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Scheduling Electric Vehicle Fleets as a Virtual Battery under Uncertainty using Quantile Forecasts

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***Abstract*—Electric vehicles have significant potential to reduce their charging costs by participating in electricity markets through electric vehicle smart charging. However, one of the main barriers to electric vehicle participation in an electricity market is the high uncertainty in their availability at the market gate closure time. Not accounting for this uncertainty when making market bids could result in high imbalance costs. This study proposes a method to determine the optimal bidding strategy for a fleet of electric vehicles under uncertainty using a scenario-based stochastic optimization algorithm. This model considers both the uncertainty in electric vehicle availability and uncertainty in imbalance prices in the electricity market, as well as the risk-aversiveness of aggregators to high charging costs using the conditional value-at-risk. It proposes to model the electric vehicle fleet as a virtual battery, and to use a set of quantile forecasts of the virtual battery parameters to account for the uncertainty in electric vehicle availability. The effectiveness of the proposed model is evaluated by testing it on an actual case study fleet. The results indicate that it is crucial to consider both the expected charging costs and the conditional value-at-risk when determining market bids for an electric vehicle fleet under uncertainty.**

***Index Terms*—Electric Vehicles, Virtual Battery, Stochastic Optimization, Quantile Forecasts, Conditional Value-at-Risk**

I. Introduction

The rapid adoption of Electric Vehicles (EVs) will have considerable impact on the future electricity system. Growth in the number of EVs will not only increase the total electricity demand to fulfil their charging needs, but will also introduce a high number of decentralized assets with high flexibility into our electricity system [1].

Due to the high charging power of most EVs, the connection time of an EV in many cases largely exceeds the time required to fully charge the vehicle. As a consequence, it is possible to shift the EV charging demand over time using the concept of *smart charging*. Different applications for EV smart charging have been studied, including i) the reduction of CO_2-emissions of a charging session [2], [3], ii) the mitigation of grid congestion and power quality problems [3], [4], iii) higher self-consumption of renewable energy [5] and iv) the provision of balancing reserves [6]. Also, due to the existence of Time-of-Use (ToU) tariffs for electricity, the charging costs of EV owners or Charge Point Operators (CPOs) can be reduced through EV smart charging.

CPOs or affiliated aggregators should make bids to one of the electricity markets to be able to cost-optimize the charging demand of a fleet of EVs based on ToU tariffs. Most electricity is traded on the day-ahead market, which usually has a Gate-Closure Time (GCT, i.e., the last moment until market participants can make a bid) of 12-36 hours before operation. The large time horizon between the GCT and actual operation is one of the main barriers to participate in a day-ahead market using a fleet of EVs, since there is uncertainty at the GCT on the future charging demand and flexibility of the EV fleet. Real-time delivery deviating from the bids to the electricity market might be inevitable if the actual EV charging demand and flexibility are different than the forecasted values. These deviations could result in high imbalance costs.

For this reason, the uncertainty in the charging demand and flexibility of an EV fleet should be considered when determining electricity market bids for this EV fleet. Different studies have proposed methods to schedule the charging of EVs under uncertainty. The work in [7] & [8] proposed a stochastic optimization method to schedule a single EV under uncertainty. However, since the charging power of a single EV is too small to meet the minimum required bid size for electricity markets, these methods cannot be used to determine an optimal market bidding strategy. Other studies proposed methods to make bids to electricity markets for an

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EV fleet under uncertainty, but these studies either solely focused on the uncertainty in EV availability [9] or on the uncertainty in market prices [10], [11]. The works in [12]–[15] considered both the uncertainty in electricity market prices and in the charging demand and departure time of EV charging transactions, but did not consider the uncertainty in the number of EV charging transactions. The work in [16], [17] optimized the charging demand of a fleet of EVs using a virtual battery approach and added noise around the virtual battery parameters to account for the uncertainty in the number of EVs charging, as well as the charging demand and the arrival/departure time of all EVs.

This literature review indicates that only few EV scheduling models are presented in scientific literature that consider uncertainty in the number of EVs charging, in the charging demand of EVs and in electricity market and imbalance prices. Besides, the use of forecasting techniques to schedule EVs under uncertainty is understudied. This study presents a novel method to determine the optimal bidding strategy for an EV fleet to the day-ahead electricity market, considering all aforementioned uncertainties. It proposes to model the EV fleet as a virtual battery and to use quantile forecasts of the parameters of this virtual battery as inputs for a novel scenario-based stochastic optimization model. This work proposes to consider the Conditional Value-at-Risk (CVaR) in the optimization model, to account for the risk-aversiveness of CPOs to downside tail-risks (i.e., high charging costs).

Sections II and III introduce the concept of a virtual battery for EV modelling and the CVaR, respectively. The methodological framework is presented in Section IV. The considered case study and the model simulations conducted in this paper are outlined in Section V. The results of this study are presented in Section VI. Lastly, the discussion and conclusion are presented in Sections VII and VIII.

II. Virtual Battery for EV modelling

The charging schedule of a fleet of EVs can be optimized efficiently by modelling this EV fleet as a virtual battery [9], [18]. This approach assures that the charging demand of all EV charging transactions is satisfied. The charging characteristics of a set of charging transactions (i.e., arrival time, departure time, charging demand and maximum charging power) are translated to one virtual battery with three parameters for each timestep: a minimum aggregated charging energy (E_{min}), a maximum aggregated charging energy (E_{max}) and a maximum aggregated charging power (P_{max}). The three parameters of the virtual battery are determined as follows:

- E_{min}: This parameter represents the minimum aggregated charged energy volume to assure that the charging demand of every EV is met at the moment of departure. It is determined by summing the charged energy in a 'latest charging' scenario at every timestep for every charging transaction. This scenario represents the case in which an EV delays its charging until the latest possible moment to still meet its charging demand before departure.
- E_{max}: This parameter represents the maximum aggregated energy that can be charged at a specific timestep. The value of this parameter at each timestep is based on the summed charging energy for all charging transactions in a scenario in which an EV charges at maximum power directly after arrival until its charging demand is met.
- P_{max}: This parameter represents the maximum available charging power for a specific EV fleet and is based on the summed maximum charging power of all EVs connected to a charging station at a specific timestep.

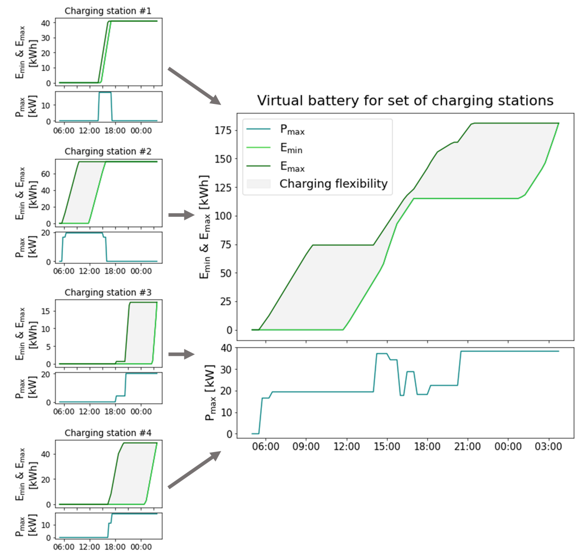

Fig. 1. Example of a EV virtual battery for one day, formed from charging data from 4 charging stations. 6am is the start/end time of the assessment timeframe.

Fig. 1 provides an example of a virtual battery for one day. It is visible that E_{min} and E_{max} increase during the day and that these values converge at the end of the day.

Using a virtual battery reduces the computational burden of optimizing the charging schedule of an EV fleet, since the number of variables in the optimization problem is significantly reduced. In contrast to the optimization of individual charging transactions, no optimization variables are required for each individual charging transaction. Instead, the charging schedule of a fleet of EVs can be optimized using one variable for the whole EV fleet.

Another reason for using a virtual battery approach in a study is that it provides an insight in the *overall* charging demand and flexibility of an EV fleet, rather than of single EV charging transactions. If a CPO or an aggregator makes a bid to an electricity market, it does so for a whole EV fleet, and is thus only interested in the overall uncertainty in charging demand and flexibility of this EV fleet for the next day. For this reason, this paper will consider the uncertainty in the virtual battery parameters to get insight in the uncertainty in the overall flexibility of an EV fleet.

III. Conditional Value-at-Risk

The CVaR is a risk metric providing insight in the downside tail-risk of the objective function [19]. Depending on whether a cost or revenue perspective is taken, CVaR measures the

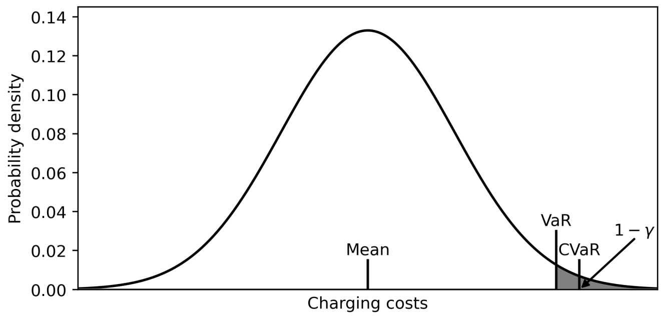

Fig. 2. Graphical illustration of the CVaR.

expected losses at the right tail or the expected gains at the left tail in the worst case scenarios. Since the financial stability of CPOs or aggregators could be affected by unexpected high charging costs, this study considers the CVaR in an optimization problem to minimize this risk.

Considering a confidence level γ, the CVaR represents the expected charging costs of the $(1-\gamma)\times 100\%$ scenarios with the highest charging costs. This is an extension of the Value-at-Risk (VaR), which presents the maximum charging costs at confidence level γ. This is illustrated in Fig. 2. The mathematical formulation of an optimization problem using the CVaR is presented in Section IV-D.

IV. Methodology

This research proposes a novel method to determine the optimal market bids of an EV fleet to an electricity market under uncertainty, and will analyze the effectiveness of this method. The method is generic and can be applied to any EV fleet size. The required methodological steps to conduct this analysis are discussed below.

A. Step 1: Virtual battery creation

In the first step of this analysis, historical transaction data of a fleet of EVs are translated to a virtual battery for every considered day. A virtual battery is created for a 24-hour period, since bids to the day-ahead market are for most regions, including Netherlands and most countries in Europe, are made for a 24-hour ahead period and the optimization of EV charging schedules therefore happens for this time horizon. All charging transactions starting between the selected start/end time of the day of this 24-hour period are considered in the virtual battery of a specific day.

B. Step 2: Scenario generation

The two main sources of uncertainty when making bids to an electricity market for a fleet of EVs are the availability of EVs and the electricity market prices. To account for the uncertainty in EV availability, this study considers a set of $\mathcal{V}$ virtual battery scenarios for each day in the analysis timeframe. Electricity day-ahead market prices can be forecasted with relatively high accuracy and are therefore out of scope in the present study. However, imbalance prices (i.e., prices in case of a deviation from the market bid) are highly volatile and therefore unpredictable, since these prices depend on imbalance volumes caused by stochastic events, such as a power plant outage. In addition, the spread in imbalance prices is considerably higher than the spread in electricity day-ahead market prices, resulting in the risk of high imbalance costs. Therefore, the risk in electricity market prices is accounted for by considering a total of $\mathcal{P}$ imbalance price scenarios for each day in the analysis timeframe.

Each possible combination of a virtual battery scenario and an imbalance price scenario will be considered in this analysis. Hence, the total number of considered scenarios for each day ($s \in S$) in the analysis timeframe equals $\mathcal{V} \times \mathcal{P}$.

1) Virtual battery scenarios

Quantile forecasts of the virtual battery parameters are used as inputs for the virtual battery scenarios. For each day in the analysis timeframe, quantile forecasts of the virtual battery parameters are generated for constant intervals between the 1% and the 99% quantile, where E_{min}, E_{max} and P_{max} are forecasted separately. Different forecasting methods can be used to generate the quantile forecasts.

These quantile forecasts are used to generate the virtual battery scenario set $\mathcal{V}$. It is well-known that the quantile function of a univariate continuous variable applied to a uniformly-distributed sample between [0,1] can be used to obtain a sample from the original distribution. This is because the cumulative distribution function (being the inverse function of the quantile function) of a continuous random variable follows a uniform distribution [20]. Acting as a quantile function conditional on regressors, quantile forecasting bridges the uniformly distributed target quantiles to the probability distribution of a point forecasted variable. As long as the target quantiles are sampled uniformly with a sufficient granularity, a full probability distribution can be effectively captured. For this reason, using the set of generated quantile forecasts as the virtual battery scenario set $\mathcal{V}$ provides a scenario set that is representative for the probability distribution. For each scenario in $\mathcal{V}$, we assume the same target quantile for forecasts of each of the three virtual battery parameters and for each timestep during the day.

2) Imbalance price scenarios

Given the highly stochastic and erratic nature of imbalance prices, no quantile forecasting is used to generate the imbalance price scenarios. The set of imbalance price scenarios is generated using random sampling of historical imbalance price deltas. The imbalance price delta represents the difference between the day-ahead electricity market price and the imbalance price, and are used since the absolute value of imbalance prices are highly related to the day-ahead price. For every imbalance price scenario in $\mathcal{P}$, the imbalance price deltas of a randomly selected historical day are used. Subsequently, these imbalance price deltas are added to the day-ahead market prices of the considered day in the analysis timeframe to generate the imbalance prices in that specific scenario.

C. Step 3: Data post-processing

Since E_{min}, E_{max} and P_{max} are forecasted separately, there could be some discrepancy between the forecasts that would make the optimization model infeasible. For this reason, different data post-processing steps for each virtual battery quantile forecast are conducted to correct for this:

- Forecasts with a negative value are changed to 0 for all three considered parameters.
- If a forecasted value of $\mathrm{E_{min}}$ is higher than $\mathrm{E_{max}}$ at a certain time, the value of $\mathrm{E_{min}}$ is changed to $\mathrm{E_{max}}$.
- Since $\mathrm{E_{min}}$ & $\mathrm{E_{max}}$ remain constant or increase during the day (see Section II), a forecasted value of $\mathrm{E_{min}}$ or $\mathrm{E_{max}}$ at time t that is higher than the value at time $t+1$ is changed to the value at time $t+1$.
- If $\mathrm{E_{min}}$ and $\mathrm{E_{max}}$ do not converge at the last timestep of a virtual battery of one day, the value of $\mathrm{E_{min}}$ at this timestep is changed to the value of $\mathrm{E_{max}}$ at this timestep.
- Forecasts of $\mathrm{E_{min}}$ using high quantile target values could provide high forecasted values at the first timesteps of a virtual battery, which would make the model infeasible. The value of $\mathrm{E_{min}}$ is set at 0 for the first 1.5 hours of the day, since high values of $\mathrm{E_{min}}$ at the first timesteps of the day are unrealistic, as this would mean a high number of EVs with high charging demand arriving and shortly after departing during the first hours of the day.

D. Step 4: Model formulation

A scenario-based stochastic linear optimization model is proposed to determine the optimal bids to the electricity day-ahead market for a fleet of EVs. An important parameter in this model is β, which reflects the risk-aversiveness of the CPO or aggregator to upper tail-risks, associated with high charging costs (fully risk-averse to downside tail-risks β=1, fully risk-neutral to downside tail-risks, β=0).

$$\min_{\substack{\mathrm{c_{exp}},\mathrm{c_{CVaR}},\mathrm{c_{VaR}},\\ \mathrm{c_{DA}},\mathrm{c_{imb}},\mathrm{p_{ch,DA}},\\ \mathrm{p_{imb}},\mathrm{p_{ch}},\mathrm{e_{ch}},\sigma_s}} \quad (1-\beta)\mathrm{c_{exp}} + \beta \mathrm{c_{CVaR,\gamma}} \tag{1a}$$

$$\text{s.t.} \quad \mathrm{c_{exp}} = \mathrm{c_{DA}} + \sum_{s=1}^{S} \pi_s \mathrm{c_{imb,}}_s, \tag{1b}$$

$$\mathrm{c_{DA}} = \sum_{t=1}^{T} (\lambda_{\mathrm{DA},t} \mathrm{p_{ch,DA,t}}) \Delta \mathrm{t}, \tag{1c}$$

$$\mathrm{c_{imb,}}_s = \sum_{t=1}^{T} (\lambda_{\mathrm{imb},s,t} \mathrm{p_{imb,s,t}}) \Delta \mathrm{t} \ \forall s, \tag{1d}$$

$$\mathrm{p_{imb}}_{,s,t} = \mathrm{p_{ch,RT}}_{,s,t} - \mathrm{p_{ch,DA}}_{,t} \ \forall s,t, \tag{1e}$$

$$0 \le \mathrm{p_{ch,RT}}_{,s,t} \le \mathrm{P_{max}}_{,s,t} \ \forall s,t, \tag{1f}$$

$$\mathrm{E_{min}}_{,s,t} \le \mathrm{e_{ch}}_{,s,t} \le \mathrm{E_{max}}_{,s,t} \ \forall s,t, \tag{1g}$$

$$\mathrm{e_{ch}}_{,s,t} = \mathrm{p_{ch,RT}}_{,s,t} \Delta \mathrm{t} \ \forall s, t \in \{1\}, \tag{1h}$$

$$\mathrm{e_{ch}}_{,s,t} = \mathrm{e_{ch}}_{,s,t-1} + \mathrm{p_{ch,RT}}_{,s,t} \Delta \mathrm{t} \ \forall s, t \in \{2,...,T\}, \tag{1i}$$

$$\sigma_s \ge (\mathrm{c_{DA}} + \mathrm{c_{imb,}}_s) - \mathrm{c_{VaR,\gamma}} \ \forall s, \tag{1j}$$

$$\sigma_s \ge 0 \ \forall s, \tag{1k}$$

$$\mathrm{c_{CVaR,\gamma}} = \mathrm{c_{VaR,\gamma}} + \frac{1}{1-\gamma} \sum_{s=1}^{S} \pi_s \sigma_s, \tag{1l}$$

$$0 \le \mathrm{p_{ch,DA,t}} \le \max\{\mathrm{P_{max}}_{,s=1,t}, \ldots, \mathrm{P_{max}}_{,S,t}\} \ \forall t. \tag{1m}$$

Depending on the value of β, the objective in (1a) is defined as an utility function to minimize weighted sum of the expected charging costs ($\mathrm{c_{exp}}$) and the CVaR ($\mathrm{c_{VaR,\gamma}}$) of the charging costs. In case of a fully risk-averse CPO or aggregator to downside tail-risk, it tries to minimize the charging costs in a worst-case scenario, reflected by $\mathrm{c_{CVaR,\gamma}}$.

$\mathrm{c_{exp}}$ is defined in (1b), which considers both the costs in the day-ahead market for electricity ($\mathrm{c_{DA}}$) and the expected imbalance costs over all scenarios ($\mathrm{c_{imb,s}}$), where π_s represents the probability of scenario s. Equation (1c) defines $\mathrm{c_{DA}}$, which is based on the day-ahead market bid ($\mathrm{p_{ch,DA,t}}$) and the day-ahead market price ($\lambda_{\mathrm{DA},t}$) at each timestep in the assessment timeframe. Δt in this equation represents the timestep duration. The imbalance costs in scenario s are formulated in (1d), which depends on the imbalance volumes ($\mathrm{p_{imb,s,t}}$) and the imbalance prices ($\lambda_{\mathrm{imb},s,t}$) at each t.

Imbalance occurs if the real-time charging power in a scenario ($\mathrm{p_{ch,RT}}_{,s,t}$) deviates from the day-ahead market bid, as formulated in (1e). This can happen due to i) beneficial imbalance prices or ii) a violation of $\mathrm{E_{min}}$, $\mathrm{E_{max}}$ or $\mathrm{P_{max}}$ for a specific scenario. The constraints for $\mathrm{p_{ch,RT}}_{,s,t}$ and the accumulated charging energy at time t in scenario s are presented in (1f)-(1i). $\mathrm{c_{CVaR,\gamma}}$ is defined using constraints (1j)-(1l). $\mathrm{c_{CVaR,\gamma}}$ represents the expected charging costs above quantile γ in the distribution of charging costs over all scenarios and can be calculated using the auxiliary variable σ_s. If the day-ahead and imbalance costs in scenario s exceed the γ quantile of the charging costs distribution (i.e., the VaR, $\mathrm{c_{VaR}}$), σ_s equals this difference, as outlined in (1j). Otherwise, σ_s equals 0 (1k). $\mathrm{c_{CVaR,\gamma}}$ is determined in (1l) by adding the average values of σ_s to $\mathrm{c_{VaR,\gamma}}$, where the term $\frac{1}{1-\gamma}$ corrects for the fact that σ_s is zero if the day-ahead and imbalance costs in a scenario are below $\mathrm{c_{VaR,\gamma}}$. Lastly, the day-ahead bid is bound by the highest forecasted value of $\mathrm{P_{max}}$ for all scenarios in (1m).

V. Case study introduction & simulation outline

This study uses EV charging data from 22 charging stations with 2 charging points between 9 January 2019 and 17 November 2019 as an input for this analysis. These charging stations are located at residential areas in the city of Utrecht, the Netherlands. The charging data contains the arrival and departure time of the EV, as well as the charged energy and the maximum charging power of each transaction.

EV virtual batteries for every day of this period were created using 6 am as the start/end time, as this was the start/end time at which the largest share of EV charging transactions of the day where the charging could be met (>98%).

The model performance was evaluated using a 17-day assessment period between 1 November 2019 and 17 November 2019. For every day in the assessment period, quantile forecasts for the virtual battery were generated using the Gradient Boosting method available in the scikit-learn library [21] in Python, using an optimized set of hyperparameters for each parameter. Historical virtual battery data up to the specific day in the assessment period was used to train the model. The following 14 features were considered in the model:

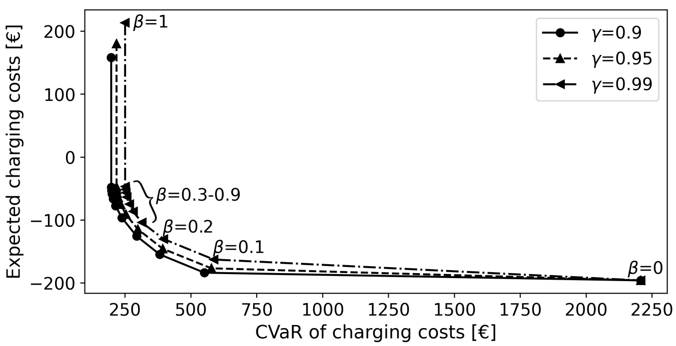

Fig. 3. Efficient frontier of total expected charging costs and CVaR of charging costs during the assessment period for different values of β & γ.

- *Date/time characteristics:* 1. Hour of day, 2. Whether the day is a weekend day, 3. Whether the day is a school holiday, 4. Whether the day is a public holiday.
- *Historical virtual battery parameter values:* 5. One day ago, 6. Two days ago, 7. Three days ago, 8. Week ago, 9. Average weekly value at same time, 10. Average monthly value at same time and day of week.
- *Day-ahead weather forecasts from [22]:* 11. Average daily temperature, 12. Average daily wind speed, 13. Total precipitation volume, 14. Number of sunshine hours.

An increment interval at 1% between 1% and 99% is used to sample the target quantiles, resulting in 99 virtual battery scenarios for each day in the assessment period. A total of 300 imbalance price scenarios was used for each day in the assessment period, hence the size of the scenario set $\mathcal{S}$ for each day of the assessment period equaled $99 \times 300 = 29700$. Equal weight was assumed for every scenario. The imbalance price scenarios were created by randomly sampling days of imbalance prices for the Netherlands between 1 January 2015 and 31 October 2019. The study also used day-ahead market prices for the Netherlands.

The model simulations for each day in the assessment period were performed in Python using the Gurobi solver [23], considering a 15 minute resolution. Different values of β and γ were considered in the analysis to generate an efficient frontier of the expected charging costs and the CVaR.

VI. Results

Fig. 3 presents the efficient frontier of the expected charging costs and the CVaR for different values of β and γ. The top left and bottom right points represent the global minimum CVaR and global minimum expected charging costs, respectively. In line with expectations, a higher risk level (i.e., lower value of β) decreases the expected charging costs but increases the CVaR. In case of a fully risk-neutral CPO or aggregator for downside tail-risks (β=0), the total expected charging costs during the assessment period equal -€196 euro, but the worst case total charging costs, reflected by the CVaR, equal €2207. The expected charging costs are negative due to revenues from the provision of passive balancing services. On the other hand, a fully risk-averse CPO or aggregator for downside tail-risks (β=1) has a considerably lower CVaR of €198-€250 (depending on γ), but the expected charging costs are significantly higher (€158-€213). The CVaR increases and the expected charging costs decrease with higher values of γ.

Considering both the expected charging costs and CVaR in the objective function (i.e., any value of β between 0-1) results in expected charging costs and a CVaR close to their optimal values. For instance, shifting from β=0 to β=0.1 reduces the CVaR by €1620-€1655, while expected charging costs only increase by €12-€32. Similarly, shifting from β=1 to β=0.9 considerably reduces the expected charging costs, while the increase in CVaR is negligible. This highlights the importance of considering both expected charging costs and CVaR in the charging optimization process.

Fig. 4 provides insight in the effect of different values of β on day-ahead market bids and imbalance volumes. A risk-neutral CPO or aggregator for downside tail-risks (β=0) bids at the maximum possible charging power for most timesteps (Fig. 4b). This is mostly induced by high average imbalance prices at these timesteps (Fig. 4a), causing the high negative average imbalance volumes (Fig. 4c) that are required to meet the virtual battery constraints reduce the expected charging costs. This explains the high CVaR with β=0, since these high negative imbalance volumes could considerably increase charging costs if imbalance prices are not beneficial. If the CVaR is (partly) considered in the objective function, day-ahead market bids are considerably lower to avoid the risk of high negative imbalance volumes.

VII. Discussion

This study proposed to model an EV fleet using a virtual battery, using forecasts of the imbalance prices and virtual battery parameters to account for main sources of uncertainty a CPO or aggregator faces when bidding in the day-ahead market. If CPOs or aggregators want to use this concept in practice when making bids to an electricity market, they should develop a method to allocate the aggregated charging demand of a virtual battery among individual EVs. Besides, CPOs and aggregators should be aware of the fact that this method can slightly underestimate charging costs [3]. Future work could expand the methods proposed in this study by including vehicle-to-grid (V2G) services and by considering to adjust market bids in intraday markets based on novel forecasts.

One of the main novelties of this study is the use of quantile forecasts to generate scenarios as input to the scenario-based stochastic optimization model. Given the fact that the cumulative probability of any continuously distributed random variable follows a uniform distribution, a scenario set based on a large number of target quantiles can provide insight in the probability density function of a particular point forecast, as long as the set of quantile forecasts reasonably covers the whole set of uniformly distributed target quantiles (i.e., between 1-99%), and that the quantile forecasts are performed with constant increments with sufficient granularity between the target quantiles. The time series forecasts used in each scenario in this study assumed the same quantile level for every timestep of the day. In practice, this could vary during the

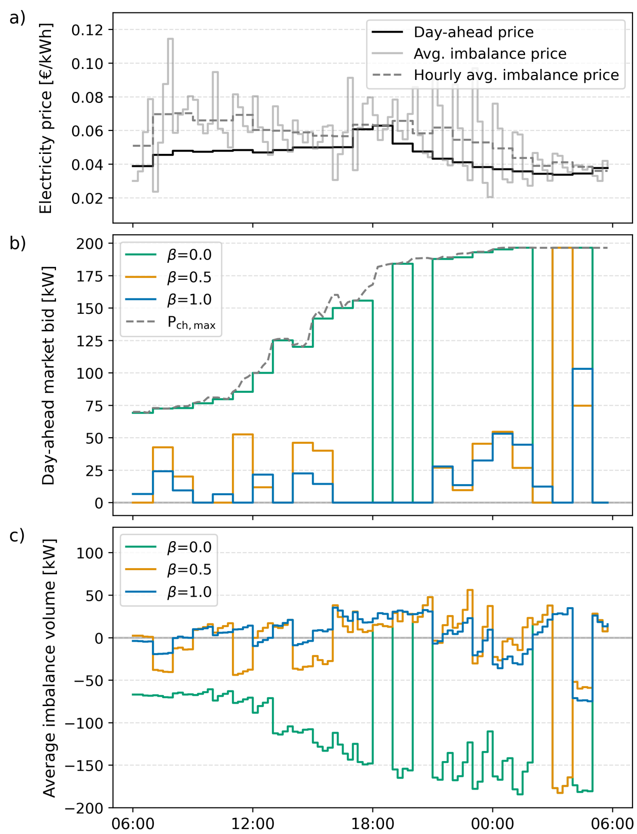

Fig. 4. Electricity prices (a), day-ahead market bids (b) and average imbalance volumes (c) for different values of β for one day in the analysis timeframe (5 Nov 2019, γ=0.9). The imbalance prices in (a) and the imbalance volumes in (c) represent the average values for all considered scenarios. The hourly average imbalance prices in (a) represent the average imbalance prices for all 15-minute blocks in one hour.

day. Future research should look into more realistic patterns of quantile forecasts during the day.

VIII. Conclusion

This study proposed a novel method to determine electricity market bids for a fleet of EVs under uncertainty of EV availability and imbalance market prices. It proposed to use virtual batteries to optimize the charging schedules of an EV fleet, and to use quantile forecasts of the different parameters of the EV virtual battery to account for the uncertainty in the EV availability. A scheduling algorithm using scenario-based stochastic optimization considering the CVaR is used to determine market bids for an EV fleet to the day-ahead market. The results of the analyses in this study indicate that it is crucial to consider both the expected costs and the CVaR when determining day-ahead bids for an EV fleet, to avoid high downside tail risks or high expected charging costs.

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