

Cooperative Decision Making of DERs in a Joint Energy and Regulation Market in Presence of Electric Vehicles

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Abstract: Today due to increasing and evolving of electrical grids, the optimal and profitable energy production is among producers' major concerns. Thus, conventional ways of production and trading energy are being replaced by modern economical procedures. In addition, distributed energy resources (DERs) in form of renewable and conventional resources as well as responsive loads play an important role in this issue. The mutual problem of DERs in joining power market is their rather small production compared to other units and intermittency of the corresponding resources. Forming coalition is an effective way to overcome DER difficulties for participating in power market. In this paper the problem of optimal bidding strategy of DERs integrated as a virtual power plant is investigated. Based on the proposed method, cooperative game is employed to obtain optimal DER outputs and the results are compared with individual non-cooperative bidding model. In order to mitigate the intermittent nature of renewable energies, existence of electric vehicles (EVs) as energy storage facilities in the proposed coalition is investigated. Due to the associated uncertainties regarding EVs and DERs, a stochastic optimization model is used. Finally, Shapley value method is employed to obtain corresponding allocated profits. Results show the eminence of forming coalition in terms of acquiring payoffs and optimal contributions.

Keywords: Distributed Energy Resources, Virtual Power Plants, Electrical Vehicles, Coalition, Cooperative Game Theory.

Nomenclature

Indices

T	Index of hours.
u	Index of DERs integrated into a coalition.
ω, ω'	Index of scenarios.
EV	Index of electric vehicles.

Constants

d_t	Duration of time period t (h).
$\underline{P}_u, \overline{P}_u$	Lower and upper power limits for dispatchable units respectively (MW).
$\underline{R}_u, \overline{R}_u$	CPP ramp-up and ramp-down rates (MW/h).
$g^{down,init}$	CPP down time period before beginning of scheduling day (h).

$g^{down,min}$	CPP minimum down time (h).
g^{on-off}	CPP on or off state before beginning of scheduling day (1 for $g^{(down,init)} > 0$ and 0 otherwise).
$g^{up,init}$	CPP up time period in the beginning of the scheduling day (h).
$g^{up,min}$	CPP minimum up time (h).
C_m^u	Marginal operation cost of CPP (\$/MWh).
C_m^L	Marginal curtailment cost of dispatchable load (\$/MWh).
C_u^f, C_u^s, C_u^d	Fixed, start-up and shut-down costs of CPP (\$).
π_ω	Occurrence probability of scenario ω .
C_{eff}	Efficiency coefficient of EV.
cap	Battery capacity of EV (MWh).
ch_{max}, dch_{max}	Charging and discharging rates of EV (MW).
k_u	Binary coefficient for state of VPP members (1 for on and 0 for off).

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Variables

$C_{u,t,\omega}$	Operation cost of dispatchable units (\$).
$E_{t,\omega}^{B+}, E_{t,\omega}^{B-}$	Energy traded in positive and negative balancing markets (MWh).
$P_{t,\omega}^D$	Power traded in day-ahead market (MW).
$P_{u,t,\omega}$	Net power injected by unit u (MW).
$P_{u,t,\omega}$	Forecasted power production and consumption for non-dispatchable units (MW).
$P_{t,\omega}^{EV,C}$	Consumed power of EV (MW).
$P_{t,\omega}^{EV,G}$	Injected power of EV (MW).
$SOC_{t,\omega}^{EV}$	State of charge of EV (MW).
$\Pi_{t,\omega}$	Gained profit (\$).
$\rho_{t,\omega}^D$	Day-ahead market price (\$/MWh).
$\rho_{t,\omega}^{B+}, \rho_{t,\omega}^{B-}$	Positive and negative balancing market prices (\$/MWh).
$\varphi_i(N, V)$	Shapley value for combination i of units.
$S_{u,t,\omega}$	Binary variable denoting on and off states of dispatchable units. (1 for on and 0 for off).
$Z_{u,t,\omega}^s, Z_{u,t,\omega}^d$	Binary variables denoting start-up and shut-down decisions of CPP (For $Z_{u,t,\omega}^s$, 1 is for turning on in time t and 0 is for shutting down. For $Z_{u,t,\omega}^d$ it is viceversa).

1 Introduction

DISTRIBUTED energy resource is the name of a wide set of different types of electrical energy producers such as wind power plants, solar plants, conventional thermal plants, pump and hydro storage power plants. Considering the intermittency of the energy resources, some DERs are not able to be available 24 hours of a day. Also renewable power plants like solar and wind plants are vulnerable to forecast errors and in many cases, the slope of energy production and market prices are not monotonous which can cause benefit loss for the DERs.

Participants in day-ahead market offer their bids a day before clearing the market considering all uncertainties. Units that are not able to fulfill their commitments in the day-ahead market, bid in balancing market. This market is divided into two subsets containing positive and negative balancing markets. The former is for units that have surplus production or consumption deficit for which the prices are lower than day-ahead market. The latter is for producers that have lack of production or the loads that have surplus demand compared to day-ahead bids. The prices in this market are higher than day-ahead market [1]. On the other hand small capacity and stochastic generation of DERs are known as an obstacle for participation of these resources in energy and

ancillary service markets. Therefore DERs need to find a suitable way for participating in market and providing reliable energy for the grid. DERs integrated in form of virtual power plant (VPP) can overcome this problem and even make a surplus profit by taking advantage of this market structure, a goal they could never achieve individually. Since VPP may have both generation and demand units, it may offer (to sell) or bid (to purchase), with the upstream network. Optimal offering problem of a VPP for participating in the day-ahead and the balancing markets is presented in [2]. Mashhour and Moghaddas-Tafreshi present an integrated operation of DERs into a VPP to participate in a joint energy and spinning reserve market without considering stochastic generation [3,4]. A non-equilibrium model based on the deterministic price-based unit commitment (PBUC) is proposed to adopt the bidding strategy problem. In [5] building an offering model for a VPP consisting of intermittent resource, storage facility, and dispatchable power plant is discussed. The proposed two-stage stochastic MILP model aims to maximize the VPP expected profit. The VPP participates in the day-ahead market as a price-taker and in the balancing market as a deviator. In order to compensate wind power deviations and reduce loss of profits incurred by wind power producer through balancing market, a combined wind farm-cascaded hydro system is proposed in [6]. The optimization model for day-ahead scheduling is formulated as a two-stage stochastic programming problem and the objective function is to maximize the VPP expected profit. In [7] a coordinated trading of wind and thermal energy is proposed and formulated as a mixed-integer stochastic linear programming. A joint cooperation of WPP and pumped-storage plant which participate in day-ahead, spinning and regulation reserve markets is proposed in [8].

Ref. [9] presents a day-ahead scheduling framework for virtual power plant (VPP) in a joint energy and regulation reserve market. It is assumed that the VPP provides required reserve through its distributed generator and pump storage units based on the delivery request probability of day-ahead market. Ref. [10] presents a novel architecture to integrate the participation of DERs into the electricity market. It concludes that the commercial and technical functionality of individual DERs are improved using the VPP concept.

DER aggregation usually needs to have a storage system in order to save their produced energy in peak hours and use it during time periods in which DERs face lack of production. Storage facilities also can be used to store produced energy when prices are low and sell it when the prices are high enough. In this regard, various types of storage units may be employed in terms of pump hydro storage, batteries, electrical vehicles (EVs), etc. EVs are being considered feasible storage sources in smart grids. Several techniques are incorporated to manage EVs interactions with the power network

[11,12]. An energy management model regarding intensive use of distributed generation and EVs is addressed in [13] that implements a sensitivity analysis to DER costs and capacities. Practically, with increasing in number of plug-in vehicles in parking lots, a great amount of storage capacity is accessible to VPP owners that do not impose usual operational storage costs.

Different types of participants face various sorts of uncertainties. The uncertainties seen in market prices and DER productions and consumptions, can have severe influences on the final revenue of DERs. Integration of DERs in the form of a coalition is a proper solution to mitigate risk of small scale and intermittency of DERs. They also can overcome the intermittency of energy resource and fluctuation in market prices by supporting each other in the coalition [14].

Forming cooperative game in terms of coalition can reassure profit-related concerns of individual participants [15]. The cooperative game theory is a well-known method to analyze and solve the cooperative game problems. With this procedure the profit acquired by a coalition can be fairly distributed between the participants [16]. In power system studies, cooperative game theory has been used for different purposes such as network cost and profit allocations [17], optimal bidding strategies [18] and transmission loss allocation [19]. Core, Nucleolus and Shapley value methods are three common techniques for profit allocation in cooperative game theory [20].

In this paper optimal bidding strategy of DERs integrated as a virtual power plant is investigated. Based on the proposed method cooperative game is employed to obtain optimal DER outputs and the results are compared with individual non-cooperative bidding model. In order to mitigate the intermittent nature of renewable energies, existence of electric vehicles (EVs) as energy storage facilities in the proposed coalition is studied. Due to the associated uncertainties regarding the EVs and DERs, a stochastic optimization model is used. Finally Shapley value method is employed to obtain corresponding allocated profits.

Considering aforementioned framework the novel contributions of this paper are summarized as follows:

1. Presenting a cooperative game procedure that allows small units to have more profitable and effective participation in power market compared to non-cooperative (individual) bidding case. Shapley value method is employed to obtain corresponding allocated profits.
2. To mitigate the intermittency of renewable outputs, impact of electric vehicles as reliable resources in DERs coalition is investigated. In this regard, probabilistic qualities for EVs entitled, time dependent features and travelled distance are modeled in order to produce more accurate estimation of EVs real life behaviors.

This article is structured as follows. In section II the

assumptions and definitions are provided. Problem formulation is expressed in section III. A case study is implemented in section IV and the results are represented and discussed in section V. Finally conclusion is represented in section VI.

2 Assumptions and Definitions

A. Types of Coalition Participants

Two major types of units containing producers and consumers are considered in this paper:

1. Dispatchable units (DUs) including conventional power plant (CPP), storage facility, and dispatchable load (DL).
2. Non-dispatchable units (NDUs) including wind power plant (WPP), photovoltaic plant (PV) and non dispatchable load (NDL).

Coalition can alter power of dispatchable units based on different variables and criteria that results in higher profits. Non-dispatchable units are defined by several scenarios with corresponding assigned probabilities. Therefore VPP is not able to make any changes in non-dispatchable unit scheduling.

B. Market Characteristics

Beside all of the advantages in profitability and reliability, integration of DERs can yield a surplus profit as a result of market structure. When a DER bids alone, because of uncertainties and forecast errors, it might not be able to fulfill previously accepted trades in day-ahead market precisely. So DER should trade its negative deviation at higher price or positive deviation at lower price in negative and positive balancing markets, respectively. Thus any trading in balancing market causes reduction in profitability. Forming a coalition can reduce the risk of participation in balancing market. Integration allows units to compensate their deviations with power produced or consumed by other units, resulting in surplus profits for the coalition after clearing the market.

C. Uncertainty Modeling

In this paper, the uncertainties addressed in the optimization problem are modeled by stochastic programming and scenarios [21]. Scenarios are used to express the uncertainties of DERs' consumed and produced powers and market prices as well. For simplicity, all of the scenarios are assumed to be equally probable.

D. Surplus Profit

Surplus profit is defined as the extra income made by each DER through forming a coalition in the power market. Suppose that DERs bid separately to the day-ahead and balancing markets. In this case, any deviation in previously scheduled trades should be compensated

in regulation balancing market. The DER can sell/buy generation surplus/deficit in positive or negative balancing markets with corresponding prices. Integrating DERs enables deviations to compensate other units' surplus/deficit which can also be used by producers with relatively high generation costs. In other words, making a coalition may decrease unnecessary interactions with regulation balancing markets that in turn results in a drastic surplus profit.

3 Problem Formulation

The offering curves proposed by integrated DERs are obtained by a two-stage stochastic optimization problem described as follows.

3.1 Objective Function

For day-ahead optimization, coalition DERs is solving an optimal dispatch problem. Dispatchable unit outputs are variables that must be dispatched based on operational constraints, however non-dispatchable units are uncontrollable due to stochastic nature of their resources. In the proposed two stage stochastic problem, taking operational constraints, costs and market prices into account, integrated DERs decide how much energy should be traded in day ahead and balancing markets in order to obtain the maximum profit.

Thus, the objective function maximizes the expected coalition profit gained from day-ahead market (DAM) and balancing market (BM) that can be formulated as below:

$$\max \sum_t \sum_{\omega} \pi_{t\omega} \Pi_{t\omega} \quad (1)$$

3.2 Trading Constraints

The profit of the integration is described in (2) as the difference between corresponding revenue and costs. It is assumed that VPP is a price-taker party in perspective of which market prices are random variables that should be estimated. Binary coefficient k_u denotes the presence and absence of DERs in different combinations. Energy balance constraint represented in Eq. (3) shows that the net difference between aggregated productions and consumptions is equal to the gross amount of energy sold. Constraints (4) and (5) are non-anticipativity constraints for day-ahead and constraint (6) ensures that the traded energy in negative and positive balancing markets are positive variables [12].

$$\Pi_{t\omega} = \rho_{t\omega}^D P_{t\omega}^D d_t + \rho_{t\omega}^{B+} E_{t\omega}^{B+} - \rho_{t\omega}^{B-} E_{t\omega}^{B-} - \sum_u C_{ut\omega} k_u, \quad \forall t, \forall \omega \quad (2)$$

$$\sum_u P_{ut\omega} d_t + [P_{t\omega}^{EVg} - P_{t\omega}^{EVc}] d_t = P_{t\omega}^D d_t + E_{t\omega}^{B+} - E_{t\omega}^{B-}, \quad \forall \omega, \forall t \quad (3)$$

$$P_{t\omega}^D < P_{t\omega'}^D, \forall \omega, \forall t \leftrightarrow \rho_{t\omega}^D < \rho_{t\omega'}^D \quad (4)$$

$$P_{t\omega}^D = P_{t\omega'}^D, \forall \omega, \forall t \leftrightarrow \rho_{t\omega}^D = \rho_{t\omega'}^D \quad (5)$$

$$E_{t\omega}^{B\pm} \geq 0, \forall \omega, \forall t \quad (6)$$

3.3 Operational Constraints

Operational constraints express the limits and equations of dispatchable units. Constraint (7) defines maximum and minimum limits of dispatchable units. Ramp up and down limits of CPP are provided in Eq. (8). Eqs. (9)-(10) set the number of time periods that CPP has to be down or up from the beginning of scheduling horizon, respectively. In constraint (11) CPP is forced to stay off; if it has been off less than minimum off time at the beginning of the scheduling horizon. Constraint (12) sets the minimum down time for any consecutive $g^{(down,min)}$ hours. Minimum down time for last $g^{(down,min)} - 1$ hours is presented in constraint (13). Similarly, Eqs. (14)-(16) illustrate the same conditions for minimum up time constraints. Constraints (17)-(19) are logical expressions for setting CPP start-up and shut-down binary variables. Eq. (19) ensures that non-dispatchable unit outputs are equal to predefined scenarios. Finally, Eqs. (20)-(21) are the cost functions of CPP and dispatchable loads, respectively [22].

$$S_{ut\omega} P_u k_u \leq P_{ut\omega} \leq S_{ut\omega} \bar{P}_u k_u, \quad \forall u \in Du, \forall t, \forall \omega \quad (7)$$

$$-R_u \leq P_{ut\omega} - P_{u,t-1\omega} \leq \bar{R}_u, \quad \forall u \in DP, \forall t, \forall \omega \quad (8)$$

$$L_{down,min} = \min \left\{ T, \left[g^{down,min} - g^{down,init} \right] \times \left[1 - g^{on-off} \right] \right\} \quad (9)$$

$$L_{(up,min)} = \min T, \left[g^{(up,min)} - g^{(up,init)} \right], g^{(on-off)} \quad (10)$$

$$\sum_{t=1}^{L_{down,min}} S_{ut\omega} = 0, \quad \forall u \in DP, \forall t, \forall \omega \quad (11)$$

$$\sum_{t=t}^{t+g^{down,min}-1} (1 - S_{ut\omega}) \geq g^{down,min} \cdot (S_{u,t-1\omega} - S_{u,t\omega}), \quad \forall L_{down,min} + 1 \leq t \leq T - g^{down,min} + 1, \quad \forall u \in DP, \forall t, \forall \omega \quad (12)$$

$$\sum_{t=t}^T (1 - S_{ut\omega} - (S_{u,t-1\omega} - S_{u,t\omega})) \geq 0, \quad \forall T - g^{down,min} + 2 \leq t \leq T, \quad \forall u \in DP, \forall t, \forall \omega \quad (13)$$

$$\sum_{t=1}^{L_{up,min}} (1 - S_{ut\omega}) = 0, \quad \forall u \in DP, \forall t, \forall \omega \quad (14)$$

$$\sum_{t=t}^{t+g^{up,min}-1} S_{ut\omega} \geq g^{up,min} \cdot Z_{u,t,\omega}^s, \quad \forall L_{up,min} + 1 \leq t \leq T - g^{up,min} + 1, \quad \forall u \in DP, \forall t, \forall \omega \quad (15)$$

$$\sum_{n=1}^T (S_{ut\omega} - Z_{u,t,\omega}^s) \geq 0, \quad (16)$$

$$\forall T - g^{up, \min} + 2 \leq t \leq T, \forall u \in DP, \forall t, \forall \omega \quad (16)$$

$$S_{ut\omega} - S_{ut-1\omega} \leq Z_{u,t,\omega}^s, \quad \forall u \in DP, \forall t, \forall \omega \quad (17)$$

$$S_{ut-1\omega} - S_{ut\omega} \leq Z_{u,t,\omega}^d, \quad \forall u \in DP, \forall t, \forall \omega \quad (18)$$

$$P_{ut\omega} = P_{ut\omega} k_u, \quad \forall u \in NDU, \forall t, \forall \omega \quad (19)$$

$$C_{ut\omega} = C_m^u P_{ut\omega} d_t + C_u^f S_{ut\omega} + C_u^s Z_{ut\omega}^s + C_u^d Z_{ut\omega}^d, \quad \forall u \in DP, \forall t, \forall \omega \quad (20)$$

$$C_{ut\omega} = C_m^u (P_{ut\omega} - P_{ut\omega}), \quad \forall u \in DL, \forall t, \forall \omega \quad (21)$$

3.4 Electric Vehicles

Several parameters such as departure time, daily travelled distance and arrival time are among the most effective factors on the EVs charging and discharging profile. Moreover, other important factors such as road traffic condition, driving habits, battery capacity, and charger efficiencies are considered as other effective factors in this regard. In this paper, probabilistic models of departure time, daily travelled distance and arrival time are used to describe stochastic behavior of EVs and storage availability of the integration. To create EVs random variables, non-Gaussian probability distribution functions (PDFs) are used due to their accurate approximations [23].

According to EVs usual departure time, Weibull is known as the most appropriate PDF describing this characteristic as shown in Eq. (22).

$$f_{d_t}(t) = \frac{\beta}{\alpha} \left(\frac{t}{\alpha} \right)^{\beta-1} e^{-\left(\frac{t}{\alpha}\right)^\beta}, \quad t > 0 \quad (22)$$

The mean and variance of the Weibull distribution can be calculated from the scale (α) and shape (β).

Similarly, in order to model EVs daily travelled distance (trd) and arrival time (at), type-III generalized expected value (GEV) PDF would be the most relevant function as represented in Eqs. (23) and (24):

$$f_{a_t}(t) = e^{-\left(1+k_{a_t} \frac{d-\mu_{a_t}}{\sigma_{a_t}}\right)^{\frac{1}{k_{a_t}}}} \frac{1}{\sigma_{a_t}} \left(1+k_{a_t} \frac{(d-\mu_{a_t})}{\sigma_{a_t}}\right)^{-\left(1+\frac{1}{k_{a_t}}\right)} \quad (23)$$

$$f_{r_d}(t) = e^{-\left(1+k_{r_d} \frac{d-\mu_{r_d}}{\sigma_{r_d}}\right)^{\frac{1}{k_{r_d}}}} \frac{1}{\sigma_{r_d}} \left(1+k_{r_d} \frac{(d-\mu_{r_d})}{\sigma_{r_d}}\right)^{-\left(1+\frac{1}{k_{r_d}}\right)} \quad (24)$$

It is notable that both aforementioned functions return GEV probability distribution with shape parameter k , scale parameter σ , and location parameter, μ .

The travelled distance for each EV is a criterion to calculate the state of charge (SOC) of the battery. The SOC shows the amount of the energy remained in the battery of each EV after returning to the parking lot. Eq.

(25) illustrates SOC formulation that is calculated based on EV daily travelled distance and corresponding battery capacity.

$$SOC_0 = 100 - \frac{tr_d}{C_{eff} \times cap} \times 100, \quad \forall EV \quad (25)$$

The rest of constraints pertaining to EVs are listed as follows.

$$\sum_{t=a_t}^{b_t} (P_{t\omega}^{EV,C} - P_{t\omega}^{EV,G}) + SOC_0 = cap, \quad \forall EV, \forall t, \forall \omega \quad (26)$$

$$SOC_{t\omega}^{EV} = SOC_{t-1\omega}^{EV} + (P_{t\omega}^{EV,C} - P_{t\omega}^{EV,G}), \quad \forall EV, \forall t, \forall \omega \quad (27)$$

$$SOC_{\min} \leq SOC_{t\omega}^{EV} \leq SOC_{\max}, \quad \forall EV, \forall t, \forall \omega \quad (28)$$

$$0 \leq P_{t\omega}^{EV,C} \leq ch_{\max}, \quad \forall EV, \forall t, \forall \omega \quad (29)$$

$$0 \leq P_{t\omega}^{EV,G} \leq dch_{\max}, \quad \forall EV, \forall t, \forall \omega \quad (30)$$

Eq. (26) enforces that each EV can be charged up to its battery capacity considering corresponding amount of SOC. The state of charge of batteries in each time step considering charging power is given in (27). EVs maximum and minimum state of charge for each interval and maximum charging and discharging rates are described in Eqs. (28), (29) and (30) respectively [12].

Profit Allocation

The cooperative game theory is an effective tool to analyze the collusive behavior of agents in a cooperative game. The main interest of the players in a coalition is profit allocation based on fairness. The cooperative game theory proposes several methodologies for this fair asset distribution. Shapley value is one of the aforementioned procedures.

The Shapley value of a given game is defined with reference to other games. It is a value or a function that assigns a unique feasible pay-off profile to every coalitional game with transferable pay-off.

This method can be described in form of objections and counter objections. To define these objections and counter objections, let (N, V) be a coalitional game with transferable pay-off and for each coalition S a sub game is defined in the form of (S, VS) to be the coalitional game with transferable pay-off $VS(T)$ for $T \subseteq S$. For a predefined value, ψ , an objection of player i against player j to the division x of $V(N)$ may take one of the following forms:

- "Give me more otherwise I will leave the game, causing you to obtain only $\psi_j(N_i, V(N_i))$ instead of larger pay-off x_j , that causes you to lose $\psi_j(N_i, V(N_i)) - x_j$."
- "Give me more otherwise I will persuade other players to exclude you from the game causing me

to obtain $\psi_i(N_j, V(N_j))$ rather than the smaller pay-off x_i , so that I will gain positive amount $\psi_i(N_j, V(N_j)) - x_i$."

A counter objection by player j can be made in the following forms respectively:

- "It is true that if you leave the game I will lose but if I leave you will lose at least as much as $x_i - \psi_i(N_j, V(N_j)) \geq x_j - \psi_j(N_i, V(N_i))$."
- "It is true that if you exclude me I will gain but if I exclude you I will gain at least as much as $\psi_j(N_i, V(N_i)) - x_j \geq \psi_i(N_j, V(N_j)) - x_i$."

The Shapley value is required to satisfy the property that for every objection of any player i there is a counter objection of player j and it is defined as a set of pay-offs that balances these objections and counter objections as represented in Eq. (31).

$$\begin{aligned} \psi_i(N, V) - \psi_i(N_j, V(N_j)) = \\ \psi_j(N, V) - \psi_j(N_i, V(N_i)) \quad \forall i, j \in N \end{aligned} \quad (31)$$

The unique value that satisfies this condition is Shapley value that is defined as follows:

$$\varphi_i(N, V) = \frac{1}{|N|!} \sum_{R \in \mathcal{R}} \Delta_i(S_i(R)), \quad \forall i \in N \quad (32)$$

$\Delta_i(S_i(R))$ is the marginal profit of player i defined in Eq. (33).

$$\Delta_i(S_i) = V(S \cup i) - V(S) \quad (33)$$

It can be interpreted that if all of the players are arranged in equally likely orders, then $\varphi_i(N, V)$ is the expected marginal contribution over all orders of player i to the sets of players which precede it [16].

To calculate the allocated profit to the VPP members by Shapley method, the binary variable k_u is set to 1 and 0 for existence and absence of each unit respectively and each time the marginal profit is calculated. After $2^{(n-1)}$ re-runs all of the marginal profits can be obtained. The weighted average for each unit gives the allocated pay-offs.

4 Case Study

A case study is implemented in which there are 5 individual DERs and loads that bid as non-cooperative competition. The assumed DERs are a wind power plant, a photovoltaic plant, a conventional power plant, and 50 EVs as well as dispatchable and non-dispatchable loads among which non-dispatchable loads and renewable producers do not impose any sort of operational cost. Tables 1 and 2 represent CPP operational characteristics and cost coefficients as well as EVs specifications.

Rated power amounts of existing units as well as dispatchable and non-dispatchable loads are represented in Table 3.

Table 1 CPP operational characteristics and cost coefficients.

Rated power (MW)	17.4
Ramp-up rate (MW/h)	3
Ramp-down rate (MW/h)	3
Minimum down time (h)	2
Minimum on time (h)	2
Minimum power (MW)	2
Marginal cost (\$/MW)	33
Fixed cost (\$)	2
Shut-down cost (\$)	2

Table 2 EVs specifications.

Number of EVs	50
Battery capacity (KWh)	30
Charging rate (KW)	3.2
Discharging rate (KW)	3.2

Table 3 Rated powers of VPP members.

Unit	Rated power
Wind power producer (MW)	24.8
Photovoltaic producer (MW)	6.1
Dispatchable load (MW)	9.5
Non dispatchable load (MW)	6.2

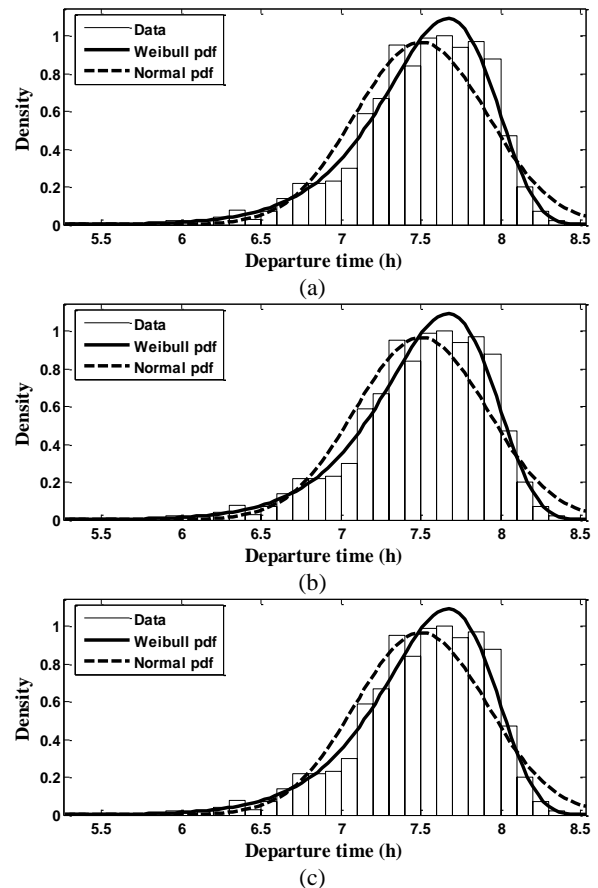


Fig. 1 Time dependent characteristics of EVs; a) Home departure time, b) Travelled distance and c) Arrival time [23].

The curtailment cost for all dispatchable loads is assumed 27 \$/MW.

As mentioned, due to stochastic behavior of EV owners, probability distribution functions are used to model these stochastic behaviors. Figs 1(a)-(c) represent Weibull and GEV probability functions related to EVs departure time, daily travelled distance and arrival time.

Table 4 shows the constants used in the PDFs of time dependent characteristics of the EVs.

In order to bid in day ahead and regulation balancing markets, each DER should forecast corresponding market prices. It is assumed that these predictions are obtained by considering several scenarios for each hour of the day. In this paper, the scenarios are assumed to occur with the same probabilities. The price scenarios for day-ahead, positive and negative balancing markets are depicted in Fig. 2 (a)-(c). The same procedure takes place for non-dispatchable productions and demands. Figs 3 (a)-(b) illustrate non-dispatchable unit output scenarios. Similarly, corresponding scenarios for non-dispatchable and dispatchable load consumptions are represented in Figs 3(c)-(d).

Table 4 EVs PDFs constants.

Data	Normal PDF	Purposed PDF
d_t	$\mu_{Nd_t} = 7.48436$	$\alpha = 7.67454$
	$\sigma_{Nd_t} = 0.43178$	$\beta = 21.3812$
tr_d	$\mu_{Nd_t} = 21.4150$	$k_{tr_d} = -0.052368$
	$\sigma_{Nd_t} = 8.58711$	$\mu_{tr_d} = 17.6568$
a_t	$\mu_{Nd_t} = 17.7170$	$k_{at} = 0.060798$
	$\sigma_{Nd_t} = 1.01385$	$\mu_{at} = 17.2700$
		$\sigma_{at} = 0.84832$

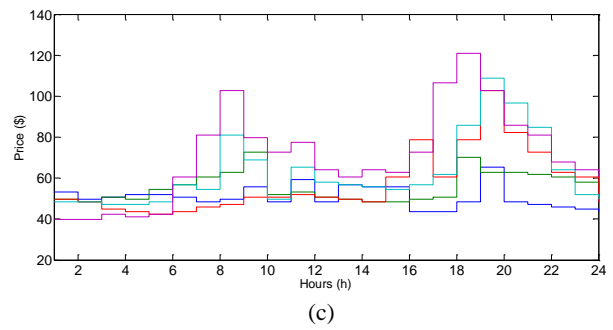
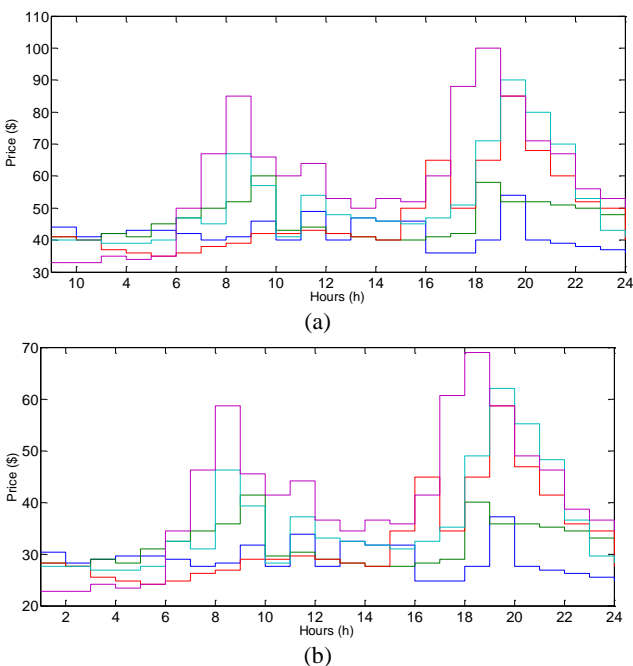


Fig. 2 Price scenarios; a) Day-ahead market prices scenarios, b) Positive BM market price scenarios and c) Negative BM price scenarios.

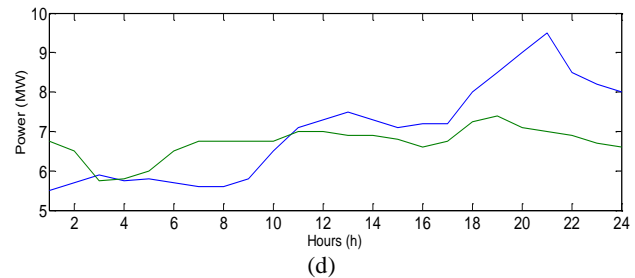
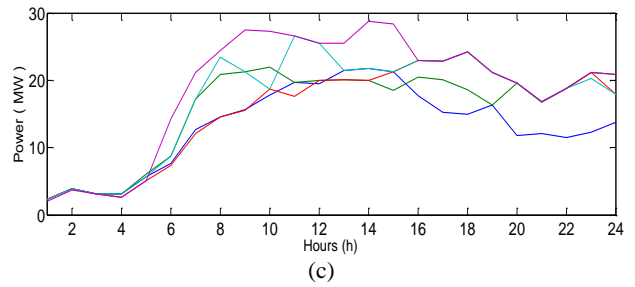
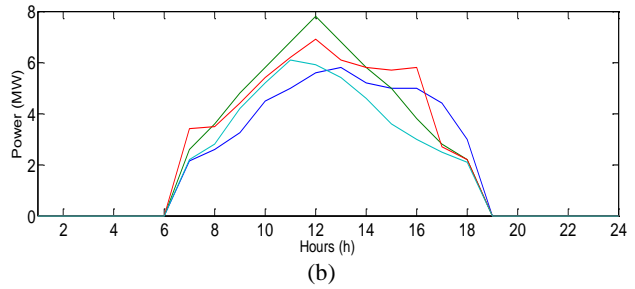
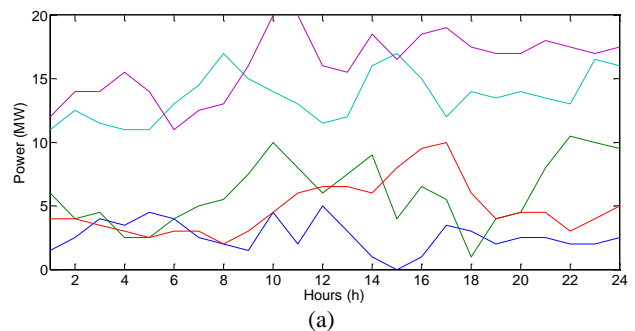


Fig. 3 DERs production and consumption; a) Wind production scenarios, b) Photovoltaic production scenarios, c) NDL consumption scenarios and d) DL forecasted consumption scenarios [15].

5 Results and Discussions

The case study is solved using CPLEX solver under GAMS software [24]. In this regard two scenarios are considered: non cooperative bidding and bidding in form of coalition entitled cooperative bidding. Accordingly, Fig. 4 depicts contributions and consumptions of each participant when they individually bid in form of non-cooperative competition and when they bid as a cooperative competition. Furthermore, summation of the produced and consumed powers in case of non-cooperative individual bidding is illustrated in Fig. 4. As it is seen, the traded power of the cooperative scenario is less than summation of DER contributions. In other words, by forming a cooperative competition, less power is produced in comparison to individual bidding in a non-cooperative one. It should be noted that for non-dispatchable units in terms of wind and PV producers and non-dispatchable loads, the plotted power curves are the expected amounts of their productions or consumption scenarios in each hour considering corresponding assigned probabilities

Figs 5 and 6 illustrate participants' tradings in terms of individual and aggregated bidding in positive and negative balancing markets, respectively. Likewise, power traded by the integration in the balancing markets is less than the summation of individual unit

contributions.

It can be interpreted that, by forming a coalition, the DERs cover for each others' deviations in production or consumption that in turn reduces DERs participation in positive and negative balancing markets.

During the planning day, coalition DERs bid less power in comparison to DERs aggregated outputs that causes higher pay-offs for the coalition. Note that, the wind power contribution exceeds coalition production in most of hours.

In order to investigate the impact of electric vehicles on cooperative trading, Table 5 represent EVs consumed and injected powers for three different expected prices at hour 23. The prices are 0.1, 0.6 of and equal to expected price at hour 23, respectively.

Comparing three rows pertaining to each expected price it can be concluded that with increasing the price, EVs consumed energy reduces. In other words, coalition decides to store much more energy when the price is cheap in order to use it or sell it in subsequent hours.

Same statement is true for EVs injected power under different price scenarios. As shown with increasing expected price, EVs injected power reduces. Thus integration can use EVs as storage to save energy when prices are low and sell it back to the grid when prices are high.

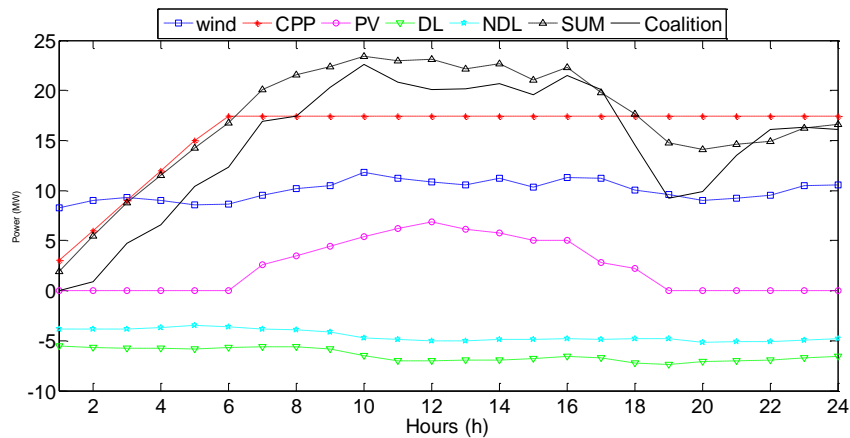


Fig. 4 Power trades in the DAM.

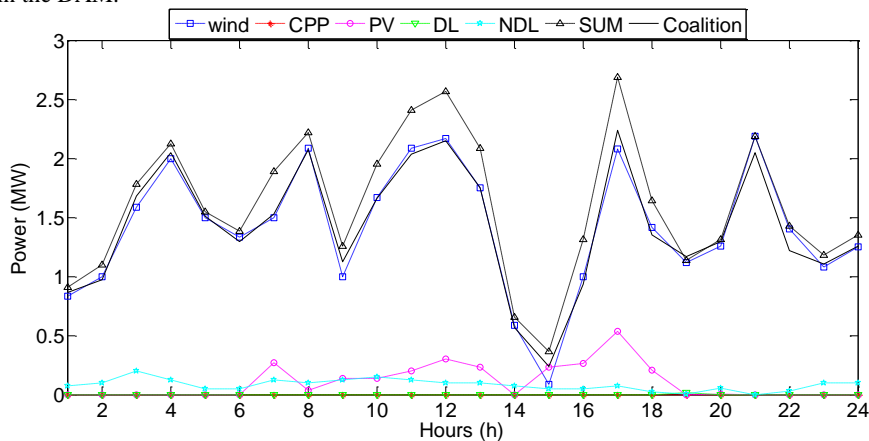


Fig. 5 Positive BM trades.

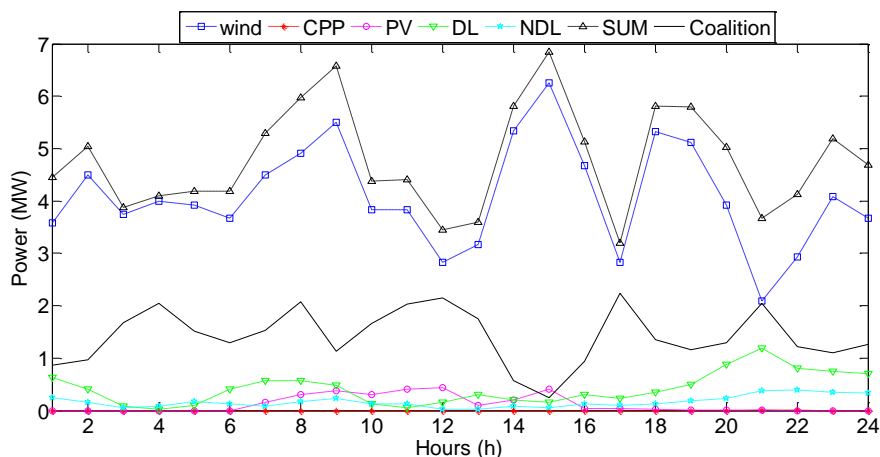


Fig. 6 Negative BM trades.

Table 5 First EVs' consumed and injected power for three price scenarios in hour 23.

Expected price (\$)	consumed power (MW)	Injected power (MW)
4.62	0.03	0
27.72	0.028	0
46.20	0	0.002

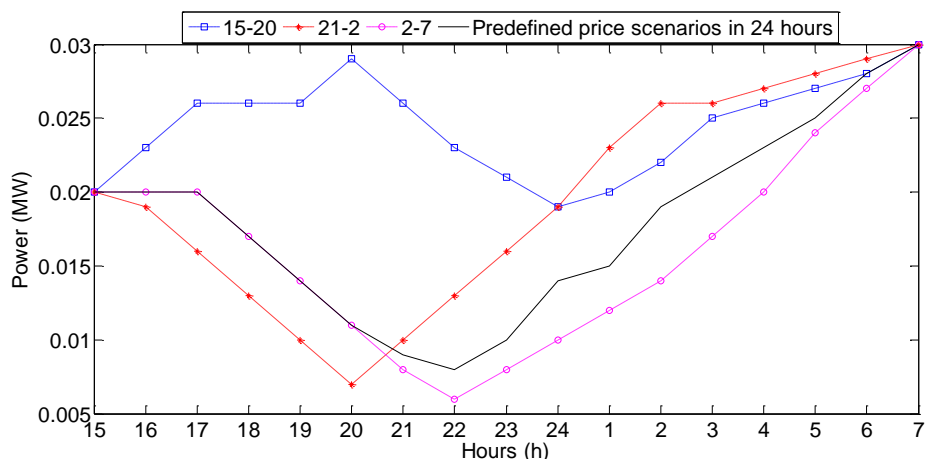


Fig. 7 SOC of the first EV for three price scenarios.

Fig. 7 represents SOC of the first EV for three different expected prices. The time period between EV's arrival and departure is divided into three intervals and in each interval, expected prices are considered equal to half of the predefined price scenarios. It is shown that in the first time period between 15 to 20 and the second between 21-2, reduction in market prices increases SOC compared to the SOC in the unmodified case. The third interval is the last hours before departure by the end of which EV needs to leave with a fully charged battery. As illustrated in Fig. 7, there is an intense increase in SOC level during these hours. Comparing three scenarios to the unmodified curve shows that most of charging process takes place within aforementioned intervals with lower prices which is a good means towards profitability for the coalition.

It can be seen that in all four scenarios, EV is fully charged before leaving the parking lot.

The profit allocation in a cooperative competition

occurs based on fairness and effectiveness of each member in profitability of the coalition. Shapley value method distributes aggregated gained profit among coalition members considering said factors. Table 6 represents allocated profit of each DER calculated based on Shapley value method. The pay-offs are expected marginal profits that each DER adds to all possible combinations of aggregated DERs.

Table 6 Profit allocation based on Shapley value method.

#	DER	Shapley pay-offs (\$)	Single DER Profits (\$)
1	WPP	10921.900	10747.126
2	PVP	3029.883	2922.389
3	NDL	-6753.020	-6886.224
4	CPP	23759.790	23702.277
5	DL	-10327.300	-10465.310
Total Coalition		DERs	
Profit		20575.580 (\$)	20020.258 (\$)

Table 6 also shows DERs individual profits in case of bidding alone in a non-cooperative competition. It appears, the allocated coalition pay-offs are more than non-cooperative ones.

Finally, Table 7 represents surplus profit gained by forming coalition for all possible VPP combinations. As it is seen, in all of the cases, surplus profit is obtained. Since VPP cannot alter non dispatchable unit outputs based on hourly market prices, it can make use of dispatchable unit and load capacities to compensate inevitable deviations. The surplus amounts in Table 7 are obtained in comparison to DER's individual bidding. Thus, surplus profit is higher for combinations with non dispatchable units compared to cases with adjustable dispatchable ones. Accordingly, maximum surpluses are obtained when all non dispatchable units and load exist in coalition. On the other hand minimum surplus occurs when the majority of coalition members are dispatchable DERs. This proves the potential capability of aggregation in increasing the incomes of DERs.

Table 7 Surplus profit for all possible combinations.

WPP	DERs				Surplus profit(\$)
	PVP	NDL	CPP	DL	
×					0
	×				0
		×			0
			×		0
				×	0
×			×		59.763
×	×				136.563
	×		×		59.760
×	×		×		196.326
×		×			168.100
	×	×			102.841
		×	×		79.763
×	×	×			304.541
	×	×	×		162.604
	×		×	×	150.088
	×	×		×	224.465
		×	×	×	187.872
×		×	×		79.763
×	×	×	×		364.304
×				×	146.162
	×			×	90.326
			×	×	59.762
		×		×	128.109
×	×			×	327.644
×			×	×	250.925
×		×		×	359.285
×	×		×	×	387.407
×	×	×		×	495.560
×		×	×	×	419.012
	×	×	×	×	284.227
×	×	×	×	×	555.322

6 Conclusion

This paper represents a cooperative competition model among individual market participants such as, DERs, dispatchable and non dispatchable loads and electric vehicles as storage facilities. It is shown that coalition can maximize its profit by optimizing the produced and consumed powers of the dispatchable units and electric vehicles transactions, considering non-dispatchable units and price scenarios. A two-stage stochastic programming problem is used to simulate a cooperative competition in form of a coalition in day-ahead and regulation balancing markets. The results shows that in the proposed market structure, DERs in form of a coalition have the advantage of losing less revenue by covering for each other's deviations and obtaining a surplus profit. The results also express that the coalition members gain more profit in comparison with the case of individual bidding in a non-cooperative competition.

It is also stated that integrated DERs can use EVs as storage facilities in order to increase the related pay-offs. Three different price scenarios are used to illustrate the validity of this statement. Finally in order to find the fair DERs sharing amounts, Shapley value method is used to allocate pay-offs based on their effectiveness in the coalition.

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