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A stochastic short-term scheduling of virtual power plants with electric vehicles under competitive markets

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ABSTRACT

This paper presents a risk-averse stochastic framework for short-term scheduling of virtual power plants (VPPs) in a competitive environment considering the potential of activating electric vehicles (EVs) and smart buildings in demand response (DR) programs. In this framework, a number of EV Parking Lots (PLs) which are under the jurisdiction of the VPP and its rivals are considered that compete to attract EVs through competitive offering strategies. On the other hand, EVs' owners try to choose a cheaper PL for EVs' charging to reduce payment costs. Therefore, the objective of EVs owners can be in conflict with the objective of PLs that provide services for EVs under each VPP. In this regard, the decision-making problem from the VPP's viewpoint should be formulated as a bi-level optimization model, in which in the upper-level, the VPP profit should be maximized and in the lower-level, procurement costs of EVs and other responsive loads should be minimized, simultaneously. To solve the proposed bi-level problem, it is transformed into a traceable mixed-integer linear programming (MILP) problem using duality theory and Karush-Kahn-Tucker (KKT) optimality conditions. The proposed model is tested on a practical system and several sensitivity analyses are carried out to confirm the capability of the proposed bi-level decision-making framework.

1. Introduction

During the last years, growing environmental concerns led to developing renewable energy resources (RESs) such as wind and photovoltaic (PV) generations worldwide. However, the uncertainty of RES output poses many challenges to the operation of the power systems such as power imbalance and increases the power regulating burden [1]. One of the promising solutions for this issue is the creation of virtual power plants (VPPs) [2]. A VPP basically acts as an aggregator of distributed generations (DGs) and RESs that are located within a certain geographical area and creates a single operating profile in order to participate in the electricity market or to provide system support services [3]. In addition, with the development of demand response (DR) resources in the restructured power systems, aggregated DR resources were proposed to balance the volatility of RESs production [4]. A VPP can enable responsive loads to actively participate in the energy trades by subscribing them for DR programs. In this way, a VPP is also considered as a DR aggregator that is able to provide or use an aggregated portfolio of demand-side services [5].

In the case of VPPs, it is possible to carry out the scheduling for different sectors and model various objective functions, including the cost and benefit functions. Moreover, it is possible to combine the energy market and the deregulated power system concepts. As can be observed in the literature, the concept of VPP in the energy market is modeled and some of the researches in the realm of VPP's energy management strategies have been focused on the active participation of smart customers in DR programs. In [6], authors have focused on utilizing DR programs and aggregating loads by a VPP to establish a demand side management framework. A hierarchical model is proposed in [7] for simultaneous modeling of a microgrid scheduling and VPP energy management problems. Given the stochastic nature of the scheduling inputs, power production and also, load demand uncertainties are modeled using a scenario-based method. A multi-agent system for VPP is presented in [8]. The generation of the VPP is based on the coordination of several DG units. However, DR, as one of the most important factors in a VPP, has not been considered. In order to

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Nomenclature

Indices and sets

$(\cdot)_{t,s}$ At time t and at scenario s.
$(\cdot)_{t,\psi}$ At time t and at scenario ψ.
N_S Set of scenario s.
T Set of time period t.

Parameters and constants

C_i Initial energy in the batteries of EVs (MWh).
r Energy consumption of EVs (kWh/mile).
d Travelled distance by EVs (mile).
a^g/b^g Factors of cost function related to DG units.
π_s Probability of scenario s.
ρ_ψ Probability of scenario ψ.
$C^g_{SU/SD}$ Start-up/shut-down cost of DGs.
$E^D_{t,s}$ Responsive loads supplied by the VPP (MWh).
$E^{DN}_{t,\psi}$ Non-responsive loads supplied by the VPP (MWh).
$\Pr^{up/dn}_{t,s}$ Up/down regulation market prices (€/MWh)
$E^{wind}_{t,s}$ Wind power output (MWh).
$\Pr^{DA}_{t,s}$ DA price (€/MWh).
$pr^F_{w,w't,\psi}$ Fictitious cost showing the reluctance of EV owners to transfer among the PLs.
$SOC_{\min}$ Minimum SOC of EVs.
$SOC_{\max}$ Maximum SOC of EVs.
$\hat{E}^{Ch}_t$ Expected values of EVs demand (MWh)
$E^{TCh}_{t,s}$ Total demand of EVs (MWh).
$X^{init,\ell}_{w,\psi}$ Initial percentage of EVs demand supplied by the VPPs.
β Risk aversion parameter
α Confidence level

VariablesUpper level variables

C_R Required energy of EVs (MWh).
$pr^D_{w0,t}$ Offering price to the loads (€/MWh).
$pr^{Ch}_{w0,t}$ Offering price of parking lots to EVs.
$E^{TCh}_{t,s}$ Total required demand of EVs (MWh).
$\hat{E}^{TCh}_t$ Expected required demand of EVs (MWh).
$e^{Ch}_{t,s}$ Demand of EVs supplied by the under study VPP (MWh).
e^R_t Demand of EVs do not transfer among the VPPs.
$e^{Ch,0}_{t,s}$ Demand of EVs remained with the under study VPP (MWh).
$e^{DA,sell/buy}_{t,s}$ DA buying/selling energy (MWh).
$e^{up/dn}_{t,s}$ Energy supplied in up/down regulation market (MWh).
$e^g_{t,s}$ Energy generated by DGs (MWh).
$SOC_{t,s}$ SOC of EVs.
η_s Variable related to CVaR.

Lower Level variables

$x^{Ch}_{w0,t,\psi}$ Percentage of EVs' demand supplied by the under study VPP.
$x^{Ch}_{w,t,\psi}$ Percentage of EVs' demand supplied by rival VPPs.
$y_{w,w',\psi}$ Percentage of EVs' demand transferred among the VPPs.

circumvent the computational difficulty of a centralized solution and to save extra cost of centralized infrastructures, an alternating direction method of multipliers (ADMM)-based decentralized optimization algorithm is proposed in [9]. Based on that algorithm, the network constraints that couple different EVs' charging power together are relaxed, and the model is thus decomposed into parallel single-EV charging subproblems that can be solved in a distributed manner. In [10], an energy management strategy has been presented for an industrial VPP and its performance under different types of DR programs has been investigated. In [11], an energy management strategy has been presented for an unbalanced distribution system with a VPP including various DERs and DR participants. In that work, a multiple optimization method has been deployed, but the uncertainties in the market prices and DG units are not considered. Furthermore, a novel optimization approach is proposed to handle uncertainties in electricity prices and RES units in [12] without considering the risks associated with the uncertainties. A decision making can be risky due to the uncertainties involved. In order to assess the risk of profit variability, uncertainties should be expressed in a proper way and also a suitable risk measure should be incorporated into the risk-neutral problem. Uncertainty modeling trends for decision making process are addressed in [13]. In the stochastic framework, the Conditional Value-at-Risk (CVaR) [14] is considered as a risk measure to lessen the danger to which the decision maker is exposed because of uncertainty. In [15], an optimization model to determine the DA inflexible bidding and real-time flexible bidding under market uncertainties is proposed where, the conditional expectation optimization model is formulated as an expectation minimization problem with the CVaR constraints. In [16], a regret-based stochastic bi-level framework for optimal decision making of a demand response (DR) aggregator to purchase energy from short term electricity market and wind generation units is proposed. Optimization and forecasting methods as in [17] and [18] are presented and applied in [19] to model the operation of multiple renewable generators across Scotland, trading energy as a single commercial VPP. Moreover, in [20], a multi-objective optimization model of the blocking flow shop scheduling problem with makespan and energy consumption criteria is constructed in which, a discrete evolutionary multi-objective optimization (DEMO) algorithm is proposed.

In recent years, the number of electric vehicles (EVs) dramatically increased in the power systems and has significant impacts on the distribution networks [20]. EVs will bring a great challenge to the power system energy management due to their specific characteristics and unpredictable dynamic behavior. As EVs cannot directly participate in the market, an intermediary agent as an EV aggregator takes part in the electricity market and dispatches aggregated EVs and transfers information between the independent system operator and individual EV owners [21]. Authors in [22] have presented a risk-averse stochastic bi-level programming approach to solve decision making of an EV aggregator in a competitive market under uncertainties. Likewise, in [23], a stochastic bi-level decision-making model has been presented for an EV aggregator in a competitive environment, in which EVs demand is the only uncertain parameter of the vehicles. A comprehensive framework for a risk-constrained optimal VPP energy management problem considering correlated demand response units is investigated in [24] without modeling the competition among the rival VPPs. Unified management of the multi-VPP through VPP central controller is investigated in [25], which reveals the controllability of the VPP as source and load in general. In that study, although multiple VPPs are considered, the competition among them is neglected. In [26], a mathematical model has been proposed for the bidding strategy of a VPP that participates in the regular electricity market and intraday DR exchange market. In that study, client response to the retail price was modeled through stepwise price-quota curves. However, price-quota curves do not explicitly model the competition among rival VPPs. In [27], an agent-based approach has been suggested for VPPs of wind generators and EVs, where wind generators seek to use EVs as storage systems to overcome the uncertainties of generation units. These studies either do not address competition among parking lots (PLs) of different VPPs or do not apply all uncertain parameters of the EVs into the optimization model. In order to compare the highlights and important aspects of this paper, Table 1 is also added to show the contributions of the works in view of the existing state of the art literature. The problems of the scheduling of a VPP are often addressed separately in the literature. In this paper, a bi-level optimization model is presented that optimizes the scheduling of DR, EVs and VPPs, simultaneously. The behavior of EV's owners involves a lot of uncertainties in the VPP decision-making model, that would cause fluctuations and lead to economic losses for the VPP. Therefore, a stochastic risk-constrained offering and bidding strategy for the VPP is proposed, in which uncertainties of EV owners and also EVs travelling pattern, that is one of the important factors in the EV charging strategies, is investigated. As the main contribution, the competition of VPPs' PLs to attract more EVs is modeled in the proposed strategy. The goal of the upper level of the bi-level stochastic model is the maximization of the total expected profit of the VPP through its participation in a competitive environment considering DR participants, EVs travelling pattern, uncertain RESs power production and other operational constraints. The aim of the lower level of the problem is the minimization of the payment costs of aggregated DR and EV owners. There are some recent works that discuss the potential benefits of DR programs for decision making strategy of different agents such as DR providers [28], wind power providers, and load serving entities [29]. However, to the best of our knowledge, none of the previous works has considered joint optimization of EV and DR management under a competitive structure.

In [28], a wind power producer participates in a competitive market to attract the loads and EV owners. However, competition among VPPs and the effect of self-sufficiency [30] of the VPP is not investigated in the previous literature based on our knowledge.

The dynamic price-responsive behavior of consumers is modeled based on scenarios in [31] where, the conditional probability of the load given a certain retail price trajectory is estimated using a non-parametric approach.

In [32], although the competition among the DR aggregators is considered, the effect of EVs and the behavior of the owners is neglected. Therefore, the main contributions of this study can be summarized as follows:

i. A risk-averse stochastic framework is presented for short-term scheduling of a VPP in the DA and regulating markets to maximize its expected profit in a competitive condition and to manage the expected revenues' risks related to the uncertainties. On the other hand, EVs' owners try to choose a cheaper PL for EVs' charging to reduce their payment costs. Therefore, the objective of EVs owners can be in conflict with the objective of PLs that provide services for EVs under the territory of each VPP. In this regard, the decision-making problem from the VPP's viewpoint should be formulated as a bi-level optimization problem, in which in the upper-level, the VPP profit should be maximized and in the lower-level, procurement costs of EVs and other responsive loads should be minimized, simultaneously.
ii. In this study, the impacts of different levels of DR participants and risk aversion parameter on the decision making of the VPP in competitive conditions are evaluated through different sensitivity analyses. Also, to assess the amount of load supplied by the VPP, self-sufficiency factor (SSF) is investigated under the competitive conditions. The findings enable the VPP operator to choose the appropriate risk factor while maximize its profit in decision-making process when it competes against other VPPs to attract the EV owners.
iii. The competition among the VPPs is also considered through a bi-level framework in which, the EVs' behavior through their reluctance to change their PLs are modeled. The proposed decision-making strategy is formulated as a bi-level problem to achieve a flexible trade-off between maximizing the VPP's expected profit and minimizing the total electricity cost of customers and EVs. To solve the proposed bi-level problem, it is transformed into a traceable mixed-integer linear programming (MILP) problem using duality theory and Karush-Kahn-Tucker (KKT) optimality conditions.

The remaining of the paper is organized as follows: the statement of the problem is presented in Section 2. The problem formulation and the problem methodology are described in Sections 3 and 4, respectively. The case studies and numerical results are provided in Section 5 and some conclusions are given in Section 6.

2. Problem statement

The problem of scheduling of a VPP that comprises several wind turbines, DG units, responsive and non-responsive loads as well as EVs' PLs is illustrated in Fig. 1. The under-study VPP can participate in the wholesale market to submit its energy offers in DA market. Since, the VPP operator encounters several uncertainties when it submits its energy blocks to the network, it takes part in regulation market to compensate both energy deficit and energy excesses. Also, the under-study VPP can participate in the wholesale market by purchasing or selling its shortage or surplus of energy through an appropriate offering price. In the wholesale market, on the DA market, the VPP operator trades power for day in advance. Then, in order to keep the balance between production and consumption in the system during the delivery hours (in real time), the system operator can use other market mechanisms. The mechanism used in this work is referred as regulating market in the Nordpool. In order to compensate the energy deviations in the regulating market, a specific mechanism is used that is explained in the Appendix A. It should be noted that scheduling of the VPP is performed for one day with the typical 24-h (even 1-h) time resolution. Based on this framework, the DA market, is cleared at 10:00 am of day d − 1,

Table 1
The contribution of literature in view of existing state of the art.

Reference	Bi-level modelling	Competitive environment	Clients: Charge of EVs	Clients: Demand response	Risk assessment Model	Self- sufficiency factor	Reaction of customers to the prices
[4]	–	–	✓	✓	–	–	–
[6]	–	–	–	✓	–	–	–
[10]	–	–	–	–	–	–	–
[26]	–	✓	–	✓	–	–	✓
[20]	–	–	✓	✓	–	–	
[24]	–	–	–	✓	✓	–	–
[28]	✓	✓	✓	✓	✓	–	✓
[30]	–	–	–	✓	–	✓	✓
[31]	–	–	–	✓	✓	–	–
[32]	✓	✓	✓	✓	✓	–	✓
This paper	✓	✓	✓	✓	✓	✓	✓

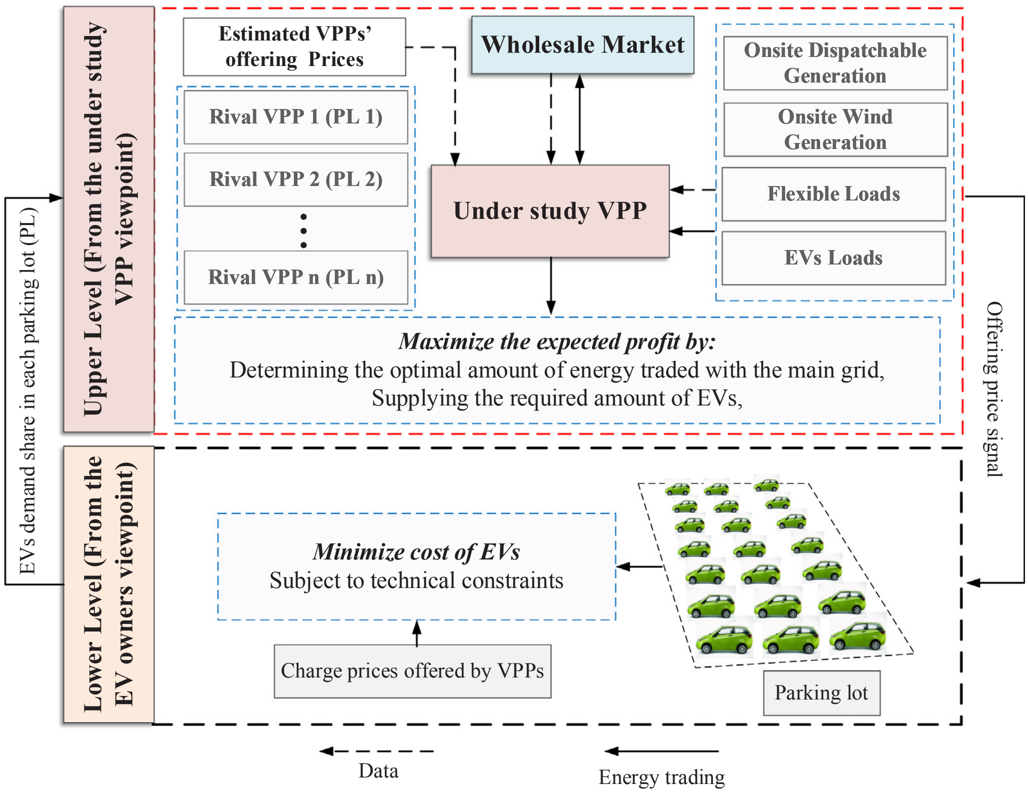

Fig. 1. The conceptual schematic of VPP model with related major components.

i.e., 14 h before the beginning of the energy delivery period (day d). Then, the regulation market, can be used by the VPP operator to alter its scheduled productions for the trading and is cleared ten minutes in advance of power delivery. Based on this mechanism, a price for the positive energy deviation (lower consumption than the scheduled one) and a price for the negative energy deviation (higher consumption than scheduled one) are settled for each time period. These prices are determined such that to counteract the unplanned deviations, and consequently, they represent the cost of the energy required to be compensated. Although, advanced VPPs are equipped with advanced forecast procedures, they may confront energy deviations due to the presence of stochastic resources such as wind energy and the behavior of EV owners. Therefore, the presence of a procedure to compensate the energy deviations is necessary. Moreover, the VPP should supply the demand of customers and EVs by offering optimal retailing prices to them. Here, it is supposed that each VPP has some PLs under its jurisdiction that in each PL, there is an operator as a middleware performing as an aggregator between the EVs and the VPP operator aggregating the requested power of EVs. Each VPP can attract the EV owners to charge their vehicles in their PLs by offering proper selling prices. However, the EVs' owners have their own objective and restrictions that can be in conflict with the objective of the PL and the VPP operator. Using bi-level optimization method, the competition among the VPPs is modeled here. Since, the prices offered by rival VPPs are uncertain to the under study VPP, the under study VPP operator considers different scenarios of prices offered by rivals to set its selling prices offered to both demand and EVs. Therefore, in the prediction unit, the scenarios are generated using probability density function (PDF). Then, in the optimization unit, the selling price of the VPP is computed based on the bi-level stochastic program in which different sources of uncertainty are accounted for via stochastic programming. The pattern of the selling price by the under study VPP is substantially influenced by the rivals' prices. Therefore, the offering prices of rival VPPs is considered as input to the bidding strategy of the under study VPP. Based on the proposed bi-level problem, in the upper-level, the objective of the VPP operator is to maximize its expected profit through its interaction with the upstream market on one hand and the energy trading with EVs in the PLs as well as implementing DR programs in the other hand.

In the lower level, there are EV owners who tend to charge their EVs in the PLs that are under the jurisdiction of the VPPs and are managed by them. Therefore, the competition among VPPs is introduced in which the EVs' owners can react to the selling price of the VPPs in the PL and choose in which PL to charge their EVs. Therefore, the VPP operator confronts with the problem of uncertainties in the market prices, demand loads, EVs requested demand and rival VPPs offering prices. On the other hand, the VPP should offer a fixed tariff price to the loads and PLs. The main challenge of this problem is the loss that the VPP may incur specifically when the market prices suddenly exceed the offering price to the lower level. Therefore, a prediction unit is required to predict the expected values of uncertainties. Also, an optimization unit should be implemented to model both the competition of VPPs to attract EV owners and to model the reaction of EVs to the VPP's offering prices. In this regard, a stochastic bi-level problem is investigated in the following section.

3. Formulation of the proposed bi-level problem

The objective of the VPP decision-making model is to maximize its expected profit in order to satisfy the loads and to compete with other VPPs to attract more EVs to charge in their own PLs. Uncertainties in the aggregated fleet characteristics of EVs are due to the random behavior of individual EV owners.

3.1. Formulation of EVs' behavior

As explained before, the prediction unit predicts the number of EVs that may ask for the charging process for their daily travel. Although it is required to scan each vehicle movement in order to achieve its required energy, for the sake of simplicity, it is assumed that all EVs have the same travelling behavior. In this regard, each EV enters a certain PL with initial battery charge ($C_{t,s,i,EV}$). The amount of energy required for daily travelled distance ($D_{t,s,EV}$) by each EV would be obtained as:

$$E_{t,s}^{TCh} = C_{t,s,i,EV} + R_{EV} \times D_{t,s,EV} \tag{1}$$

where R_{EV} denotes the electrical energy consumption of EV. A normal PDF is used to estimate the daily travelled distance of each EV. Driving habits of EV owners can probably change to satisfy charging restrictions. In case of conventional internal combustion engine vehicles, each PL duration is restricted by the owner's future program, but for EVs, *SOC* of the battery is also a determinant factor. An EV owner charges the EV battery to reach the maximum *SOC* and finishes his travel with a minimum *SOC*. Therefore, the *SOC* is restricted within its limitations:

$$SOC_{\min} \leqslant SOC_{t,s} \leqslant SOC_{\max} \tag{2}$$

The required energy of EVs is considered instead of *SOC*, because of the easy derivation of power and energy quantities in the model. So, in Eq. (2), *SOC* is used to show the limitation of the EV battery. However, since in other formulations in the lower level problem, the total required energy of EVs is necessary, in Eq. (1), the amount of required energy of EVs is modeled.

The prediction unit of the PLs sends the predicted data to the VPP operator for the energy management strategy (the optimization unit) as explained in the next section.

3.2. Formulation of upper-level problem

The objective of the VPP is to maximize its expected profit as below:

$$Maximize \sum_{s\in N_S} \pi_s \sum_{t\in T} \begin{bmatrix} e_{t,s}^{D} pr_{w0,t}^{D} + e_{t,s}^{Ch} pr_{w0,t}^{Ch} + e_{t,s}^{Ch,0} pr_{w0,t}^{Ch} \\ e_{t,s}^{DA,sell} \mathrm{Pr}_{t,s}^{DA} - e_{t,s}^{DA,buy} \mathrm{Pr}_{t,s}^{DA} \\ \sum_{g\in G} -C_{SU}^{g} - C_{SD}^{g} - (a^{g} + E_{t,s}^{g} b^{g}) \\ - e_{t,s}^{up} \mathrm{Pr}_{t,s}^{up} + e_{t,s}^{dn} \mathrm{Pr}_{t,s}^{dn} \end{bmatrix} + \beta \left(\xi - \frac{1}{1-\alpha} \sum_{s=1}^{N_S} \pi_s . \eta_s \right) \tag{3}$$

The profit includes the revenue from selling energy to the loads and EVs. The third term in the first line models the reluctance of those EV owners that do not have the willingness to change their PL and stay with each PL. The second line gives the revenue and costs from energy transaction with DA market. The third line shows the start-up, shut-down and the costs of generated energy by DG units. Also, the costs due to being penalized in the regulation market because of the deviations occurred as the result of forecasts are given in the last line. Also, the uncertainties are controlled by adding CVaR term to the objective function [34]. In fact, in the presence of variability, it may be useful to adapt its policy according to its tolerance for risk. For this reason, CVaR is introduced into the formulation. The CVaR allows taking more conservative solutions in order to be more robust towards extreme scenarios (i.e. reduce volatility of expected profit), but at the expense of the profit generated for more likely situations. Moreover, it can be expressed by means of linear expressions and offer the opportunity to choose among different risk levels by adjusting the ?? parameter [35]. The risk aversion factor is a weighting parameter used to materialize the trade-off between expected profit and risk aversion. In lower values of β, the risk term in the objective function is neglected and the obtained problem becomes risk-neutral. As intended, the expected profit increases when risk aversion decreases. In this situation, as β increases, the expected profit term becomes less significant with respect to the risk term. While, vice versa occurs in higher values of β. For a discrete profit distribution, CVaR is approximately the expected profit of (1-α)100% scenarios with lower profit [32]. When the α-confidence level of CVaR is set close to 1, which will correspond to more conservative behavior, the CVaR risk measure approximates the worst scenario risk measure. In this work, we have employed 95% for α to avoid being either pessimistic or optimistic in approximating the profit distribution tail, meanwhile playing with β parameter instead to reflect the VPP desired risk level in optimization procedure based on underlying CVaR measure. The upper level is restricted with the following constraints:

Eq. (4) ensures the energy balance between demand and generation.

$$E_{t,s}^{wind} + e_{t,s}^{DA,buy} - e_{t,s}^{DA,sell} + e_{t,s}^{up} - e_{t,s}^{dn} + \sum_{g\in G} e_{t,s}^{g} = e_{t,s}^{D} + e_{t,s}^{Ch} + e_{t,s}^{Ch,0} \tag{4}$$

The CVaR term is subject to the following terms:

$$\sum_{t\in T} \begin{bmatrix} e_{t,s}^{D} pr_{w0,t}^{D} + e_{t,s}^{Ch} pr_{w0,t}^{Ch} + e_{t,s}^{Ch,0} pr_{w0,t}^{Ch} \\ e_{t,s}^{DA,sell} \mathrm{Pr}_{t,s}^{DA} - e_{t,s}^{DA,buy} \mathrm{Pr}_{t,s}^{DA} \\ \sum_{g\in G} -C_{SU}^{g} - C_{SD}^{g} - (a^{g} + e_{t,s}^{g} b^{g}) \\ -e_{t,s}^{up} \mathrm{Pr}_{t,s}^{up} - e_{t,s}^{dn} \mathrm{Pr}_{t,s}^{dn} \end{bmatrix} + \eta_s - \xi \geqslant 0 \; ; \eta_s \geqslant 0 \tag{5}$$

where, η_s is an auxiliary non-negative variable equals to the difference between auxiliary variable ξ and the profit, when the profit is smaller than ξ.

3.3. Formulation of lower-level problem

In the lower level, EVs are equipped with smart applications and can receive electricity prices from the PLs. Then, the owners can choose the cheapest PL to charge their EVs. To this end, EV owners and loads tend to minimize their costs as below:

$$Minimize \left[\hat{E}_t^{TCh} [pr_{w0,t}^{Ch} X_{w0,t,\psi}^{Ch}] + \sum_{\substack{w\in N_w \\ w\neq 0}} \hat{E}_t^{TCh} pr_{w,t,\psi}^{Ch} X_{w,t,\psi}^{Ch} + e_{t,s}^{D} pr_{w0,t}^{D} + E_{t,s}^{DN} pr_{w0,t}^{D} + \sum e_t^{R} pr_{w,w't,\psi}^{F} \right] \tag{6}$$

The EVs costs include the payments to the PL that is under the jurisdiction of the under-study VPP and the payments to the PLs of the rival VPPs. Also, the two second terms explain the costs of energy procurement of the responsive and non-responsive loads. The last term describes the reluctance of EV owners to the cheapest PL.

The reaction of responsive loads to the electricity price is obtained with the following relation:

$$E_{h,s}^{D} = D_t^{\mathrm{int}} \exp \sum_{h\in T} Elas_{t,h} \ln \left[\frac{\mathrm{Pr}_{h,s}^{DA}}{\bar{\mathrm{Pr}}_{h}^{DA}} + \frac{1}{1 + Elas_{t,h}^{-1}} \right] \tag{7}$$

where $Elas_{t,h}$ is the elasticity of demand of responsive loads, $\bar{\mathrm{Pr}}_h^{DA}$ denotes the average of DA market prices and D_t^{int} is the initial demand of responsive loads.

The lower level is restricted to the following constraints:

Constraint (8) discusses the share of the PLs of the VPPs to supply EVs.

$$x_{w,\psi} = X_{w,\psi}^{init,Ch} + \sum_{\substack{w\in N_w \\ w'\neq w}} y_{w,w',\psi} - \sum_{\substack{w'\in N_w \\ w'\neq w}} y_{w,w',\psi} : \phi_{\psi} \tag{8}$$

where, $X_{w,\psi}^{init,Ch}$ is the initial percentage of EVs supplied by each PL. Moreover, constraint (9) states that the total required demand of EVs should be supplied by the PLs of all VPPs.

$$x_{t,w_0,\psi} + \sum_{\substack{w\in N_w \\ w\neq w_0}} x_{t,w,\psi} = 100\% : \varepsilon_{w,\psi} \tag{9}$$

3.4. Decision-making model of the VPP

The problem discussed in the optimization unit consists of a bi-level problem that the two levels have inter-related objectives. The upper-level problem includes the VPP's decision making and the lower level problem contains the decision making of EV owners and loads. Such a decision-making conflict between the two levels of players is modeled as a bi-level problem in [34]. Then, this bi-level problem is converted to a single level mixed-integer linear programming (MILP) by implementing KKT conditions and the duality theorem [29–36]. Also, the non-linear term $e_{t,s}^{Ch}pr_{w0,t}^{Ch}$ is obtained as a linear expression as below:

$$e_{t,s}^{Ch}pr_{w0,t}^{Ch} = -\frac{E_{t,s}^{TCh}}{\widehat{E}_t^{TCh}}\sum_{\psi\in\Psi}\rho_\psi^{Ch}\left[\sum_{\substack{w\in N_w\\ w\neq 0}} pr_{w,t,\psi}^{Ch}x_{w,\psi}^{Ch} - \sum_{w\in N_w} X_{w,\psi}^{init.Ch}\varepsilon_{w,\psi}^{Ch} + \phi_\psi^{Ch}\right] \tag{10}$$

The variables $\varepsilon_{w,\psi}$ and ϕ_ψ are the Lagrange multipliers associated with the lower-level constraints.

3.5. Assessment metric for the performance of the VPP

Some of the uncertainties of the problem stem from the RESs that is considered in the scenario generation. Therefore, the results are obtained by considering all of the uncertainties including the uncertainties of RESs, loads, EVs and market prices. In order to assess the performance of the VPP to utilize its local resources, index of self-sufficiency factor (SSF) as the relative of its total expected generation to its demand is defined as:

$$SSF = \frac{\sum_{t\in T}\sum_{s\in N_s}\pi_s\left(E_{t,s}^{wind} + \sum_{g\in G} e_{t,s}^{g}\right)}{\sum_{t\in T}\sum_{s\in N}\pi_s(e_{t,s}^{D} + e_{t,s}^{Ch} + e_{t,s}^{Ch,0})} \tag{11}$$

This index indicates how much the local demand of the VPP is supplied by its local generation that reflects the dependency of the VPP on the main grid. So the SSF would be obtained as:

$$SSF = \begin{cases} 0 \ No\ Generation \\ 1 \ Generation = demand \\ <1 \begin{cases} Generation < demand \\ High\ \ demand \end{cases} \\ >1 \begin{cases} Generation > demand \\ Low\ \ demand \end{cases} \end{cases} \tag{12}$$

From (12), it can be seen that when SSF equals zero, it means that the VPP should supply its total demand from the main grid. When SSF is 1, the local generation can supply its local demand. When SSF is lower than 1, it means that its local demand is higher than its generation or the local generation is not sufficient to supply its loads. When the SSF is higher than 1, then the VPP coordinator may sell its surplus energy to the main grid. In this regard, two different conditions may occur:

- The local generation production is higher than the local demand. Such a condition may occur during high renewable generation, specifically when the penetration level of renewables is high.
- Total demand is very low so, the local loads do not consume the energy produced from the local generation. Even, in a competitive environment, the VPP may lose its load, because the prosumers may choose another rival VPP to supply their demand. In such condition, the VPP's local load reduces.

In both conditions, the VPP can sell its surplus generation to the main grid. Therefore, the SSF as a performance index can measure the portion of utilizing the local generations to supply the local loads and the dependency of the VPP from the main grid. In this regard, in the scenarios that wind generation is high, the dependency of the VPP on the main grid reduces. However, in the scenarios that the wind generation is low, the VPP operator should supply its required demand through the electricity market. Therefore, it is concluded that the uncertainty of wind generation as RES unit can affect the energy exchange of the VPP with the electricity market and even, it affects the generation of DG units. The higher the wind generation, the lower the purchased energy from the market and the lower the generated energy of DGs.

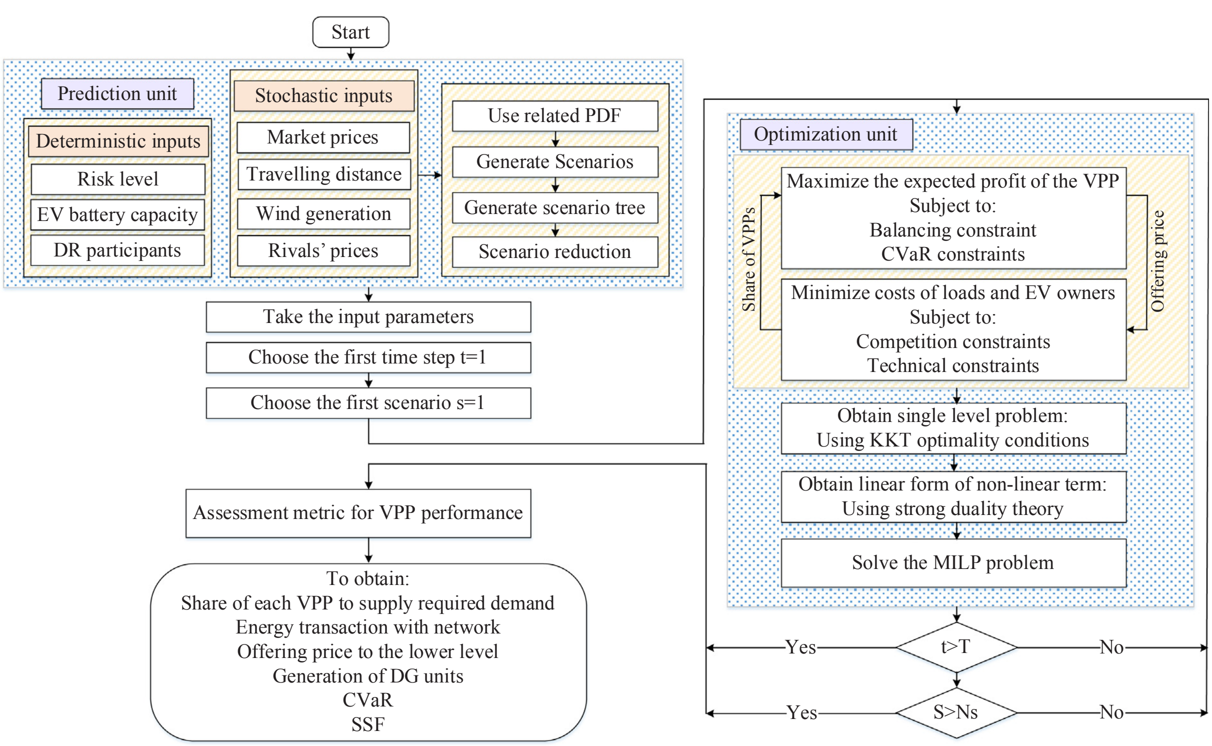

Fig. 2. Flowchart of scheduling problem of the VPP coordinator.

4. Problem methodology

In order to solve the stochastic bi-level problem, a prediction unit is considered in which the expected values of each uncertain item such as market prices, EVs travelled distance, wind generation, rivals' prices and demand of loads is forecasted. Fig. 2 illustrates the flowchart of the proposed method for solving the scheduling problem for the VPP. As observed, the structure of the offering strategy for the energy management of the VPP consists of two units including prediction and optimization units. To simplify analysis in this study, it is assumed that the forecast error statistics do not change significantly with time and thus can be approximated by a constant probability distribution. As seen in this figure, in the prediction unit, two groups of inputs are predicted. First, the deterministic parameters as the risk aversion parameter, DR participants and EVs battery capacity are considered. Then, the stochastic parameter such as DA and regulating market prices, EVs travelling distance, wind power generation and offering prices by rival VPPs are forecasted and then a number of scenarios are generated based on the forecasted values. In order to make the problem tractable, the generated scenarios are reduced to a limited set using *K*-means algorithm and then the selected scenarios are sent to the optimization unit as input data. More details about the scenarios are provided in Appendix B. The optimization unit receives the data of the electricity market, rivals' prices and the required demand of EVs from the prediction unit. The goal of the VPP operator is to maximize its expected profit from trading energy with the market and supplying loads and EVs. But, due to the presence of rival VPPs, EV owners' reaction to the prices offered by the rivals is also modeled through a bi-level program. This decision-making problem pertaining to the decision-making system of the VPP should jointly maximize the expected profit of the under-study VPP and minimize the total operation cost of the EV owners. This energy management system can be formulated as a bi-level problem, in which, in the upper level, the VPP operator maximizes its expected profit through energy transactions and in the lower level, EV owners try to choose the PL with lower charging prices to minimize their costs. Therefore, in the optimization unit, that is the combination of the two levels, the proposed bi-level problem is transformed into a MILP problem using KKT optimality conditions and strong duality theory [16]. In this regard, the steps required for such conversion are given as below:

1) The bi-level programming problem is transformed into an equivalent single-level nonlinear optimization problem through the KKT optimality conditions of the lower-level problem. KKT conditions are applied here since the lower-level problem is convex. In this regard, Lagrange function of lower level is obtained as bellow:

$$\begin{aligned} L = {} & \hat{E}_t^{TCh}\left[pr_{w0,t}^{Ch}X_{w0,t,\psi}^{Ch}\right] + \sum\nolimits_{\substack{w\in N_w\\ w\neq 0}} \hat{E}_t^{TCh}\, pr_{w,t,\psi}^{Ch}X_{w,t,\psi}^{Ch} + e_{t,s}^{D}pr_{w0,t}^{D} \\ & + E_{t,s}^{DN}pr_{w0,t}^{D} \\ & + \phi_\psi\left(X_{w,\psi}^{init,Ch} + \sum\nolimits_{\substack{w\in N_w\\ w'\neq w}} y_{w,w',\psi} - \sum\nolimits_{\substack{w'\in N_w\\ w'\neq w}} y_{w,w',\psi}\right) + \\ & \varepsilon_{w,\psi}\left(x_{t,w0,\psi} + \sum\nolimits_{\substack{w\in N_w\\ w\neq w_0}} x_{t,w,\psi}\right) \end{aligned} \tag{13}$$

Then, by taking partial derivation of the Lagrange function, the KKT optimality conditions would be obtained.

2) The bilinear production of the variables would be obtained by the linearization methodology explained in [33]. In this regard, the nonlinear complementary slackness conditions are given as linear expressions as bellow:

$$\hat{E}_t^{TCh}\, pr_{w0,t,\psi}^{Ch} - \varepsilon_{w0,\psi} - \phi_\psi \geq 0 \tag{14}$$

$$\hat{E}_t^{TCh}\, pr_{w0,t,\psi}^{Ch} - \varepsilon_{w0,\psi} - \phi_\psi \leq M_1 U_{w0,\psi}^{x} \tag{15}$$

$$\hat{E}_t^{TCh}\, pr_{w,t,\psi}^{Ch} - \varepsilon_{w,\psi} - \phi_\psi \geq 0 \tag{16}$$

$$\hat{E}_t^{TCh}\, pr_{w,t,\psi}^{Ch} - \varepsilon_{w,\psi} - \phi_\psi \leq M_1 U_{w,\psi}^{x} \tag{17}$$

$$x_{t,w,\psi} \leq M_2\left[1 - U_{w,\psi}^{x}\right] \tag{18}$$

where, $U_{w0,\psi}^{x}$ and $U_{w,w',\psi}^{y}$ are binary variables and M_1 and M_2 are large constants that are chosen such that not to lead ill-conditioning.

3) Also, the non-linear term $e_{t,s}^{Ch}pr_{w0,t}^{Ch}$ can be replaced by its linear expression using duality theory. Based on duality theory, the dual of the lower level problem can be obtained as bellow:

$$Maximize \sum_{w\in N_w}\left[X_{w,\psi}^{init,Ch}\phi_\psi + \varepsilon_{w,\psi}\right] \tag{19}$$

So, the linear form of $e_{t,s}^{Ch}pr_{w0,t}^{Ch}$ is achieved as bellow. More details can be found in [28].

$$e_{t,s}^{Ch}pr_{w0,t}^{Ch} = -\frac{E_{t,s}^{TCh}}{\hat{E}_t^{TCh}}\sum_{\psi\in\Psi}\rho_\psi^{Ch}\left[\sum_{\substack{w\in N_w\\ w\neq 0}} pr_{w,t,\psi}^{Ch}x_{w,\psi}^{Ch} - \sum_{w\in N_w} X_{w,\psi}^{init,Ch}\varepsilon_{w,\psi}^{Ch} + \phi_\psi^{Ch}\right] \tag{20}$$

In this regard, the bi-level problem is transformed into its single level model that can be implemented in GAMS using CPLEX solver.

5. Case study and numerical results

5.1. Case study description and input data

The proposed optimal decision-making strategy has been tested for a VPP portfolio comprising wind farms with an aggregated installed capacity equal to 10 MW, and residential consumers and two DG units. The operating costs of DG units are 27 and 29 €/MWh, and the maximum generation limits of DG units also are 2 and 4MWh, respectively [34]. Wind generation cost is null for the VPP. Also, there are about 300 EVs and the EV owners desire to charge their EVs with the lower charging prices. In this regard, in a smart grid paradigm, the EV drivers can choose the PL with the cheapest prices to minimize the charging procurement costs. Three VPPs are considered and each one owns one PL. The under-study VPP as a decision-maker is represented by VPP_0 and the rival VPPs are VPP_1 and VPP_2. The mean value of the offering price by the rival VPPs to the PLs under their jurisdiction is forecasted and prefixed as a percentage of DA prices [31]. Then the related scenarios are generated using normal PDF with the standard deviation of 10% [22]. Since the number of generated scenarios directly affects the computation complexity of optimization problem, it is needed to be reduced into a smaller number of scenarios representing well enough the uncertainties. To reduce the computational burden of the stochastic procedure, K-means algorithm is applied to mitigate the number of scenarios into a limited set providing well enough the uncertainties. Finally, 243 scenarios are selected as input to the program. Fig. 3 shows the electricity market price signals that are extracted from the Nordpool market [37], and demand of EVs and other customers' loads that about 40% of them are responsive and can adjust their consumption. It is supposed that the VPP operator plays as a price taker that affirms that its bids cannot affect the clearing price of the wholesale market. Also, the structure of liberalized power markets is considered which includes a DA market and a real-time market where unforeseen events can be balanced [38]. Bidirectional bids are allowed for the VPP in the electricity market. Therefore, it can both purchase and sell energy from/ to the grid. The scheduling time horizon is one day with the typical 24-h (even 1-h) time resolution. The proposed problem is developed using mixed-integer programming (MIP) and solved by CPLEX solver using GAMS software [39] on a PC with 4 GB of RAM and Intel Core i7 @ 2.60 GHz processor. It should be noted that with considering a MIP gap of 0%, the computation time for different studied cases was less than

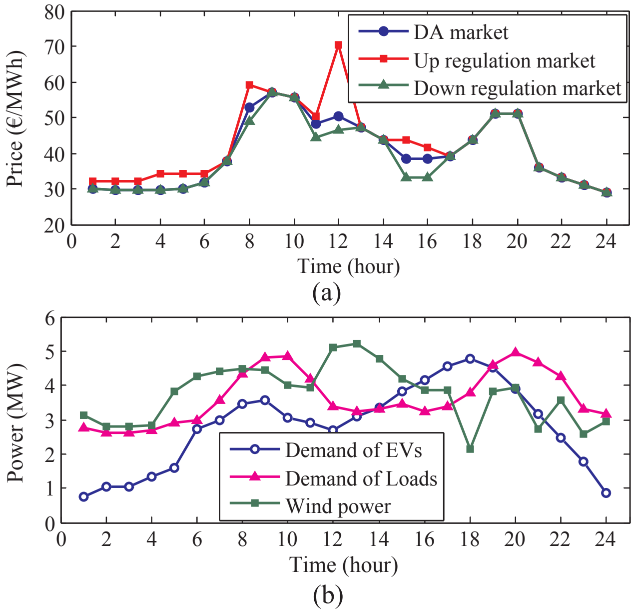

Fig. 3. (a) Market prices, (b) demand loads and wind energy.

four minutes [40].

5.2. Results and numerical discussions

Fig. 4 depicts the expected energy arbitrage of the VPP in the DA market. The VPP plays both roles of producer and consumer to sell and purchase energy to/from the DA market. Be noted that the VPP operator cannot sell and purchase energy at the same time. However, at each hour, it may purchase energy in some scenarios and sell it in other scenarios. Therefore, the expected energy exchange with the grid is brought in this figure. From Fig. 4, it is seen that DA energy transaction of the VPP with DA market, follows the wind production pattern, loads and DA prices. The VPP purchases energy during low DA price periods and low wind production such as night-time hours. While it sells energy to the DA market during all-day hours in order to open an opportunity to make a profit. Also, the VPP purchases energy from the DA market, during low DA market prices. Moreover, the VPP requires to participate in the regulation market when its generation/consumption pattern deviates from the settled one in the DA market.

Fig. 5 shows the expected quantities of surplus and deficit energy to be compensated in down and up-regulation markets. As expected, the VPP purchases the energy deficit when the electricity demand is high (18:00–24:00) or when the wind generation is low (during night hours). While it sells the energy surplus during 0:00–6:00 with low demand and during 12:00–14:00 with high wind generation. During (17:00–23:00) that the EVs are more likely to be plugged-in while wind generation is low, the VPP participates in up-regulation to purchase the energy deficit. Noted that simultaneous arbitrage in up and down-regulation market is prohibited, however, in some scenarios the VPP may confront with energy surplus that should be sold to the down-regulation market, while in some other scenarios the opposite happens. Although down-regulation prices are cheaper than the DA energy prices (Fig. 3 (a)), the VPP schedules a majority of down-regulation services to sell the surplus energy that it may obtain from its local generation such as wind or DG units.

All VPPs are assumed to offer charging prices to the PLs under their own jurisdiction aiming at the maximization of their profits. Then, the EV owners will decide which PL to choose according to the charging prices. On this basis, by comparing Figs. 6 and 7, it can be conceived that EVs charging energy is allocated during low price periods which results in a significant reduction in the cost of owners. However, it is observed that all PLs even if offer a high price, have at least a low demand. That is because of the unwillingness of the EV owners to shift among the PLs to charge their EVs.

Fig. 8 illustrates the generation power of DG units during scheduled horizon. Due to cheaper operating price of DG units than the DA market, the VPP schedules to commit both DG units. Therefore, both DG units are utilized not only to reduce the supplied loads from the market but also to sell their surplus generated energy to the market. Both DGs are committed with their maximum capacity specifically during the middle hours of the day. But, during the night time that the demand load is low and DA market prices are cheap, the VPP purchases energy from the DA market as seen in Fig. 4 (a).

Table 2 presents the effect of DR and risk aversion parameter on the expected profit, CVaR, SSF rate and energy transaction with the wholesale market. Because of limited space, the results for only three values of DR participants corresponding to the low, medium and high participation levels as DR = 0%, 40% and 80% are indicated. Also, different risk aversion levels for $\beta = 0.01$, 1, and 10 denoting relatively risk-neutral, medium and risk-averse behavior of the VPP coordinator are provided. In a fixed DR, with increasing β, as the concern on risk increases, the expected profit of the VPP reduces. In fact, in low values of β, the profits that are far from the mean value exist, however, with increasing β, those scenarios that are far from the mean value of the profit are eliminated. This shows the applicability of CVaR concept in which with increasing risk parameter, the lower values of profit with low probability are omitted. Therefore, CVaR can propose a relatively proper profit with high probability and low variance. So, the VPP coordinator can choose its desired level of risk aversion. Also, with increasing DR participants, the expected profit of the VPP increases because the participation of loads in DR programs can reduce the participation of VPP in the electricity market or even dispatching the DG units.

In this table, also the SSF is given in different β and DR participants. As seen, the SSF reduces with increasing DR participants. In fact, there are more loads who can reduce their demand. So, the generation units of the VPP such as wind and DGs are utilized less to supply all these loads. However, with varying risk-averse parameter, the SSF remains constant approximately.

Moreover, in Table 2, the energy transaction with the main grid is given. As more loads become responsive, they may shift to the hours when the local generation of the VPP is low. So, the VPP coordinator should enter the DA market and purchase the required energy.

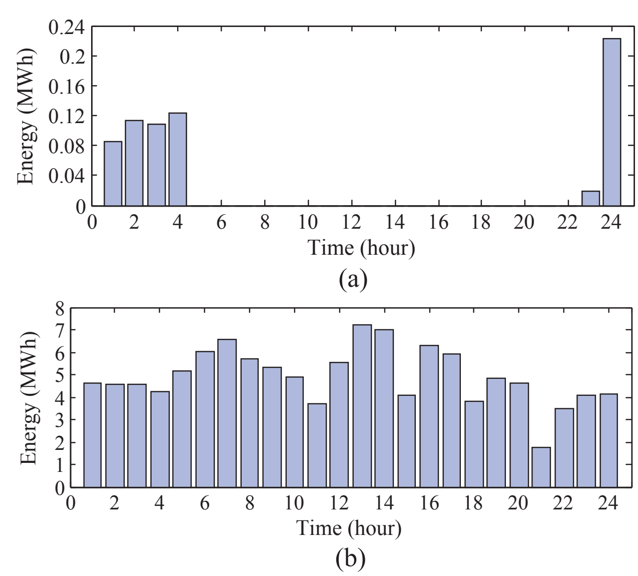

Fig. 4. Energy transaction with DA market (a) Energy purchasing (b) Energy selling.

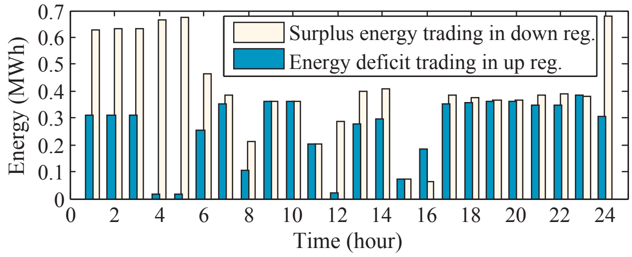

Fig. 5. Expected values of energy compensation in the regulation market.

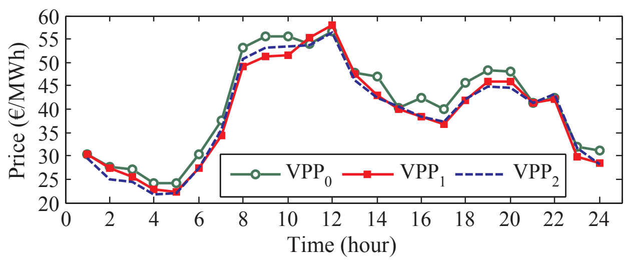

Fig. 6. Offering prices by all VPPs.

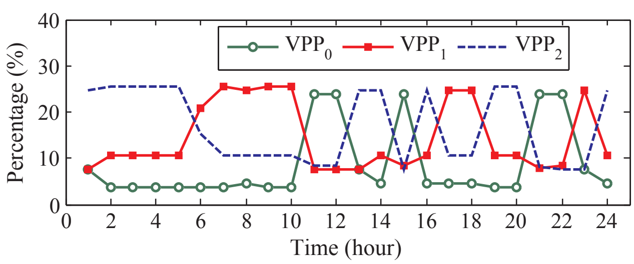

Fig. 7. Percentage of EVs demand supplied by the PLs of all VPPs.

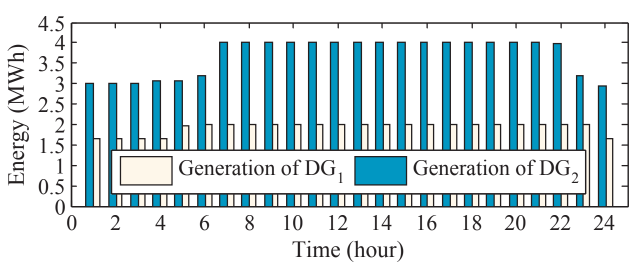

Fig. 8. Generation power of DG units during scheduled horizon.

Therefore, as expected, the energy selling to DA market reduces. Be noted that with increasing DR participants, the VPP coordinator may require more energy to supply the loads in up-regulation market, specifically during hours with a low generation of its local units. However, it may have a lower surplus generation to sell in down-regulation trading floor. Based on the proposed bi-level stochastic framework, the under-study VPP operator can optimally compute its selling prices and offer the parking lots under its jurisdiction. In the competitive market, the reaction of EV owners to the prices offered by the rival VPPs are also modelled. In this regard, client response to rivals' prices and competition among rival VPPs are both explicitly considered in the proposed bi-level model. Also, the sensitivity analysis for different values of DR participants and risk aversion parameters can give a collection of responses to the VPP operator. Practically, the VPP operator as decision maker find a compromise between the expected profit and the worst-case scenarios based on its own willingness.

Furthermore, with increasing β, as the VPP coordinator behaves more risk aversely, the energy purchase from the DA market augments, however, the energy selling reduces. The conservative VPP concerns about supplying its loads. So, with increasing β, the energy purchases from DA market increases in the hope of supplying more loads, while, the energy selling to DA market reduces due to the fear of confronting the energy deficit to supply the loads. Although, as the VPP coordinator becomes more risk-averse, its energy exchange with the regulation market approximately remains the same in all values of β. Finally, by implementing DR programs and including CVaR metric in the formulation problem, the VPP coordinator can choose its desired level of risk aversion and DR participants prior to the construction of its optimal bidding strategy.

Fig. 9 illustrates the hourly SSF associated with the scenarios with minimum profit (scenario 12), maximum profit (scenario 223), and the scenario with the highest probability (scenario 121) in β = 0.01 and DR = 40%. As observed, when the SSF is approximately the same, it means that internal generation can supply the share of the VPP in all scenarios. But when SSF value differs substantially, (i.e. during 0:00–7:00), either of the share of the VPP to supply the loads or its internal generation differs in the mentioned scenarios. In this regard, Fig. 9 (b) depicts the share of the VPP to supply the demand. As seen, the demand for VPP in all scenarios is the same for the whole day. So, the SSF differences natured from the internal generation. Therefore, the VPP coordinator can perceive that its achieved profit is due to selling the extra energy to the wholesale market and the VPP could not attract more loads from scenario to scenario in the competitive market. In other words, SSF can tell the VPP coordinator, if it was successful in the competitive environment and could attract loads or not.

Table 3 is provided to compare the results in the conditions without and with competition among the VPPs. As observed, without competitive conditions, the expected profit of the VPP is more than that of in the competitive environment. In fact, with the presence of rivals, the EV owners are allowed to choose their VPP in order to supply their vehicles. Therefore, the under study VPP operator may lose its expected profit due to losing its clients. In these conditions, the generated energy from the DG units is lower than that of when rivals exist. Also, the operator does not purchase energy from DA market, while it sells the

Table 2
Impact of DR participants and risk levels on the decision variables.

DR participant (%)	No DR (0)			Average (40)			High (80)		
Risk averse (β)	0.01	1	10	0.01	1	10	0.01	1	10
Total revenue	6843.02	6843.02	6842.76	8072.83	8072.96	8082.93	9217.749	9219.700	9237.007
Total costs	3962.34	3962.34	3962.09	4065.79	4065.94	4076.67	4117.019	4118.988	4137.605
Expected profit	2880.68	2880.68	2880.66	4007.03	4007.02	4006.26	5100.73	5100.71	5099.40
CVaR	10.33	10.33	10.35	46.63	46.84	46.92	65.73	66.07	66.21
SSF	2.81	2.81	2.81	2.21	2.20	2.20	1.79	1.79	1.78
DA purchases	0.11	0.11	0.11	1.00	1.03	1.03	2.99	3.02	3.02
DA selling	129.44	129.44	129.43	112.96	112.85	112.76	92.23	92.10	91.95
Up regulation	5.23	5.23	5.23	7.64	7.63	7.63	8.53	8.51	8.51
Down regulation	19.35	19.35	19.35	17.47	17.47	17.47	17.05	17.05	17.05
DGs' generation	132.9	139.2	132.9	132.5	132.5	132.9	130.9	130.9	131.5

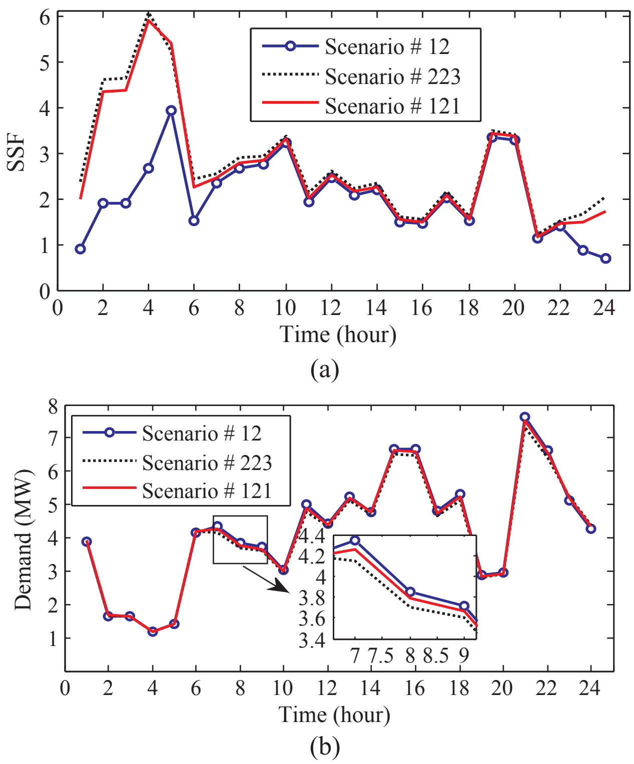

Fig. 9. (a) SSF in different scenarios (b) Supplied demand by the VPP.

surplus energy to DA trading floor. In a non-competitive environment, the SSF is higher than the SSF in competitive trading floor, that is because of the EV owners may transfer to the other VPPs when there are rivals. Moreover, in the state without considering the competition among the VPPs, since the operator does not confront the uncertainties of rivals' prices, lower values of CVaR is obtained.

5.3. Discussion

Based on the proposed bi-level stochastic framework, the under-study VPP operator can optimally compute its selling prices and offer the parking lots under its jurisdiction. In the competitive market, the reaction of EV owners to the prices offered by the rival VPPs are also modelled. In this regard, client response to rivals' prices and competition among rival VPPs are both explicitly considered in the proposed bi-level model. Through this bi-level framework, the competition among the VPPs is also considered in which, the EVs' behavior through their reluctance to change their PLs are modeled. Also, the sensitivity analysis for different values of DR participants and risk aversion parameters can give a collection of responses to the VPP operator. Practically, the VPP operator as decision maker finds a compromise between the expected profit and the worst-case scenarios based on its own willingness.

One of the real applications explained in this problem is the SSF index that is as the ratio of total expected generation of the VPP to its demand and is defined to assess how much the local demand of the VPP is supplied by its local generation (including both wind and DG units). This reflects the dependency of the VPP on the main grid that indicates the real application of the problem. So, in the scenarios that wind generation is high, the dependency of the VPP on the main grid reduces. However, in the scenarios that the wind generation is low, the VPP operator should supply its required demand through the electricity market. Therefore, it is concluded that the uncertainty of wind generation as RES units can affect the energy exchange of the VPP with the electricity market and even, it affects the generation of the DG units. The higher the wind generation, the lower the purchased energy from the market and the lower the generated energy of DGs.

6. Conclusions

This paper presented a risk-averse bi-level programming model for the competitive decision making of a VPP considering stochastic behavior of EVs owners and other smart customers in a competitive environment. In this model, the competitive bidding strategy of the VPP to attract EVs to charge inappropriate PLs under the jurisdiction of the VPPs was investigated. The results indicate that a suitable offering price in the PLs of the VPP can attract more EV owners and therefore, guarantee the VPP bidding strategy will result in high overall profits for the VPP. Moreover, the effect of DR participant and risk-averse decision making of the VPP on the SSF, expected profit and CVaR criteria were investigated. It was shown that as the VPP coordinator becomes more risk-averse, it may lose its demand and consequently its related profit. Finally, by implementing DR programs and including CVaR metric in the formulation problem and based on the SSF, the VPP coordinator can choose its desired level of risk-aversion and DR participants prior the construction of its optimal bidding strategy. Also, the VPP coordinator can perceive its successfulness in the competitive environment based on the values of the SSF metric. The sensitivity analysis for different values of DR participants and risk aversion parameters given in the results, provides a collection of responses to the VPP operator. Practically, the VPP operator as decision maker can find a compromise between the expected profit and the worst-case scenarios based on its own willingness.

It is worth pointing out that, even in the case that all VPPs use the same bidding strategy, their input data are surely different and also the number and data related to EVs differ for different VPPs. So, even all VPPs use the proposed program, it is still effective. For example, each VPP includes different resources. Therefore, the same bidding strategy that is applied by all VPPs, may lead to different results. The proposed framework can be separated into three main units including data collection and storage, prediction, and optimization units. The data collection and storage unit collect the information related to the demand of loads and EVs, market prices and rivals' offering prices and the data of resources of the VPP. Then, the prediction unit provides accurate forecasts of these uncertain resources. Different VPPs may use different methods to generate scenarios such as PDF and even time series. The outputs of the prediction unit are the scenarios related to the market

Table 3
Comparison between the two cases: without and with competition among the VPPs.

Risk aversion	DA purchase	DA selling	DG generation	Up regulation	Down regulation	Expected profit	SSF	CVaR
	Without competition							
β = 0.01	0	135.306	122.4	2.320	21.012	2897.867	3.64	10.063
β = 1	0	135.306	122.4	2.320	21.012	2897.867	3.64	10.063
β = 10	0	135.278	122.4	2.497	21.195	2897.80	3.64	10.09
	With competition							
β = 0.01	0.11	129.44	132.9	5.23	19.35	2880.68	2.81	10.33
β = 1	0.11	129.44	132.9	5.23	19.35	2880.68	2.81	10.33
β = 10	0.11	129.43	132.9	5.23	19.35	2880.66	2.81	10.35

prices, rivals' prices and demand of loads, charge and discharge of EVs as well as the data of energy resources with a small probability of prediction error. Based on this information, the optimization unit should solve the bi-level optimization problem to maximize the expected profit of the VPP while minimize the costs of the EV owners. The output of the optimization unit is the optimal bidding in electricity market and offering proper prices to the EV parking lots as well as satisfying system constraints. Therefore, it is observed that different inputs lead to different outputs.

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.

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Appendix A

Although, today's VPPs are equipped with advanced forecast procedures and can have a relatively perfect forecast about the future, they may confront with energy deviations due to the presence of uncertain resources such as wind and photovoltaic power and also the behavior of EVs owners. Therefore, the presence of a procedure to compensate the energy deviations is necessary. The market model of this paper is considered as a structure of joint DA and real time electricity market that is common in European electricity pools such as the Nordpool. In the DA market, the VPP schedules its energy resources and determines the offering/bidding power for each hour of the coming day before the gate closure (e.g. 12:00 pm). The VPP's energy imbalance due to the unpredictable fluctuations of power production or consumption should be compensated in the real time regulation market on the basis of a regulation price. The real time balancing price at time t and scenario s is represented by a pair of up and down regulation prices that can be calculated as a proportion of the DA market price ($\Pr_{t,s}^{DA}$) as follow:.

$$regulation\ price = \begin{cases} \Pr_{t,s}^{up} = (1 + \lambda_t^{up})\Pr_{t,s}^{DA} \\ \Pr_{t,s}^{dn} = (1 - \lambda_t^{dn})\Pr_{t,s}^{DA} \end{cases} \tag{1}$$

where, λ_t^{up} and λ_t^{dn} are positive constants that show the relationship between the DA price and up-regulation and down-regulation prices, respectively. In particular, the power shortage is purchased at an up-regulation price, which is usually higher than the DA price, while, the power surplus is sold at a down-regulation price, which is usually lower than the DA price [38]. Therefore, the dual pricing policy for balancing markets that are widely used in European pool markets is applied in the proposed framework of this paper.

Appendix B

In this paper, inaccuracies are considered as independent random variables. Stochastic properties of convolutions of independent random variables are of great importance and have been discussed extensively in the literature. In particular, stochastic comparisons of convolutions of random variables when they are independent but not identically distributed have been studied in [R24-R30]. In this paper, a large enough number of scenarios of each random variable are first generated by PDF models. For the convolution of independent random variables we descripted each random variables based on [R28] and [R29], and then density function of the sum of three independent random variables (i.e., wind output power and load demand), computed using a discrete convolution algorithm such as that found in [R30]. Based on this reference the PDF of the sum of the two discrete random variables, $Z = X_{wind} + X_{load}$, can be derived as follows. Given that the cumulative distributed function of Z can be written as:

$$P(Z \leqslant z) = F_Z(z) = \sum \sum_{x_{wind}+x_{load} \leqslant z} f_{X_{wind}+X_{load}}(x_{wind} + x_{load}) \tag{B.1}$$

The density function, assuming independence is

$$f_Z(z) = \frac{F_z(z)}{dz} = \sum_{x_{load}=0}^{u_{load}} f_{X_{wind}}(z - x_{load}) f_{X_{load}}(x_{load}) \tag{B.2}$$

where u_{load} is upper limit of x_{load}. The density of the sum of three independent discrete random variables, $Z = X_{wind} + X_{load} + X_{price}$, can be derived using substitution, by considering the sum of the X_{wind} and X_{load} to be as an independent discrete random variables X_1. So that $Z = (X_{wind} + X_{load}) + X_{price} = X_1 + X_{price}$. Using (2), the density of X_1 can be written as:

$$f_{X_1}(x_1) = \frac{F_{x_1}(x_1)}{dx_1} = \sum_{x_{load}=0}^{u_{load}} f_{X_{wind}}(x_1 - x_{load}) f_{X_{load}}(x_{load}) \tag{B.3}$$

Substituting (3) into (2), we obtain the density of $Z = X_{wind} + X_{load} + X_{price}$ as bellow:

$$f_Z(z) = \sum_{x_1=0}^{u_1} f_{X_{price}}(z - x_1). \left[\sum_{x_{load}=0}^{u_{load}} f_{X_{wind}}(x_1 - x_{load}) f_{X_{load}}(x_{load}) \right] \tag{B.4}$$

where u_1 is upper limit of x_1.

Appendix C. Supplementary material

Supplementary data to this article can be found online at https://doi.org/10.1016/j.ijepes.2020.106343.

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