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Optimal Decision Making Framework of an Electric Vehicle Aggregator in Future and Pool markets

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Abstract— An electric vehicle (EV) aggregator, as an agent between power producers and EV owners, participates in the future and pool market to supply EVs' requirement. Because of uncertain nature of pool prices and EVs' behavior, this paper proposed a two stage scenario-based model to obtain optimal decision making of an EV aggregator. To deal with mentioned uncertainties, the aggregator's risk aversion is taken into account using conditional value at risk (CVaR) method in the proposed model. The proposed two stage risk-constrained decision making problem is applied to maximize EV aggregator's expected profit in an uncertain environment. The aggregator can participate in the future and pool market to buy required energy of EVs and offer optimal charge/discharge prices to the EV owners. In this model, in order to assess the effects of EVs owners' reaction to the aggregator's offered prices on the purchases from electricity markets, a sensitivity analysis over risk factor is performed. The numerical results demonstrate that with the application of the proposed model, the aggregator can supply EVs with lower purchases from markets.

Keywords— Aggregator, Conditional Value at Risk (CVaR), Electric Vehicle, future market, Pool market.

Abbreviation

EV	Electric vehicle.
VaR	Value-at-risk.
CVaR	Conditional VaR .

Nomenclature

f	Index of forward contracts, running from 1 to N_F .
j	Index of blocks in the forward contracting curves, running from 1 to N_J .
$i_{ch/dsch}$	Index of blocks in the charge/discharge price-quota curves, running from 1 to $N_{i-ch/dsch}$.
t	Index of time periods, running from 1 to N_T .
ω	Index of scenarios, running from 1 to N_Ω .
C_t^F	Cost of purchasing from forward contracts in period *t* ($).
$C^P(\omega,t)$	Total cost of trading in the pool.
$E_{t\omega}^P$	The energy traded in scenario ω and period *t*.
$E_{t\omega}^{R\_ch/dsch}$	Energy supplied/bought by/from the aggregator in period *t* (MWh) in scenario ω.

P_f^F	Power contracted from forward contract *f* (MW).
P_{fj}^F	Power contracted from block *j* of forward contracting curve of forward contract *f* (MW).
$\lambda_i^{R\_ch/dsch}$	Selling/buying price associated with block *i* of the charge/discharge price-quota curve ($/MWh), Limited to $\overline{\lambda}_{i-1}^{R\_ch/dsch}$.
ζ	Auxiliary variable used to calculate the CVaR ($).
η_ω	Auxiliary variable related to scenario ω used to calculate the CVaR ($).
$v_{ich/dsch}^{ch/dsch}$	Binary variable. 1 if the selling/buying price offered by the aggregator to the EVs belongs to block *i* of the price quota curve, being 0 otherwise.
$\lambda_{t\omega}^{P}$	Electricity pool price in scenario ω and period *t*.
d_t	Duration of period *t* (h).
$\overline{E}_{ti\omega}^{R\_ch/dsch}$	Energy associated with block *i* of the charge/discharge price-quota curve in period *t* and scenario ω (MWh).
$\overline{P}_{fj}^F$	Upper limit of the power contracted from block *j* of the forward contracting curve of forward contract *f* (MW).
$\overline{\lambda}_{i,\min}^{R\_ch/dsch}$	Minimum selling/buying prices associated with block *i* of the price-quota curve of EVs ($/MWh).
λ_{fj}^F	Price of block *j* of the forward contracting curve of forward contract *f* ($/MWh).
α	Confidence level used in the calculation of the CVaR.
β	Weighting factor used to materialize the tradeoff between expected profit and CVaR.
$prob_\omega$	Probability of occurrence of scenario ω.
F_t	Set of forward contracts available in period *t*.
Ω	Set of scenarios.

I. INTRODUCTION

An electric vehicle (EV) Aggregator participates in electricity market to supply EVs' charging needs. During a medium-term planning time period, an aggregator may meet the unknown pool prices and EVs charge/discharge behaviors. Because these uncertain parameters can affect the aggregator participation in electricity market, they should be taken into account in the aggregator's decision making process. The medium-term decision making of the aggregator has been also formulated in some literatures to include the optimal involvement in the future market through forward contracts and pool markets [1]-[2] as well as the optimal setting of charge/discharge prices to the EV owners to maximize the expected profit from electricity dealing in different risk level of profit variation [3]-[4]. In [5], joint day-ahead scheduling and real-time regulations have been considered to investigate the uncertainties from electricity price and household device usages. Authors in [6] have proposed a new model for participation of electric vehicle parking lots in both energy and reserve markets in order to compensate renewable power production and load uncertainties. A framework with considering optimal charging of EVs which allows a retailer to have different alternatives for electricity procurement based on bilateral contracts is proposed in [7]. Authors of [8] have proposed different algorithms to find optimal charging rates of EVs inspecting maximum aggregator's profit. Reference [9] has provided a stochastic model for optimal decision making of an aggregator while [10] has done the same task using forecasting techniques for EVs' mobility such as availability and the desired energy during the scheduling period. In [11], it has been assumed that the aggregator suggests charge bids to day-ahead market with the objective of minimizing charging costs while satisfying the plug-in EVs' flexible demand. However, vehicle-to-grid mode has not been considered and it has been assumed that the aggregator could influence market prices in opposite to what is generally expressed in the literatures. EV aggregators' participation in energy and ancillary services markets has been analyzed in [12]. Authors of [13] have used stochastic programming techniques to consider uncertainties in prices via time-series models, and have utilized a conditional value-at-risk (CVaR) term [14] in their formulation. A scenario-based stochastic framework for obtaining optimal bidding and offering of a retailer in the presence of market price uncertainty with considering risk aversion and risk taking decisions is discussed in [15]. Plug-in EV load-serving entity with deterministic behavior of vehicles has been taken into account in the mentioned work. A methodology to maximize aggregator's profits in day-ahead and balancing markets with considering risk aversion, has been studied in [16]. Coordination of renewable energies and energy storage in energy and balancing markets has also been examined in [17] to show its benefits on the risk analysis. A stochastic optimization model for optimal bidding strategies of EV aggregators in day-ahead energy and ancillary services markets with variable wind energy has been assessed in [18]. Participation of energy producers in real-time and day-ahead electricity markets has been studied in [19] and [20], respectively. Authors in [21] modeled day-ahead and real-time energy and reserve markets as oligopoly markets with considering several uncertainties and constraints using a two-stage stochastic programing approach. In [22], the uncertainty of energy spot market prices, imbalance penalties, and wind power outputs have been considered to maximize the profits with considering CVaR. Reference [23] has focused on the optimal bidding of an aggregator subject to the optimal power flow and market clearing constraints without paying attention to the risk aversion associated with decision making of the aggregator. In [24], a game model has been presented to deal with the interactions between utilities and parking lots. The EV aggregators can participate in the spinning reserve market to control the variations of renewable power and load forecasting error. In this regard, the distribution system operator can control a fleet of EVs by charging signals in order to provide reserve to compensate the intermittency of renewable generation [25]. In [26], a stochastic programming approach is provided for a retailer who participates in a mixed bilateral-pool market. So, a two-stage operational framework is presented where the retailer and aggregator do their medium-term planning that is made one month prior to real-time market. A multi-objective stochastic framework for participation in the energy and up/down spinning reserve markets to schedule conventional generation units, bulk energy storages, and DR resources along with wind integration is proposed in [27]. Authors in [28] represented a stochastic robust optimization model in which uncertainties in day-ahead market prices and in the driving requirements of EVs are modeled using scenarios and confidence bounds, respectively. A two-stage stochastic programming model to concentrate the importance of uncertainty and risk in scheduling of plug-in EVs has been investigated in [29], without considering forward contracts. The problem of scheduling the plug-in electric vehicle aggregators in electricity market considering the uncertainties of market prices, EVs availabilities, and status of being called by the independent system operator in the reserve market is discussed in [30]. In [31], a stochastic approach has been represented for an EV aggregator offering regulation services to the electricity market. To this end, a predefined contract has also been assumed to be signed between the aggregator and the market operator which determines the regulation capacity to be provided by the aggregator at a predetermined price. An algorithm for day-ahead scheduling and a dynamic dispatch algorithm for distributing purchased energy to plug-in EVs has been presented in [32]. In this algorithm, electricity prices and Plug-in EV charging behavior have been considered deterministic. A mathematical programming with equilibrium constraints has been proposed in [33] and [34] to optimize the aggregator's decisions in energy markets. Authors in [33] have endogenously determined the profit-optimal price level subject to the cost minimizing charging schedule of the EV owners, but not the discharging process. A stochastic mathematical program with equilibrium constraints model for making optimal bidding strategies for wind power producers with considering risk management is investigated in [35].

In this paper, the problem of optimal decision making of an EV aggregator in a medium-term horizon under uncertain conditions is investigated. To this end, the aggregator is envisaged to maximize its expected profit by trading energy in the future and pool market as well as offering appropriate charge/discharge prices to the EV owners. However, in this context, the aggregator may face varying pool prices and stochastic EVs' behavior which can negatively affect the aggregator's profit. Thus to assess the influence of the indicated uncertainties on the expected profit of the EV aggregator, risk management approach is used. So the main highlights of this paper are as bellow:

- Proposing a two stage scenario based optimization model for optimal bidding strategy of an EV aggregator in a medium-term horizon,
- Utilizing CVaR as a risk measurement index in order to evaluate EV aggregator's financial risks and to inspect the influence of risk aversion in decision making process,
- Investigating the uncertainties due to pool prices and the forecast errors of EVs charge/discharge behavior as a set of probabilistic time-varying power using a scenario-based approach.
- Investigation the effects of EVs charge/discharge process on the energy procured by an aggregator for the EVs fleet by participating in the Future and pool markets.

The remaining sections are outlined as follows: section II describes decision making framework and market structure. Section III presents the problem formulation of decision making of an EV aggregator as a two-stage stochastic programming model and section IV provides numerical results. Finally, relevant conclusions are drawn in section V.

II. Decision Making Framework and Market Structure

A. Model description

In an electricity market, decision-making of an EV aggregator can be discussed similar to that of a retailer; however their inherent market behavior is different [36].Aggregators are entities who act independently and as a middleman combine dispersed EVs into a single purchasing group in order to negotiate on the behalf of individual EVs with the retailers to purchase electricity. Here, this agent is supposed to determine its optimal participation in the future market to control pool price volatility and EVs' stochastic behavior. Moreover, from an aggregator point of view, the future market contracting and the designation of charge/discharge prices offered to the EVs are medium-term decisions, while transactions in the pool market and EVs' participation level in charge/discharge services are decided in the short-term ones. The aggregator makes medium-term decisions at the beginning of the planning horizon while it makes short-time decisions during it. So, the difference between these groups of decision making is at the moment of their occurring. In this regard, two kinds of decisions can be introduced: *here-and-now* and wait-and-see decisions. Considering a two-stage stochastic programming model, *here-and-now* decisions are such decisions that are made in a deterministic way and without considering uncertainty. In a medium-term horizon, these decisions correspond to the forward contracting and charge/discharge prices determination. While, the decisions referred to as *wait-and-see* are made in an uncertain environment. Typically, the pool trading is supposed as a *wait-and-see* decision in medium-term. The problem of aggregator's participation in the future and pool markets in order to supply EVs demand with considering the effects of EVs reaction to the charge/discharge prices such that it maximizes the expected profit of the EV aggregator is proposed here. To this aim, the following assumptions are taken in to account:

- The aggregator provides the required energy to the EV owners in three ways: forward contracts, electricity pool market, and buying energy from EVs when they discharge.
- EV owners cannot buy energy from the electricity pool directly and they only procure their required energy from the aggregator.
- EV owners can discharge their EVs and sell the stored energy to the aggregator.
- The aggregator does not sell energy to the pool and it can only purchase energy from pool market.

B. Future Market Modeling

Typically, an aggregator participates in the future market with forward contracts to supply a part of the required energy for EV owners. In this market, the aggregator buys energy at a fixed price before selling to the EV owners. The aggregator takes prices from forward contracts based on contracting curve depicted in Figure 1.

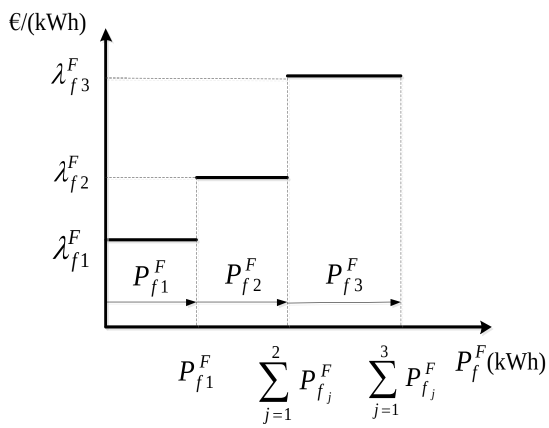

Figure 1.Forward contracting curve

Equation (1) states the cost of purchasing energy from forward contracts in each time period t that depends on the contracted power P_{fj}^F, energy price in each block of the forward contracting curve λ_{fj}^F, and d_t as the duration of period t. Constraint (2) expresses that the power purchased from each block of the forward contracting curve is positive and is limited within a bound. Finally, relation (3) describes the power purchased from each contract that is the sum of the powers bought from each block.

$$C_t^F = \sum_{f \in F_t} \sum_{j=1}^{N_J} \lambda_{fj}^F P_{fj}^F d_t \quad ;\forall t \tag{1}$$

$$0 \le P_{fj}^{F} \le \overline{P}_{fj}^{F}, \forall f, \forall j \quad (2)$$

$$P_{f}^{F} = \sum_{j=1}^{N_J} P_{f,j}^{F} \quad ; \forall t \quad (3)$$

C. Electricity pool market modeling

Here, it is supposed that the aggregator can purchase energy in the electricity pool in order to meet the energy for EV owners; however it is assumed not to sell back energy to the pool market. The cost of the energy traded in the pool is represented as follows [9]:

$$C^{P}(\omega,t) = \lambda_{t\omega}^{P} E_{t\omega}^{P} \quad (4)$$

where $C^{P}(\omega,t)$, $E_{t\omega}^{P}$ and $\lambda_{t\omega}^{P}$ are the total cost of trading in the pool, the energy traded and electricity pool price in scenario ω and period t, respectively.

D. Offering Charge/ Discharge Prices

The EVs are free to react to the price signals. Here, it is assumed that EVs behave elastically with respect to the charging/discharging price offered by the aggregator. The elastic behavior of the EV owners means that if the selling (buying) price is too high (low), EVs will choose a rival aggregator for their electricity supply (discharge). In fact, the EV aggregator competes with the other aggregators for retaining the EV customers as well as acquiring new owners. The relationship between the offered price and a fleet of EVs supplied by the aggregator can be modeled through a stepwise price-quota curve. A price-quota curve determines the amount of electricity provided (purchased) by (from) the aggregator and the associated price. These curves are estimated by the aggregator before solving the decision-making problem, and therefore, they are input data to the problem under consideration [37].

Here, the aggregator's bidding strategy for charging/discharging processes are modeled with price-quota curves. The buying and selling prices are bounded between their minimum and maximum limitations ($\overline{\lambda}_{i,\min}^{R\_ch/dsch}$ and $\overline{\lambda}_{i,\max}^{R\_ch/dsch}$ (\$/MWh)) and each block i illustrates the percentage of EVs participation that transact energy with their aggregator. As Figure 2 shows, when the offered charging price increases to $\overline{\lambda}_{i,\max}^{R\_ch}$, the energy provided for charge will decrease that shows the EVs' demand decrement. However, when charging price approaches to $\overline{\lambda}_{i,\min}^{R\_ch}$, EVs' demand augments as well. Opposite procedure is observed for discharge process. As discharge prices increases, EV owners are more willing to discharge their vehicles and obtain more advantage. The relationship between supplied/purchased power by the aggregator to/from EVs and the related prices, are given as a curve with these relations:

$$E_{ti\omega}^{R\_ch} = \sum_{i_{ch}=1}^{N_{i-ch}} \overline{E}_{ti\omega}^{R\_ch} v_{i}^{ch} \quad \forall t, \forall \omega \quad (5)$$

$$E_{ti\omega}^{R\_dsch} = \sum_{i_{dsch}=1}^{N_{i-dsch}} \overline{E}_{ti\omega}^{R\_dsch} v_i^{dsch} \quad \forall t, \forall \omega \tag{6}$$

$$\overline{\lambda}_{i-1}^{R\_ch} v_i^{ch} \le \lambda_i^{R-ch} \le \overline{\lambda}_i^{R-ch} v_i^{ch}, \forall i_{ch} \tag{7}$$

$$\overline{\lambda}_{i-1}^{R\_dsch} v_i^{dsch} \le \lambda_i^{R-dsch} \le \overline{\lambda}_i^{R-dsch} v_i^{dsch}, \forall i_{dsch} \tag{8}$$

$$\sum_{i\_ch=1}^{N_{i\_ch}} v_i^{ch} = 1 \tag{9}$$

$$\sum_{i\_dsch=1}^{N_{i\_dsch}} v_i^{dsch} = 1 \tag{10}$$

Where, λ_i^{R-ch} and λ_i^{R-dsch} are the charge and discharge prices offered to EV owners related to the block i of their price quota curves, respectively. $E_{ti\omega}^{R\_ch/dscch}$ indicates the transacted energy between EVs and aggregator in period t and scenario ω (MWh). $\overline{E}_{ti\omega}^{R\_ch/dsch}$ shows the energy associated with block i of the foresaid curves in period t and scenario ω (MWh). Equation (7) and (8) declare that both charge/discharge prices are limited between the minimum and maximum bounds of the blocks. Equation (9) and (10) guarantee that only one block is selected. Each block shows a particular offering charge or discharge price step. The offered charge/discharge prices depict the selected blocks. It should be noted that the aggregator can propose only one charge or discharge price to the owners.

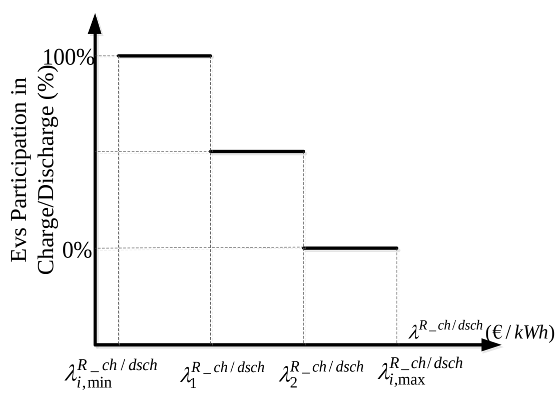

Figure 2. Price quota curve for EVs reaction to the offered prices

E. Scenario Tree of Decision Making framework

F.

The decision-making problem for aggregator participation in the future and pool market is outlined as follows:

1) *Determining forward contract and selling price:*

At the beginning of the planning horizon, the aggregator decides the forward contracts to be used during the planning horizon and the selling price offered to the clients. These decisions are made under uncertainty on the pool prices and the EVs demands.

2) *Trading in the pool by the aggregator:*

After fixing the forward contract and the selling prices, the aggregator decides the amount of energy that should be purchased in the pool to supply the EVs demands, in each period of the planning horizon. In fact, when forward contracting and price-setting decisions are made, the aggregator encounters the sources of uncertainty including: future pool prices and EVs demands. Here, it is assumed that the aggregator acts as a price-taker and the pool prices are independent of the aggregator's actions. Similarly, EVs demands are also unknown to the aggregator. So, a stochastic programming approach is proposed to solve the uncertainty on pool prices and EVs demands. In this problem, uncertain pool prices and client demands are modeled with a set of scenarios. Each scenario comprises a vector of pool prices and EVs demands as follows:

$$Scenario \quad \omega = \left\{\lambda^{\mathrm{P}}_{\mathrm{t}\omega}, E^{R\_ch}_{ti\omega}, E^{R\_dsch}_{ti\omega}\right\} \quad \forall t \in T$$

When the aggregator purchases energy from future market and wants to determine charge/discharge prices, EVs behavior and pool prices, as unknown sources to the aggregator, are represented by a set of scenarios. Let Ω introduce a group of scenarios and N_{Ω} state the number of scenarios in Ω. Each scenario ω includes a vector of pool prices, EVs charge/discharge required energy and occurrence probability shown with $prob_{\omega}$. Note that the sum of all probabilities in all scenarios is 1. This set of scenarios is arranged in a two-stage scenario tree as shown in Figure 3. The purchases from future market and the charge/discharge prices offered to the EVs are both decided at the first stage while buying in the pool market is determined at the second stage. Each scenario ω in the tree represents the realizations of the stochastic processes involved in the vector of pool prices and EVs demands. The probability of occurrence associated with each scenario is the product of the probabilities associated with each vector.

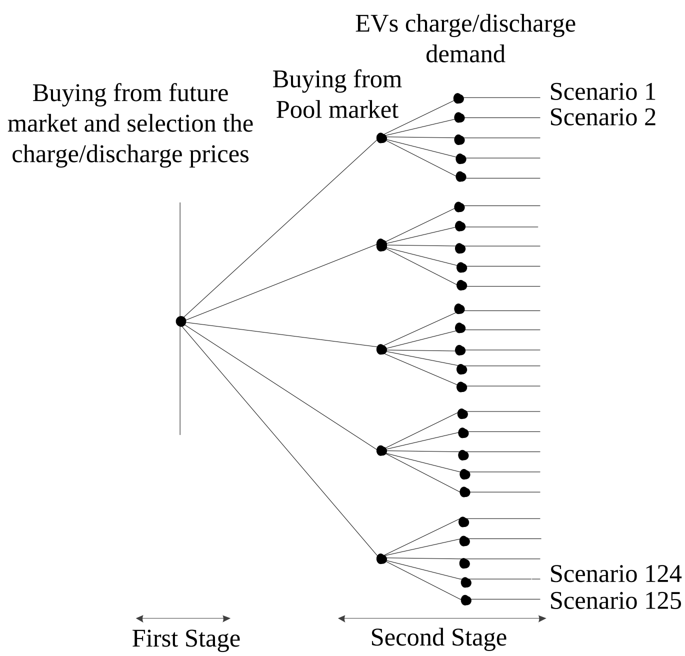

Figure 3. Sequence of aggregator decision making problem.

III. Problem Formulation

The aggregator tries to maximize its profit by selling electric energy to the EV owners. To this end, it buys energy in both pool and future market and also it can purchase energy from EVs when they discharge. The price of the energy in the pool in each period t is assumed to be unknown and is introduced as a random variable and is stated with a category of scenarios. The aggregator also participates in the futures market and buys energy in different forward contracts, f = 1, 2, … that are defined by a special price, λ_f^F. The profit is then defined as the revenue from selling electricity to the EV owners minus the purchase costs of forward contracts, the electricity pool and discharge of EVs. A two-stage stochastic programming problem is formulated here, with regard to the mentioned objective taking into account the CVaR:

$$Max:$$

$$\sum_{\omega=1}^{N_\Omega} prob_\omega \sum_{t=1}^{N_T} \Big(\sum_{i_{ch}=1}^{N_{i-ch}} \sum_{i_{dsch}=1}^{N_{i-dsch}} (\lambda_i^{R-ch} \overline{E}_{ti\omega}^{R-ch}) - (\lambda_i^{\text{R-dsch}} \overline{E}_{ti\omega}^{R-dsch}) - (\lambda_{t\omega}^{P} E_{t\omega}^{P}) - \sum_{f\in F_t} \sum_{j=1}^{N_J} \lambda_{fj}^F P_{fj}^F d_t \Big) + \beta \Big(\zeta - \frac{1}{1-\alpha} \sum_{\omega=1}^{N_\Omega} prob_\omega \eta_\omega \Big) \tag{11}$$

$$0 \le P_{fj}^F \le \overline{P}_{fj}^F, \forall f, \forall j \tag{12}$$

$$\overline{\lambda}_{i-1}^{R-ch} v_i^{ch} \le \lambda_i^{R-ch} \le \overline{\lambda}_i^{R-ch} v_i^{ch}, \forall i_{ch} \tag{13}$$

$$\overline{\lambda}_{i-1}^{R-dsch} v_i^{dsch} \le \lambda_i^{R-dsch} \le \overline{\lambda}_i^{R-dsch} v_i^{dsch}, \forall i_{dsch} \tag{14}$$

$$\sum_{i\_ch=1}^{N_{i\_ch}} v_i^{ch} = 1 \tag{15}$$

$$\sum_{i\_dsch=1}^{N_{i\_dsch}} v_i^{dsch} = 1 \tag{16}$$

$$\sum_{i_{ch}=1}^{N_{i\_ch}} \overline{E}_{ti\omega}^{R-ch} v_i^{ch} = \sum_{i_{dsch}=1}^{N_{i\_dsch}} \overline{E}_{ti\omega}^{R-dsch} v_i^{dsch} + E_{t\omega}^{P} + \sum_{f\in F_t} P_f^F d_t + E_t^{PC}; \forall t, \forall \omega \tag{17}$$

$$\zeta - \sum_{t=1}^{N_T} \Big(\sum_{i_{ch}=1}^{N_{i\_ch}} \sum_{i_{dsch}=1}^{N_{i\_dsch}} (\lambda_i^{R-ch} \overline{E}_{ti\omega}^{R-ch}) - (\lambda_i^{R-dsch} \overline{E}_{ti\omega}^{R-dsch}) - (\lambda_{t\omega}^{\mathrm{P}} E_{t\omega}^{P}) - \sum_{f\in F_t} \sum_{j=1}^{N_J} \lambda_{fj}^F P_{fj}^F d_t \Big) \le \eta_\omega, \forall_\omega \tag{18}$$

$$v_i^{ch} \in \{0,1\}, \forall i_{ch} \tag{19}$$

$$v_i^{dsch} \in \{0,1\}, \forall i_{dsch} \tag{20}$$

$$\eta_\omega \ge 0, \forall \omega \tag{21}$$

where α , β and η_{ω} are the confidence level, risk coefficient and auxiliary variable, respectively. The first term is the main profit objective and the second one is CVaR. The tradeoff between expected profit and CVaR is represented by β. Constraint (12) states the margin for the purchased power from block j of the forward contracts. Constraints (13)-(16) define the blocks of the charge/discharge price curves. Constraint (17) describes the energy balance in each period and scenario. Constraint (18) presents CVaR and finally, constraints (19)-(21) define the variables.

IV. NUMERICAL RESULTS

The mentioned formulation is tested with the electricity market data obtained from [1]. Here, it is supposed to have a parking lot with 100 charging plugs and the nominal capacity of each EV is 7.4 kWh. It is supposed that about fifty percent of these EVs will connect to the network. The characteristics of the forward contracts with six bidding-steps are provided in Table 1. EVs charge/discharge energy and pool prices are modeled using a set of scenarios defined over a normal distribution with forecasted mean as shown in Figure 4. The EVs loads are obtained from [34] and the range of pool prices and forward payments are also extracted from [1]. In order to model the forecast inaccuracies stem from the uncertain nature of pool prices and EVs charge/ discharge demand, normal Probability Distribution Functions (PDF) is used. In this case, the mean values are equivalent to the forecasted values of prices and EVs demand. Then the PDFs are divided into five discrete intervals with different probability levels as illustrated in Figure 4. The forecasted errors correspond to the mentioned uncertain resources are given by intervals equal to the standard deviation. The forecast error probabilities are normalized and filled out over the range of between 0 and 1. The generated scenarios are combined all-against-all, resulting in a vector of independent random variables but the size of the tree grows exponentially. Therefore, an effective scenario reduction algorithm proposed in [37] is applied. The generated scenarios for each variable are reduced by Roulette Wheel Mechanism and then the reduced scenarios associated with the variables are combined through a scenario tree. The confidence level α is 0.95 and the problem is solved by CPLEX 10.2 solver [38] using GAMS software [39].

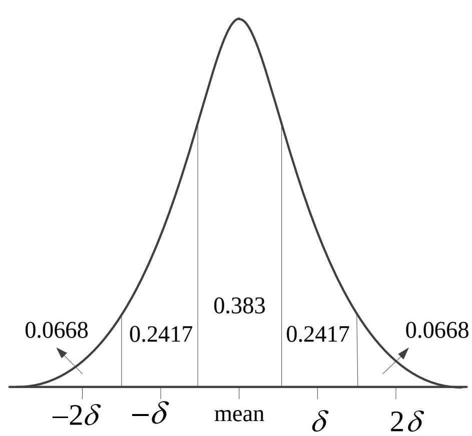

Figure 4.Five segment approximation of normal distribution

TABLE 1. FORWARD CONTRACT DATA

Contract #	λ_f^F (€/kWh)	P_f^F (kWh)
1	0.0650	15
	0.0630	10
	0.0650	15
	0.0630	10
	0.0650	15
	0.0630	10
2	0.0655	20
	0.0630	10
	0.0655	20
	0.0630	10
	0.0655	20
	0.0655	20

EVs' responses to charge/discharge prices are presented by price quota curves shown in Figure 5 and Figure 6, respectively. The range of prices associated with the charge/discharge price quota curves are extracted from [1]. The two curves depict that EVs' charge/discharge behaviors are variable because of changes in the charge/discharge prices. As can be seen from Figure 5, within a specific price limitation, majority of EVs contribute in charge process however for higher prices the aggregator may lose its demand. Likewise, from Figure 6, it is observed that if discharge price increases, more EVs will participate in discharge service, so the aggregator can buy energy from EV owners with lower prices instead of purchases from electricity market with higher prices and in this case, it can improve its profit. As described before, an aggregator requests to investigate the purchases from forward contracting, pool market and discharge of EVs, in order to maximize its expected profit while satisfying EVs' demand.

In order to inspect the effects of uncertain parameters on the expected profit of the aggregator, risk control is considered as an important factor. In this regard, Figure 7 illustrates the variation of expected profit against CVaR for different values of β. As expected, the highest expected profit is achieved for β = 0 that shows the highest risk. The expected profit for β =15 decreases 12.6% to obtain an increment of 21.35% in CVaR. The frontier representing the expected profit versus the CVaR for different values of β and shows that high values of CVaR are associated with lower expected profit that is resulted from different EVs reaction to charge/discharge prices.

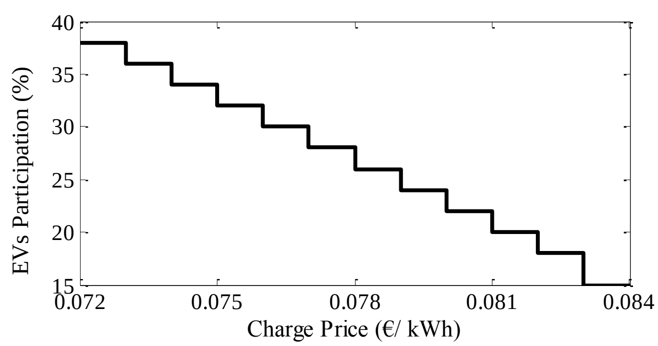

Figure 5.Charge price quota curve

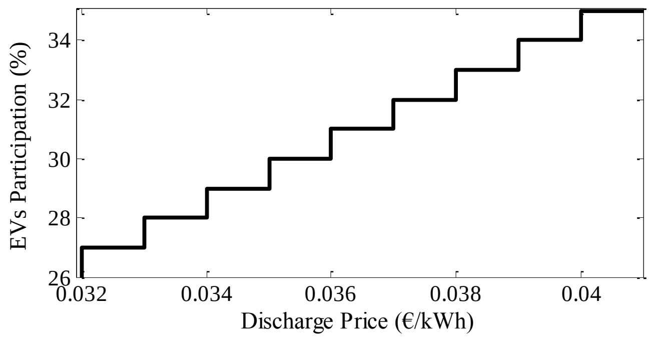

Figure 6. Discharge Price quota curve

Table 2 represents EVs participation in charge/discharge processes. For more risk aversion conditions, EVs' demand reduces with increasing β. So the aggregator tries to buy energy from future market with fixed prices. Since the future prices are on average more expensive than pool prices, as Figure 7 shows, the aggregator's expected profit decreases and consequently it tries to compensate the losses of its income. Therefore it sells energy to EVs with higher charge prices as β augments. The results show that with increasing β from 0 to 0.5, EVs participation in discharge mode increases to 32%. Also, further increase of β (up to 1), results in an increase in the charge price which in turn affects the contribution of EVs owners' and the aggregator's benefit. By growing β up to 5, EVs participation in charge process declines while the opposite happens in discharge mode. In fact, the aggregator investigates to buy more energy from EVs with lower prices than those offered in the market. In this regard, it saves its payments. For β=10 and 15, it is observed that a few owners ask the aggregator for charge services (about 18% and 15%, respectively) and the majority of customers might find another aggregator with better offers. It is also observed from Table 1 and Table 2 that discharge prices (λ_i^{R-dsch}) are lower than the forward contracting prices (λ_f^F). In other words, it can be seen from Table 1 and Table 2 that the aggregator pays to EV owners with lower discharge prices than the forward ones. So, it can be advantageous for it to buy energy from EV owners in addition to forward contracts. As we know, generally, with increasing β, the aggregator tries to participate in the future market to buy electricity and as the result to control the volatility of pool prices. In fact, it tries to control risk due to the indeterminacy of pool market by participating in the future market. Here, with considering discharging mode for EVs, by considering more risk aversion and increasing CVaR, the expected profit decreases. So, the aggregator tries to propose higher charge/discharge prices to the EVs to avoid substantial decrement of its expected profit.

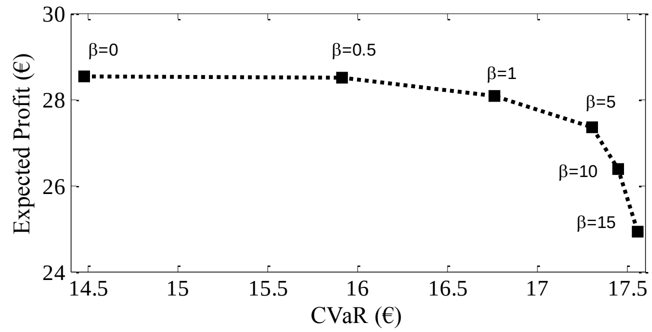

Figure 7. Variation of Expected Profit versus CVaR in different β

Table 2. EVs participation in charge/discharge process and the offered charge/discharge prices.

β	$\lambda_i^{R\_ch}$ **(€/kWh)**	**Charge participation**	$\lambda_i^{R\_dsch}$ **(€/kWh)**	**Discharge participation**
0	0.079	24%	0.036	30%
0.5	0.079	24%	0.038	32%
1	0.080	22%	0.039	32%
5	0.081	20%	0.039	33%
10	0.082	18%	0.039	33%
15	0.084	15%	0.039	33%

Moreover, as EVs demand decreases, the aggregator requires buying less energy in the future and pool markets as illustrated in Figure 8 and Figure 9, respectively. The reason is that the aggregator tries to increase the charging prices to compensate its expected profit. Since the aggregator lost its customers due to high offered charging prices, it requires buying less energy from both forward and pool markets. Also it pays the EV owners for their discharge with lower prices than the price of forward contracts. In this case, its expected profit would not decrease severely (see Figure 7). Moreover, it should be mentioned that since the aggregator can participate in the pool market during the day, it does not require buying high amount of energy from this market. In fact, if the number of EVs asking for charge services exceeds (compared to what is estimated) or less EVs are accessible for discharge mode, then the aggregator can attend pool market and purchase its required energy in order to compensate the extra energy that EVs require.

To explain generally, at the beginning of the planning horizon, the aggregator decides to choose the forward contracts as Figure 8 shows and it gives charging/discharging price signal offered to the EV owners as provided in Table 2. They are both considered as *here-and-now* decisions. At the first stage, these decisions were made under uncertainty of pool prices and EVs demands. After fixing the forward contract and the selling/ buying prices, the aggregator decides the amount of energy that should be purchased in the pool to supply EVs demands, in each period of the planning horizon. The amount of energy that should be purchased from pool market in different βs is illustrated in Figure 9. Pool prices and client demands refer to *wait-and-see* decisions and are made after uncertainty is revealed.

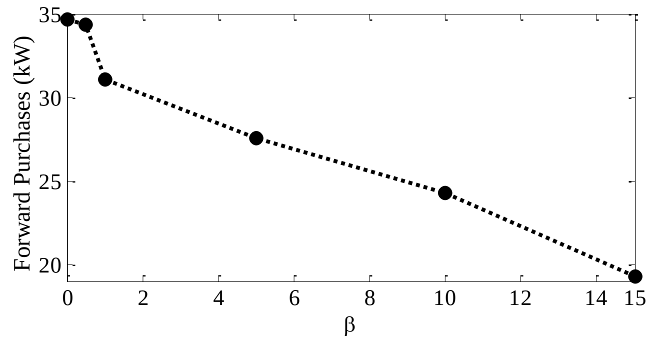

Figure 8. Procured power from forward contracts versus β

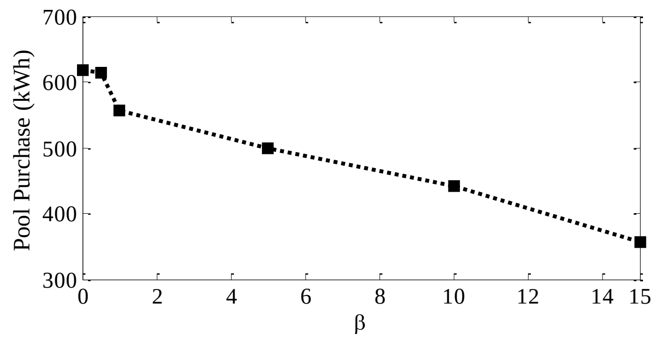

Figure 9.Variation of purchased energy in pool market versus β

The obtained revenues associated with charge process accompanied with the costs of discharge, forward and pool purchases for different βs are provided in Table 3. With increasing β, as it was mentioned in Table 2, the participation of EVs in charge process is decreased. Accordingly, the expected revenue is reduced from 128.792€ for β=0 to 85.589€ for β=15. This revenue mitigation makes the aggregator sell the electricity to EVs with higher charge prices as it was given in Table 2. With increasing β, the aggregator offers higher discharge prices and consequently, its payment due to discharge process increases. However, as the average of discharge prices offered to the owners is not higher than charge prices and also lower number of EVs usually participate in discharge mode compared with charge one, the payments due to discharge are very lower than charge revenue. In addition, with increasing β, the payments in future and pool markets decrease about two times. It is because of high charge price that leads to loosing EVs demand. Moreover, the owners are motivated to sell back the energy of their batteries because of high discharge prices. To show the possibility of experiencing losses, Table 4 illustrates the simulation results for β=15 in all scenarios with regard to aggregator's profit. As it is observed, in scenarios 14 and 15, the profit values are negative which mentions financial losses to the aggregator. This is very probable in β=15 as the aggregator increases its proposed prices to the owners and consequently, it loses its revenue because of losing its customers due to high offered charge prices and high discharge payments. Figure 10 illustrates the expected profit against the standard deviation of the profit in different βs. It should be noted that the decisions made by the aggregator have an important effect on the variability of the profit. If the aggregator considers EVs involvement in charge/discharge mode instead of more purchases from forward contracts to increase its revenue, the volatility of its profit occurs much more in higher βs than that if it depends more on the future market which occurs in lower βs. In this context, as Figure 10 shows, with increasing β, the profit standard deviation grows up. That is because the aggregator considers EVs responses to the charge/discharge prices. So, the unpredictability of EVs behavior may influence the aggregator's expected profit and the decisions determined by it for buying from forward contracts. Thus, inspecting the uncertain nature of EVs behavior for decision making in the forward contracts is a reason of profit volatility.

Table 3. The Expected revenues ($) and costs ($) of the aggregator for different βs

β	R^{ch} **(€)**	C^{dsch} **(€)**	C^{F} **(€)**	C^{P} **(€)**
0	128.792	6.509	52.391	41.369
0.5	128.792	7.328	51.892	41.069
1	119.553	7.328	46.902	37.246
5	110.043	7.756	41.663	33.273
10	100.262	7.756	36.674	29.450
15	85.589	7.756	29.189	23.716

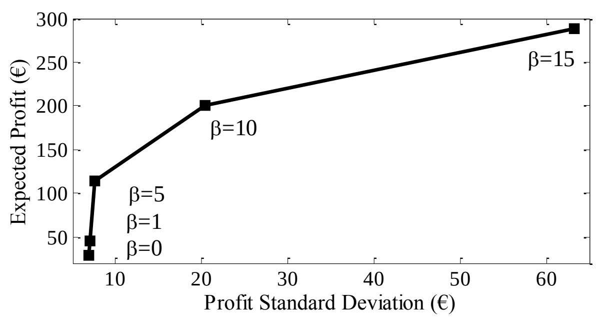

Figure 10 Expected profit against profit standard deviation in different βs

Table 4. Profit in all scenarios in β=15

Scenario	**Profit (€)**				
$\omega_1 - \omega_5$	301.023	303.187	305.899	298.864	296.452
$\omega_6 - \omega_{10}$	297.468	298.864	300.490	296.084	294.743
$\omega_{11} - \omega_{15}$	109.039	294.526	295.078	-74.196	-156.373
$\omega_{16} - \omega_{20}$	304.580	307.518	311.315	301.646	298.164
$\omega_{21} - \omega_{25}$	308.146	311.849	316.747	304.437	299.885

Sensitivity analysis is carried out to investigate the effect of EVs discharging on the forward and pool purchases. In this regard, the reaction of EVs to three different cases are considered: base case that was shown in Figure 5 and Figure 6, case 1 which denotes 10% decrease in EVs participation compared to the base case, and case 2 which shows 10% increase in EVs participation. Table 5 shows the result of future and pool procurements, the charge/discharge prices offered to EV owners and their participation percentage in different β values. It is observed that with increasing β, the aggregator purchased lower amount of electricity from future and pool markets and it bought energy from EV owners. Moreover, in all three cases, it offers charge prices to the EV owners not more than 0.084 (€/kWh), else it may lose its customers. Also, in case 2 (with 10% increment in EVs participation), in β=15, about 36.3% of EVs discharged their vehicles and the aggregator bought the lower amount of power from future market. Thereafter, the aggregator tried to buy more energy from EVs instead of future and pool markets.

Table 5 Sensitivity analysis of EVs reaction to discharge process

Base Case						
β	**Future purchase**	**Pool purchase**	$\lambda_i^{R\_ch}$	**charge participation (%)**	$\lambda_i^{R\_dsch}$	**discharge participation (%)**
0	34.650	617.870	0.079	24%	0.036	30%
0.5	34.320	613.736	0.079	24%	0.038	32%
1	31.020	557.081	0.080	22%	0.039	32%
5	27.555	498.358	0.081	20%	0.039	33%
10	24.255	441.702	0.082	18%	0.039	33%
15	19.305	356.718	0.084	15%	0.039	33%
Case 1 10% (decrease in EVs participation)						
β	**Future purchase**	**Pool purchase**	$\lambda_i^{R\_ch}$	**charge participation (%)**	$\lambda_i^{R\_dsch}$	**discharge participation (%)**
0	35.640	630.270	0.079	24%	0.036	27%
0.5	35.376	626.963	0.079	24%	0.038	28.8%
1	32.076	570.307	0.080	22%	0.038	28.8%
5	25.344	455.342	0.082	18%	0.039	29.7%
10	20.394	370.359	0.084	15%	0.039	29.7%
15	20.394	370.359	0.084	15%	0.039	29.7%
Case 2 (10% increase in EVs participation)						
β	**Future purchase**	**Pool purchase**	$\lambda_i^{R\_ch}$	**charge participation (%)**	$\lambda_i^{R\_dsch}$	**discharge participation (%)**
0	34.155	611.670	0.079	24%	0.036	33%
0.5	33.792	607.123	0.079	24%	0.038	35.2%
1	30.492	550.467	0.080	22%	0.038	35.2%
5	27.010	491.538	0.081	20%	0.039	36.3%
10	23.710	434.882	0.082	18%	0.039	36.3%
15	18.760	349.898	0.084	15%	0.039	36.3%

V. Conclusions

This paper proposed a two-stage stochastic programming model for effective participation of an EV aggregator in the future and pool markets. The optimal aggregator's decision making process was considered as an optimization problem to specify the forward contract purchases and to offer optimal charge/discharge prices to EV owners on a medium-term planning horizon in the first stage. In this way, a number of prominent uncertainties such as pool prices and EVs behavior were also investigated in the second stage. The risk aversion of the aggregator was modeled by CVaR of the profit. The effects of EVs response to charge/discharge prices on the forward contracting and pool procurements were also inquired. It was shown that the aggregator tried to buy from EV owners instead of buying from forward contracts to avoid substantial decrement of its expected profit. Moreover, a sensitivity analysis was carried out to see the effects of EVs discharge mode on the forward and pool purchases.

The results revealed that with increasing the EVs contribution in discharge process, less energy is needed to be purchased from forward market. Also, if the number of EVs augments, the aggregator should buy more energy from forward and pool market in order to supply EVs demand, because the obtained energy from discharging EVs might not be enough to supply the EVs requirements.

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