp(-W_1 \Delta C) \tag{7}$$

$$\Delta C = \frac{TC - TC_{\min}}{TC_{\min}} \tag{8}$$

In Eqs. (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:

$$TL = \sum_{i=1}^{N_l} P_{loss,i} \tag{9}$$

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. The fuzzy membership function has been defined to limit the true power losses.

$$\mu_L = \exp(-W_3 \Delta L) \tag{10}$$

$$\Delta L = \frac{TL - TL_{\min}}{TL_{\min}} \tag{11}$$

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, $P_{L\,i}$ and $Q_{L\,i}$ are predicted active and reactive power demand, $P_{G\,i}$ and $Q_{G\,i}$ 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

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

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

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

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

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

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

2.3. Level II

Fuzzy logic unit: Since a DER unit supplies 90% of the load power required, it should receive a higher return on 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 participating in the market structure under the study, using the Sugeno method. This method is preferred over the Mamdani method because of the better performance with the linear techniques and the continuity of the output level is guaranteed. Therefore, all units were classified into 2 groups. In fact, units with production less than 50% is in group 1, and units with more than 50% production rate is in group 2. In other words, group 1 entities could share profits with each other, while in group 2 manufacturing units could share their profits. Under these conditions, in addition to gaining more profit for members in a group, players would tend to generate more power and earn higher profits. In addition, at this level, players in group 1 will be able to increase their production by participating in the game and join with group 2 players.

2.4. Level III

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

2.4.1. Unit for coalition formation

In the retail market, distributed energy sources sell electricity directly at contract prices. In particular, the power is transmitted from the generator to the load by transmission and distribution lines owned by the distribution company, DERs must pay a periodic charge to the distribution company for power transferring [25]. Therefore, the ith (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 of each DER_i (pound per hour), ρ_i of the sales price to the generator consumer i (pounds per megawatt-hour), P_i the effective power of each generator, ω_i the periodic charge rate, $f(i)$ 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 they form a coalition. In this coalition, to reduce production costs, DERs determine their production of DERs in accordance with the law of the fuel expense increase equation as follows [26].

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

$$\frac{d f_i}{d P_i} = 2a_i P_i + b_i = \lambda \tag{21}$$

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

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

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

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 some coalitions, different DERs would earn different profits in different coalitions. Although a DER could earn the most out of its own profits in some coalitions, but this does not imply that another DER cannot earn its maximum profit out of the same coalition. Therefore, it is important how a balanced strategy decides for each of them. In the game theory, two important issues are considered: the formation of a coalition and the allocation of profits through collaboration and partnership. Since the coalition participants could gain more profit than independent functioning mode by cooperating with each other, they would perform the best to form the best coalition. Each participant wants to get the most out of the coalition, hence providing a satisfactory plan for allocating profits for each one is important in a coalition.

It is worth noting that, individual rational means that the player can make a profit in a coalition, not less than his single function and group rational means that all the values obtained in a coalition are distributed among the players within the coalition. An essential solution to the collaborative game is the core, which is directly related to the stability of the grand coalition. The Core is a cooperative game, a set of profit allocations that guarantee that no group of players has the incentive to leave the grand coalition.

2.4.3. Shapley unit

When the players try to participate in the game, they could predict how much profit they earn. 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 Eq. (19), according to the concept of "fairness" in the distribution of overall profits in the big coalition [40].

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

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 that the player "i" will join the coalition $\varepsilon s - \{i\}\varepsilon$.

2.4.4. Nucleolus unit

The Nucleolus method is, an effective profit allocation 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:

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

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 earning a greater profit [41]. To implement this unit, a distributed algorithm has used to form a coalition and the allocation mechanism as follows: For DER_i in coalition "s", profits could be calculated as follows:

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

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

$$Z = \left\{ \begin{array}{lll} Merge & if & \left\{\cup_{i=1}^{\prime} S_i\right\} \rhd \left\{S_1, S_2, \dots, S_m\right\} \\ Split & if & \left\{S_1, S_2, \dots, S_m\right\} \rhd \left\{\cup_{i=1}^{\prime} S_i\right\} \end{array} \right\} \quad (30)$$

In this equation, it is stated that, if $\left\{\cup_{i=1}^{\prime} S_i\right\}$ is preferred to $S = \{S_1, S_2, \dots, S_m\}$, 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 $S = \{S_1, S_2, \dots, S_m\}$ is preferred to $\left\{\cup_{i=1}^{\prime} S_i\right\}$, 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 a large coalition and total profits allocated to the units in that coalition. For play "υ" with n player, if "S" is a coalition and $(x_1, x_2, \dots, x_n)$ is a vector of benefit for this coalition, surplus S to x for play "υ" with n player, the coalition "S" and the profit vector could be calculated from the following equation:

$$e(s, x) = \mathrm{V(s)} - \sum_{\mathrm{i \in S}} x_{\mathrm{i}} \quad (31)$$

And

$$\sum_{\mathrm{i \in S}} x_{\mathrm{i}} = \upsilon(123) \quad (32)$$

"S" is a coalition.

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

3. Grid under study

In this study, the IEEE 30-Bus modified 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 [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 Fig. 2, while the load values and cost function coefficient values are listed in Tables A.17 and A.18 of Appendix.

4. Simulation results

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

Case study 1: There is a coalition formation between DERs (the group with 3 DERs and 4 DERs). DERs are grouped based on their production capacity. That is, in case 1, the seven DERs in this paper are divided into two groups (for example, one group with 3 DERs and one group with 4 DERs), and each group can independently cooperate with each other. (A group with 3 DERs forms a coalition and a group with four DERs as well). Finally, each group's allocated profit from the coalition is computed using the proposed methods.

Case study 2: It is a grand coalition. We do not pay attention to the placement of all DERs (in a group with 7 DERs) within a coalition and the amount of their production capacity, because each DER is supposed to benefit from the amount of production they have in the final coalition (grand coalition) and each to produce more. They make more profit. This scenario is the basis of our work in this study. That is, we show that unlike case study 1, where DERs could be classified, here (case study 2) we only have one group, which includes all DERs, to satisfy our primary goal, which is to form a grand coalition.

Definitions:

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

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

Group 1: The purpose of creating Group 1 in case study 1 is to form a coalition since DERs are mainly looking for a way to increase their 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 their production capacity to their 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 ally 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 can finally participate in the formation of a grand coalition.

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

4.1. Case study 1

As shown in Fig. 3, in this case study, seven DERs in the studied system are divided into two groups, and each group forms a coalition independently, while calculating allocated profit of the coalition by the proposed methods. Power generated by each DER is determined using load flow and results are listed in Table A.19 in 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. The Tables 2 is the result of power flow which have done by PSO algorithm and the Table 3 is the input data for simulation.

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 $u(N) - u(N - i) \geq u(S) - u(S - i), \forall i, S \subset N$, which means that no players tend to exit from the big coalition.

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

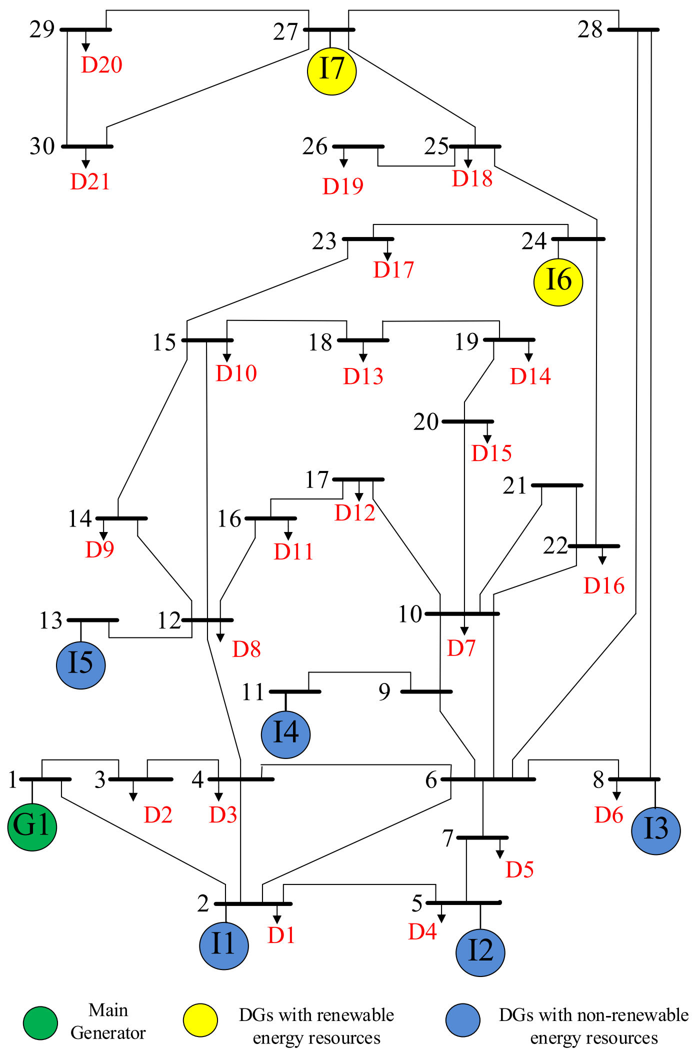

Fig. 2. IEEE 30-Bus modified system under study.

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

In DER 1, the profit increased by the merge/split method is 1.7% and 3.12%, than Shapely and Nucleolus, 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 grew by 4.4% and 2.38%, compared to Shapely and Nucleolus methods, respectively The surplus profit of each coalition compared to coalition “S” is obtained separately by calculating the profit after different DERs coalition is listed in Table 7. In addition, the allocated profit of each DERs with different game theory methods is calculated, as follows:

The specifications of the group 2 is presented in Tables 8 and 9. Table 8 shows the power generated bi DER in 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, that 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 has compared in Table 11. In DER 1, profit earned by merge/split method

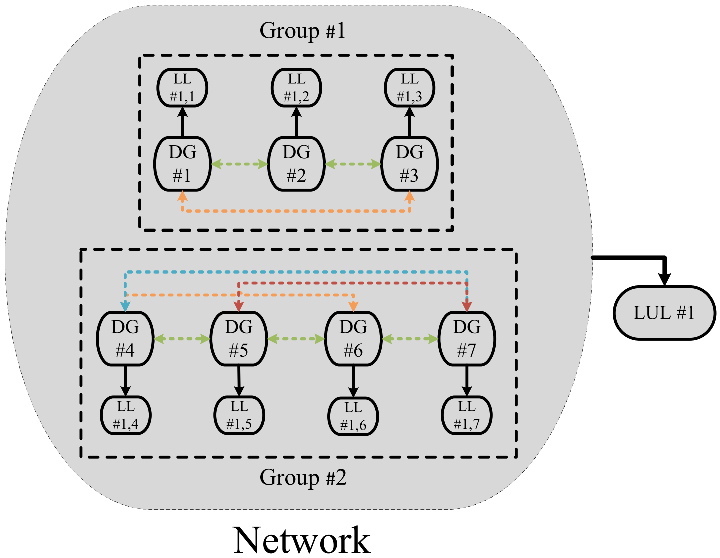

Fig. 3. DERs Classification in case study 1.

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

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

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

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. Further, 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, 1.01% and 31.98% profit increment 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, it is presented that both the profit after a coalition of each unit in all three profit allocation methods and general profit or large coalition has been increased, which was the main purpose of this paper. In group 2, the profit allocated to each unit by Shapley and Nucleolus methods are much different and are not fairly divided. Therefore, among four generation units, the profit of DER 1 and DER 2 are higher than before the coalition, while the profit of two other units are lower than before the coalition. Nevertheless, the key goal of this paper is the profit of a grand coalition with the cooperative game, which is more than the previous one in this group. 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 Eqs. (31) and (32) are satisfied. Further, in other conditions, their profit increases or decreases satisfactorily. Finally, allocated profit to each DERs is significant. Although, 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 has 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 profit of DER 1 increased by 31.16% compared to before coalition, while the profit of DERs 2, 3, and 4 increased by 1.26%, 1.8%, and 32.89% compared to pre-coalition, respectively.

In Table 15, the profit allocation of each coalition in group 2 according to Shapley, Nucleolus, and merge/split methods is compared with earned profit in each unit alone. 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 implemented units in level III for coalition forming and profits allocating, However, there is a significant difference between the proposed algorithms. Although, earned profit after coalition for DER 1 with merge/split algorithm has increased by

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

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	–	–

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

46.02% and 50.67% compared to Shapley and Nucleolus algorithms respectively and this procedure is true for DERs # 2, # 3 and # 4, profit reduction rate in Shapley algorithm for DER 1 and DER 2 is 28.68% and 26.26% compared to merge/split algorithm, respectively, and profit reduction rate in Nucleolus algorithm for DER 1 and DER 3 is 49%, 75% and 58.6% compared to merge/split algorithm, respectively.

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

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

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 Fig. 4.

In this case study, it is observed that by increasing DERs and coalition forming, 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 using case study 1, allocated profits of units located in buses 2, 5, and 8 belonging to group 1 increased by 1.68%, 5.83%, and 1.84% than before coalition, respectively, while, in case study 2, they decreased by 67.06%, 61.11%, and 36.13%, 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 indicate unbalanced profits in DERs. In the Nucleolus method using case study 1, allocated profits of units located in buses 2, 5, and 8 belonging to group 1 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, using case study 1, allocated profits of units in buses 11, 13, 24, and 27 belonging to group 2 decreased by 49.93%, increased by 11.21%, decreased by 5.16%, and increase by 49.17% compared to before coalition, accordingly. In case study 2, it decreased by 2.39% and increased by 56.45%, 45.35%, and 11.23%, respectively. Further, the gained values in case study 2 indicate unbalanced profits in DERs.

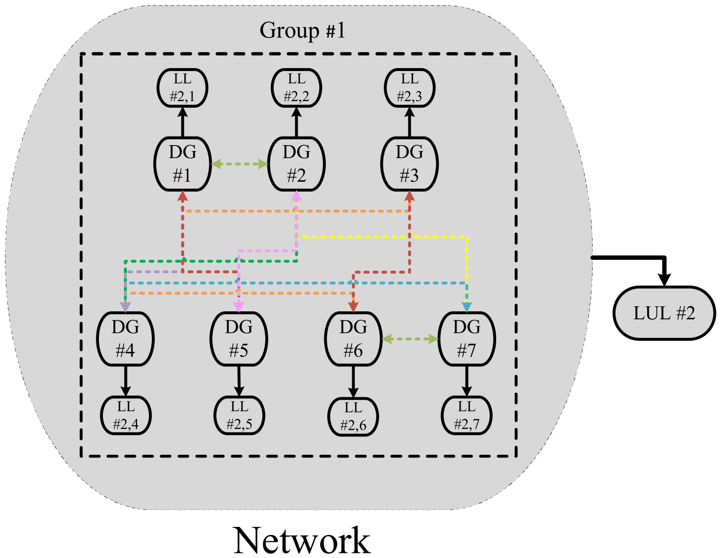

Fig. 4. DERs group in case study 2.

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 coalition	case study 1	63773.41	86472.21	85405.15	23467.58	18137.95	35820.5	68491.14
	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 coalition	case study 1	62789.26	88275.24	84586.27	21443.74	22894.64	32499.47	69079.32
	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 coalition	case study 1	64821.76	84181.45	86647.55	43478.24	20637.34	34788.94	47012.65
	case study 2	61190.28	79465.39	81793.33	41797.75	19839.68	33444.31	45195.56

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

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 IEEE 30-Bus modified 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 confirmed by the 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.

Table A.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 A.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

Table A.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

CRediT authorship contribution statement

Milad Moafi: Conceptualization, Methodology, Software, Writing, Visualization, Investigation. **Reza Rouhi Ardeshiri:** Conceptualization, Methodology, Software, Writing, Visualization, Investigation. **Manthila Wijesooriya Mudiyanselage:** Writing. **Mousa Marzband:** Conceptualization, Methodology, Writing, Supervision, Validation. **Abdullah Abusorrah:** Supervision, Validation. **Muhyaddin Rawa:** Supervision, Validation. **Josep M. Guerrero:** Supervision, Validation.

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.

Data availability

No data was used for the research described in the article.

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Appendix

See Tables A.17–A.19.

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