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A Mid-Term DSO Market for Capacity Limits: How to Estimate Opportunity Costs of Aggregators?

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Abstract—A large number of mechanisms are proposed to manage potential problems in distribution networks caused by the participation of distributed energy resources (DERs) in the wholesale markets. In this paper, we first introduce a practical and straightforward mechanism, based on *capacity limits*, which avoids conflicts between the transmission system operator and the distribution system operators (DSOs). Using a large number of real electric vehicle (EV) commercial charging stations we then show how an EV aggregator can forecast the *opportunity cost* incurred by offering a mid-term capacity limit service to the DSO. This cost is computed based on the estimated profit that the aggregator could gain in the day-ahead and real-time markets. The proposed methodology guarantees robustness against evolving EV uncertainty, both in terms of service delivery and driving requirements. It also allows the use of a variety of time-series forecasting methods without forecasting electricity prices and EV scenarios. The results of our empirical analysis show the exponential increase of opportunity cost and the considerable increase of the prediction intervals as the capacity limit decreases. The produced offering curves can be used as an indication of the underutilization cost of DERs caused by the DSO's limitations.

Index Terms—Aggregator, capacity limit, DSO service, electric vehicles, offering curve, opportunity cost.

NOMENCLATURE

Abbreviations

ARIMA	Autoregressive integrated moving average
CVaR	Conditional value at risk
DA	Day ahead
DER	Distributed energy resource
DLMP	Distribution locational marginal pricing
DN	Distribution network
DSO	Distribution system operator
EV	Electric vehicle
MA	Moving average
MAE	Mean absolute error
PI	Prediction interval
RT	Real time
TSO	Transmission system operator

Battery model characteristics

ΔT	Duration of battery model's time step
η	Charging efficiency
$\hat{A}_{i,j}$	Inflexible EV sessions matrix for charger i at step j
$A_{i,j}$	EV connection matrix for charger i at step j
C_t^{d}	Battery model's lower energy limit at step t
C_t^{up}	Battery model's upper energy limit at step t
C_t	Battery model's energy state at step t
N	Number of EV chargers
N_{T}	Number of battery model's time steps
P_t^{d}	Battery model's lower power limit at step t
P_t^{up}	Battery model's upper power limit at step t
$S_{i,j}$	Matrix of EV charging needs for charger i at step j

Indices

ω	Index for scenario
d	Index for service day
i	Index for EV chargers
j	Index for RT time steps
m	Index for DA time steps
t	Index for the battery model's time steps

Forecast/optimization parameters and variables

λ_m^{DA}	DA price at step m
$\lambda_{j,w}^{\mathrm{RT}}$	RT price at step j and scenario ω
π_w	Probability of occurrence for scenario ω
$\tilde{P}_d^{\mathrm{cap},*}$	Forecast of $P^{\mathrm{cap},*}$ at day d
E_j^{acu}	Maximum accumulated consumption at step j
J_d	Accuracy of $P^{\mathrm{cap},*}$ forecast at day d
N_{DA}	Number of DA market's time steps
N_{e}	Years of EV data
N_{p}	Years of price data
N_{RT}	Number of RT market's time steps
$P_d^{\mathrm{cap},*}$	Minimum value of capacity limit at day d
P_m^{DA}	Aggregate DA power at step m
$P_i^{\max}$	Nominal charging power of charger i
$P_{j,w}^{\mathrm{RT}}$	Aggregate RT power at step j and scenario ω
P_t	Aggregate power consumption at step t
$Q_{\mathbf{P}^{\mathrm{cap}},d}^{\mathrm{MA}}$	Cost's moving average at day d
t_{MA}	Days for moving average window
$U_{\mathbf{P}^{\mathrm{cap}},d}^{\mathrm{MA}}$	Cost's price component at day d
$Y_{\mathbf{P}^{\mathrm{cap}},d}^{\mathrm{MA}}$	Price adjustment factor at day d

I. INTRODUCTION

A. Motivation

The continuously increasing production share of renewable energy sources, together with the growing numbers of controllable distributed energy resources (DERs) connected to the distribution network (DN), bring important challenges to power systems operation. More specifically, large renewable production tends to decrease the correlation between wholesale prices and electricity demand [1]. Moreover, the presence of flexible DERs, their coordinated response to price signals, and their participation in the volatile real-time markets may cause operational problems in DNs.

The unrestricted operation of DERs in general maximizes their profits and minimizes the overall system cost. However, this may bring operational problems to distribution system operators (DSOs), since wholesale markets do not necessarily respect DN constraints. Therefore, DSOs may desire to constrain DERs, or partially utilize them for their own needs, to guarantee the reliable DN operation. A large number of DSO congestion management mechanisms have been proposed, but all have considerable weaknesses and may not facilitate the optimal utilization of DERs. To this purpose, we present a mid-term capacity limitation service, which will be tested in the Danish demonstration project Ecogrid 2.0 [2]. In this context, we address the following questions: (a) why a capacity limitation service is a more appealing mechanism to DSOs compared to other existing congestion management mechanisms?, (b) how can an aggregator forecast the opportunity cost of providing such a capacity limitation service?, and (c) how can we consider the DER uncertainties to provide a robust service, while respecting their operational constraints?

We calculate the opportunity cost of an aggregator of electric vehicle (EV) charging stations participating in both day-ahead (DA) and real-time (RT) markets when offering such a capacity limitation service over a mid-term horizon. By mid-term we refer to a period of at least one month. In this paper we study the case of a monthly period, but this period can be longer, to allow the DSOs enough lead time for grid reinforcement, if they are unable to acquire the desired services. Due to the rapid growth rate of EVs, we focus on aggregated EV chargers and present an empirical analysis based on real EV charging data from the state of California. However, a similar approach with slight modifications can be used for other types of DER aggregations. The evolving EV uncertainties and the volatile, unknown electricity prices over a relatively large time horizon, would require advanced forecasting methods for future EV scenarios and prices. We present a different approach, where service delivery and driving requirements are guaranteed over a forecast horizon without explicitly forecasting the upcoming EV scenarios. Similarly, we forecast the opportunity cost without modeling and forecasting electricity prices, by employing a more straightforward and practical approach, which allows the use of a variety of time-series forecasting methods.

B. Existing DSO Mechanisms: Pros and Cons

The works of [1] and [3] provide a comprehensive overview of various congestion management mechanisms. These resolve DN operational problems and attempt to maximize social welfare. Li et al. [4] propose the use of distribution locational marginal pricing (DLMP) to alleviate DN congestions caused by EV loads. By using the DA prices, the schedules of aggregators of DERs may create operational problems in the DN, if the market is cleared by the Transmission System Operator (TSO) without taking DN constraints into account. According to this method, dynamic tariffs are calculated by the DSO before the clearing of the wholesale market and are sent to the aggregators. Aggregators then modify their market offers to alleviate congestions [4]–[6]. To this end, the DSO must predict the uncontrollable load and the price responsiveness

of the aggregators to the tariffs. An iterative procedure for obtaining DLMP tariffs is proposed in [7] to respect user privacy, whereas in [8] and [9] some potential sources of uncertainty are incorporated in the DLMP framework.

While DLMP may give the optimal solution for DA congestion management, many important practical, operational and market-related issues make its implementation difficult. First, it imposes explicit schedules on potentially very low aggregation levels. The net balance between a player's market position and its actual net load is currently calculated on a much higher aggregation level. Enforcing this balancing on medium- or low-voltage levels would require a huge increase of system complexity. Additionally, uncertainties on such small aggregations can be very high and hard to manage in such a context. Most importantly, it is very difficult to incorporate the participation of DERs on the RT or ancillary services markets to the DLMP framework, thus hindering the optimal utilization of DERs on all markets concurrently.

Time of use and power tariffs are other existing mechanisms for dealing with DN congestion problems [1], [10], [11]. Under these two mechanisms, DSOs impose time-variant tariffs and charge customers according to their peak consumption over a period to encourage price-driven peak shaving and valley filling of consumption. Such a type of tariffs is a simple and in many cases effective way for dealing with congestion issues. However, they cannot address specific DSO needs and due to regulations they cannot vary frequently and over locations of a given DN. This limits their effectiveness, whereas due to the high level of uncertainty on low aggregation levels these tariffs cannot guarantee that DN operational constraints are always fulfilled. Besides, such tariffs may not lead to an optimal utilization of DERs for two reasons. First, they are designed by the DSO and serve its own objectives, disregarding the impact on the economic performance of DERs on the TSO-level markets. Second, they cannot be very adaptive to each DN location's needs, and are in general inefficient because they are not calculated through a market mechanism.

Other existing methods include variations of local flexibility markets [12]–[15] or local coordination schema [16]. In these mechanisms, the DSO acquires and activates flexibility services or the aggregators coordinate to resolve DN operational problems. One disadvantage of such methods is that they rely on established baseline consumptions between the DSO and aggregators. In many cases this is problematic due to small aggregation sizes and the apparent conflict of interest among the parties. They may also require explicit schedules on points of the DN with very low consumption levels, which is in general not desirable. Moreover, the continuous participation of DERs in the energy and/or reserves markets in many cases may render baselines meaningless. Furthermore, the nature of such markets contradicts with common DSO operational requirements, which are secure operation and minimal market involvement. Operation so close to RT, or relying on aggregators to resolve DN problems, may result in strategic behavior of the aggregators or violation of operational constraints, if the aggregators are not willing or able to offer flexibility.

Various forms of capacity allocation mechanisms have been proposed to alleviate DN congestions. In [17] aggregators bid

for capacity on a network feeder. However, such a mechanism requires a very active DSO involvement. To avoid customer discrimination, it should be expanded to all customers, who would need to pay for capacity. This could lead to significant complexity and uncertainty for all involved parties. In [18] a market mechanism which coordinates demand response to adjust the aggregated load at a minimum utility loss is proposed. Besides, in [19] an extension for multiple stages which includes uncertainty is provided. Such methods, along with the proposed transactive methods in [20] and [21] require very active DSO involvement and increase system complexity. Finally, they are not compatible with the current power system structure, and do not provide congestion guarantees over longer time periods.

C. Contributions

Considering the practical limitations of the existing DSO congestion mechanisms, we investigate in this paper an alternative approach to manage congestions in DNs. The contributions of this work are as follows: First, we introduce a mid-term DSO service and explain its advantages over other existing DSO congestion management mechanisms. Second, we propose a method to guarantee robustness in both service provision and driving requirements, without forecasting evolving EV scenarios. Third, this paper develops a method for forecasting an aggregator's opportunity cost, incurred by providing the proposed DSO service. This forecast method relies on decomposing the effect of EV scenarios and prices on opportunity cost. Our opportunity cost estimation methodology does not require explicit price forecasts. It also allows for the use of different time-series forecasting methods.

D. Paper Organization

The remainder of the paper is organized as follows. In Section II the proposed mid-term DSO service is presented. In Section III an aggregated EV model and the aggregator's stochastic offering strategy problem in the DA and RT markets are presented. In Section IV EV uncertainty is characterized, and a method to handle it in a robust manner is proposed. In Section V a strategy to estimate opportunity cost is presented. In Section VI we present results for a real case study, and finally, Section VII concludes the paper.

II. PROPOSED DSO CONGESTION MECHANISM

Each mechanism for handling DN operational problems by involving customers and DERs has its own requirements, advantages and disadvantages, and therefore a strictly defined optimal solution may not exist. In the Danish demonstration project Ecogrid 2.0 [2], a new way of handling DERs integration in DNs is proposed. This framework is compatible with the current power system operation and the markets' structure. This means that such a mechanism can be viewed as an additional layer which does not create conflicts with the aggregators' participation in the DA, RT or ancillary service markets. In this context, the DSO identifies in advance critical points of the network which may become congested during some hours of the day and requests capacity limitation services by DER aggregators. Aggregators submit price/power curves

to the DSO, which correspond to the price requested by the aggregators for guaranteeing that their total consumption does not exceed a specific power limit.

The advantage of this service is that it does not rely on baseline references, which present many challenges for the DSOs [22], and thus it is much more straightforward to verify. Compared to DLMP, it does not require the aggregators to follow specific schedules on low aggregation points, whereas all DER-related uncertainties are internalized in the aggregators' individual offering strategy problems. Furthermore, the significant challenges of implementing DLMP while considering the RT and the ancillary service markets are bypassed. The proposed service does not require ex-post coordination between the DSO and the aggregators, once the service has been purchased. In other words, aggregators bid their capacity limit curves and then they are responsible for keeping their consumption below the cleared level. The DSO is then not involved in the aggregators' daily operation (for instance via monitoring the DERs consumption or disconnecting customers). Then, aggregators are free to participate in any power market/service they wish, as long as the allocated capacity limit is not exceeded throughout the service provision period. It is thus much simpler to implement compared to transactive control, and guarantees can be provided regarding the DERs consumption (or production in a more generalized setup), which is not the case with other DSO mechanisms. Most importantly, a DSO capacity service can be offered by aggregators in parallel to the TSO-level markets/services, promoting competition and the optimal use of DERs. On the contrary, the other aforementioned mechanisms prioritize the DSO needs at the expense of overall DER performance on all possible DSO/TSO services. As already mentioned, no congestion mechanism is ideal, and each mechanism may have its own shortcomings. However, a mechanism based on capacity limits concentrates very desirable characteristics for the DSOs, such as: simplicity, security, easy verification, minimum infrastructure requirements, and little DSO involvement.

A key feature of this service is its "mid-term" nature; in this paper we consider a monthly period. A shorter service period would probably result in increased efficiency, because of the reduced uncertainty. However, a long enough time horizon is crucial to allow the DSOs to implement grid reinforcement, so that DSOs can consider this mechanism as a reliable alternative in the network planning. Additionally, daily auctions could result in strategic behavior and potentially no participation from the aggregators in certain days. Finally, considering the size of DNs, daily auctions for several points in the network would increase administrative costs and the complexity of the DSOs' operation.

From a market design perspective, it is not challenging for a DSO to develop a market for purchasing capacity limits from aggregators – it is based on a simple supply-demand auction. The most challenging part is to develop a systematic methodology for an aggregator to calculate its opportunity cost incurred by capacity limits provision. This cost will indeed be the offer price of the aggregator in the proposed market, if it is assumed to be a price-taker. This becomes more challenging if we aim at deriving a curve of opportunity cost, i.e. a curve
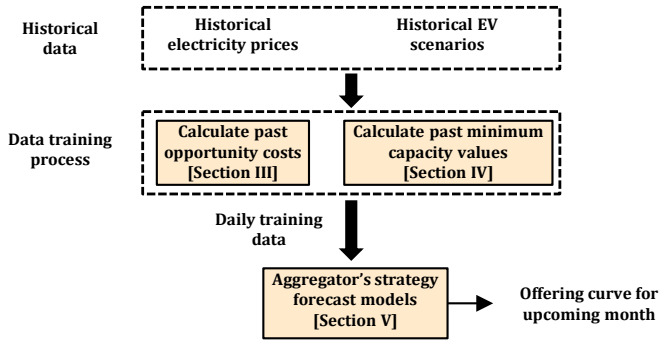
Fig. 1: Flowchart describing the different steps required to produce an offering curve for an aggregator.

which expresses the aggregator's opportunity cost (in USD) for various capacity limit values (in kW). Given the novelty of this capacity mechanism due to its mid-term nature, in this work we propose a methodology to estimate the opportunity costs of aggregators who offer a capacity service to the DSO. In the following section we present an aggregate EV chargers model, which we will use to formulate the aggregator's stochastic offering strategy problem, and manage the EV charging needs uncertainty.

III. EV CHARGERS AGGREGATION

We consider the case of an aggregator managing a number of EV charging stations. Here, we summarize the assumptions considered in this work: First, the aggregator participates in the DA and RT wholesale markets, and participates in the DSO market auctions. Second, all charging stations belong to a point of common coupling, for which the DSO desires to acquire a capacity limitation service. Third, this service must be offered to the DSO with 100% reliability. Fourth, the aggregator always fully satisfies the drivers energy needs. This assumption is derived by the actual setup from which data was collected, where charging starts immediately after the EVs are parked, and drivers have no control over how this will be performed, nor do they respond to any prices/incentives. Finally, since there is no available efficiency data, we treat the recorded consumption of a charging session as the actual EV energy need.

Fig. 1 shows an overview of the different steps required to produce an offering curve for the capacity service. Instead of forecasting EV scenarios and electricity prices, and use those forecasts to determine opportunity costs, we propose a more straightforward and easy to implement approach. Based on this approach, historical data for EV scenarios and prices are used to calculate the opportunity costs in past days, and then we create a training dataset. This dataset is eventually used to directly forecast the aggregator's opportunity cost in an upcoming period.

A. EV Aggregate Model

We employ a battery model similar to the one proposed in [23] to represent the aggregate EV chargers flexibility. However, given the mid-term nature of the service and time-evolving nature of the EV scenarios, uncertainty in our model cannot be readily handled in the same way as proposed

in [23]–[26] for a DA scheduling problem. We propose an alternative way to deal with uncertainty in our work, as will be explained later in Section IV. We now present our battery model. Consider a population of N unidirectional EV chargers, indexed by i, and a horizon of N_T steps; each step j has a duration equal to ΔT. We denote each station's nominal charging power and efficiency by P_i^max and η respectively. We introduce the EVs connection matrix $\mathbf{A} \in \mathbb{R}^{N \times N_\mathrm{T}}$; $A_{i,j} = 1$ if an EV is connected to charger i at time step j, otherwise $A_{i,j} = 0$. We denote by $\mathbf{S} \in \mathbb{R}^{N \times N_\mathrm{T}}$ the energy needs matrix. A bold variable denotes a variable in matrix form. If a charging session with energy needs E starts at $j = k$ and ends at $j = l$, then $S_{i,k} = E$ and $S_{i,l} = -E$; in all other cases $S_{i,j} = 0$. The aggregation's maximum potential consumption P_t^up at each time step t is given by

$$P_t^\mathrm{up} = \sum_{i=1}^{N} P_i^\mathrm{max} \cdot A_{i,t}, \ \forall \ t. \tag{1}$$

The aggregation's energy state C_t is modeled similar to a virtual battery. Assuming that the charging strategy always satisfies the customers energy needs, an enclosing envelope can be constructed which will bound energy state C_t. The upper limit is defined by the EV arrivals and energy needs, and expresses the maximum charged energy that can be stored in the connected EVs at time step t; it is calculated as

$$C_t^\mathrm{up} = \sum_{i=1}^{N} \sum_{j=1}^{t} S_{i,j}, \ \text{if } S_{i,j} > 0, \ \forall \ t. \tag{2}$$

In other words, C_t^up represents the total energy which can be provided to the EVs until step t. Lower energy limit C_t^d depends on the EVs departures and the EVs energy needs. It expresses the minimum amount of energy that needs to be provided until time step t, so that enough energy is provided to the EVs, and all charging needs are satisfied.

$$C_t^\mathrm{d} = \sum_{i=1}^{N} \sum_{j=1}^{t} |S_{i,j}|, \ \text{if } S_{i,j} < 0, \ \forall \ t. \tag{3}$$

When aggregate charging power P_t is consumed, C_t increases by $P_t \cdot \eta$. For each time step, the evolution of C_t is calculated as

$$C_t = C_{t-1} + P_t \cdot \Delta T \cdot \eta, \ \forall \ t. \tag{4}$$

A minimum power limit P_t^d is added to the model for charging sessions corresponding to energy needs equal to the chargers nominal charging power. In those cases there is no flexibility and each EV charges at full capacity until it departs. Let $\hat{A}$ denote a matrix of zeros; consider a session from time step k to l in charger i with energy needs $S_{i,k}$. We set $\hat{A}$ equal to a constant power profile $S_{i,k}/[P_i^\mathrm{max}(l - k)\Delta T]$ for $j \in [k, ..., l]$. Note that this profile may be different from P_i^max due to the model's granularity ΔT; this mismatch diminishes as $\Delta T \to 0$ and for the used $5-$minute granularity we found that the difference is negligible. The resulting lower power limit is thus given by

$$P_t^\mathrm{d} = \sum_{i=1}^{N} \hat{A}_{i,t}, \ \forall \ t. \tag{5}$$

We will use the outcomes of this battery model as inputs of the optimization model in the next subsection to model the aggregator's participation in the DA/RT markets.

B. Aggregator's Two-stage Stochastic Optimization

The aggregator purchases energy in the DA market and participates in the RT market by modifying his aggregate consumption with the DA schedule as a reference. Both markets have a $24-$hour horizon but the DA market granularity is equal to one hour and that of the RT market is equal to five minutes. The corresponding time steps are $N_{\text{DA}} = 24$ and $N_{\text{RT}} = 288$. We denote by P_m^{DA} the DA schedule for $m = 1, ..., N_{\text{DA}}$ and by P_j^{RT} the RT adjustment of consumption for $j = 1, ..., N_{\text{RT}}$. We model the aggregator's daily operation as a two-stage optimization problem. The first-stage decision is the set of DA schedule values. EV uncertainties and electricity prices (λ_m^{DA} and λ_j^{RT} denote the DA and RT prices respectively) are expressed via scenarios $w \in W$, each with an occurrence probability π_w. EV uncertainty is expressed by the battery model's energy and power limits.

If the RT market and the aggregate EV model have different time step durations, then all necessary variables and parameters must be aligned to the smallest duration. We use the same duration ΔT, whereas $n = N_{\text{RT}}/N_{\text{DA}}$ is the ratio between the RT and DA time steps. The decision variables set $\mathbf{U} = \{\mathbf{P^{DA}}, \mathbf{P^{RT}}, \mathbf{C}\}$ includes the DA schedule, the RT adjustment and the energy state for each scenario. It is assumed that the necessary control/communication capabilities exist, to allow the aggregator to control the chargers with a delay considerably shorter than the $5-$minute granularity of the RT market. At this point we introduce parameter $\mathbf{P^{cap}}$, which is the capacity limit of the provided service by the aggregator to the DSO. RT prices are in general more volatile than DA prices and an aggregator can forecast the latter more accurately. Thus, we assume that DA prices are known, and uncertainty originates from RT prices and the EV charging sessions. The aggregator's optimization problem is formulated as follows

$$\min_{\mathbf{U}} \quad \sum_{m=1}^{N_{\text{DA}}} P_m^{\text{DA}} \cdot \lambda_m^{\text{DA}} + \sum_{w \in W} \pi_w \sum_{j=1}^{N_{\text{RT}}} P_{j,w}^{\text{RT}} \cdot \lambda_{j,w}^{\text{RT}} \cdot \Delta T \quad \text{(6a)}$$

$$\text{s.t.} \quad C_{j,w}^{\text{d}} \leq C_{j,w} \leq C_{j,w}^{\text{up}}, \ \forall \ j, w \quad \text{(6b)}$$

$$P_{j,w}^{\text{d}} \leq P_{j,w}^{\text{RT}} + P_{j|m}^{\text{DA}} \leq P_{j,w}^{\text{up}}, \ \forall \ j, w \quad \text{(6c)}$$

$$C_{j,w} = C_{j-1,w} + (P_{j|m}^{\text{DA}} + P_{j,w}^{\text{RT}}) \cdot \Delta T \cdot \eta, \ \forall \ j, w \quad \text{(6d)}$$

$$C_{0,w} = 0, \ \forall \ w \quad \text{(6e)}$$

$$P_{j|m}^{\text{DA}} + P_{j,w}^{\text{RT}} \leq P_j^{\text{cap}}, \ \forall \ j, w. \quad \text{(6f)}$$

In (6) each scenario w corresponds to a joint realization of the RT price $\boldsymbol{\lambda}_w^{\text{RT}}$ and EV uncertain parameters $\mathbf{C}_w^{\text{up}}, \mathbf{C}_w^{\text{d}}, \mathbf{P}_w^{\text{up}}, \mathbf{P}_w^{\text{d}}$. Because of the RT market's smaller time granularity, we use $j|m$ to express the quotient $(j-1)/_{mn} + 1$ for the time steps j which are included within the hourly step m of the DA market. Objective function (6a) minimizes the aggregator's expected cost in DA and RT markets. Constraints (6b) and (6c) express the power/energy limitations of the battery model, (6d) describes the energy state evolution, and (6e) imposes the initial energy condition.

Constraint (6f) limits the total consumption to the level of a contracted capacity P_j^{cap} at each time step j, only when the DSO service is requested. Problem (6) is formulated as a cost-minimization problem. If drivers do not pay for charging (as is the case for many of the chargers in the dataset, which are installed in workplaces) or pay a fixed price, then casting (6) as a utility-maximization problem is equivalent. If a reliable and realistic price sensitivity value is available, then it is straightforward to transform (6) to a utility maximization problem. Since (6) is a linear program, its computational requirements are in general low, even with a large number of scenarios.

Unlike [27], where the recourse actions are affine, we employ second-stage decision variables to obtain further flexibility by allowing different recourse actions for each scenario. It is possible to express EV uncertainty via confidence intervals around the expected values of the power and energy limits, which transforms the problem into a hybrid robust-stochastic optimization problem [25]. This alternative formulation has the advantage of avoiding infeasible solutions for some special EV session realizations, but in general results in more conservative solutions as it fails to capture a number of statistical properties of the uncertainty. Techniques to control the level of conservativeness of the robust optimization solution can also be used [28]. However, the issue of evolving EV uncertainties may not be readily addressed. We retain the advantages of using scenarios while guaranteeing robustness against EV uncertainty by employing a worst-case identification method, which is presented in the following section.

IV. EV Uncertainty Characterization

We use a dataset from year 2013 consisting of 412 level 2 commercial chargers with a capacity of 6.6 kW each, installed in sites across the state of California. The majority of the sessions occur during working days, and for this reason load is considerably lower during the weekends and holidays. Since we are estimating the cost of a capacity service, we neglect days with very low charging needs because in those days a capacity limitation has a negligible effect on opportunity cost; this results in 245 working days per year. A key characteristic of the dataset is that chargers utilization increases over time. This reflects the increasing EV adoption and introduces additional uncertainties in the chargers operation, both from an aggregator's and DSO's perspective.

We used a $5-$minute time step to align the battery model's granularity with that of the RT market. For each session the exact arrival and departure times were recorded, as well as the energy consumption with a $15-$minute sample rate. From this information the battery model's parameters $\mathbf{C^{up}}, \mathbf{C^d}, \mathbf{P^{up}}, \mathbf{P^d}$ for each day can be calculated with a $5-$minute resolution, which improves the accuracy of the aggregated model. We desire to model the daily EVs operation and thus calculate $\mathbf{C^{up}}, \mathbf{C^d}, \mathbf{P^{up}}, \mathbf{P^d}$ for each day. For sessions covering more than one day we distributed the energy needs to each day, proportionally to the time the EV is parked. Finally, $\mathbf{P^d}$ was found to be very small and its effect negligible; consequently, we consider the lower power limit to be equal to zero.

This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/TSG.2019.2921402, IEEE Transactions on Smart Grid

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Day-to-day variations of the uncertain parameters can be quite large; this variation decreases as the aggregation size increases, as shown in [23] and verified by our data. Since uncertainty is evolving over time, describing it through distributions constructed by all past realizations or sampling over all of them does not capture the changes in the uncertainty set. In Fig. 2 the average values of $\mathbf{C^{up}}$, $\mathbf{C^d}$ and $\mathbf{P^{up}}$ over 20 days with a $5-$minute time resolution for 412 EV chargers for two different periods are shown.
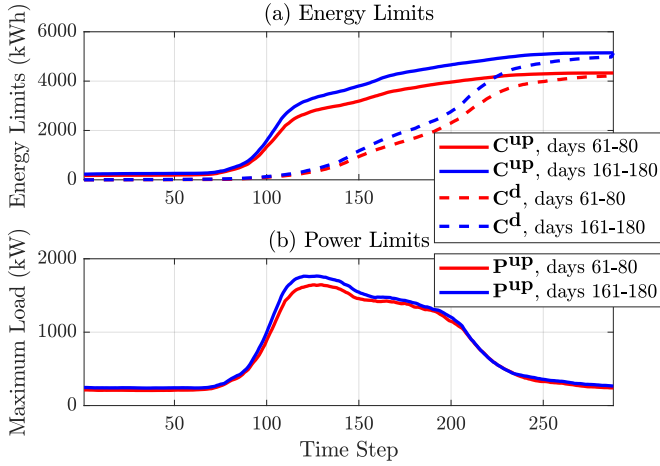

Fig. 2: Evolution of the average energy (upper subplot) and power (lower subplot) limits of 412 EV chargers during two 20-day sample periods.

It is important to identify the *worst-case* realization of the EVs uncertainty to provide a robust capacity limitation service. This is not straightforward when intertemporal constraints exist, and when the aggregator wants to retain robustness against an evolving uncertainty. To avoid overly conservative bounds, we propose a method to address this uncertainty. We introduce variable E_j^{acu}, which expresses the maximum possible accumulated consumption at each time step. In other words, E_j^{acu} gives the accumulated energy corresponding to the maximum load P_j^{up} for each time step j, unless a capacity limit (in terms of power or energy) is imposed, which limits energy consumption. E_j^{acu} cannot take a value larger than C_j^{up} because this will violate the aggregate upper energy limit. Besides, a value of E_j^{acu} smaller than C_j^{d} would result in user disutility, i.e. not enough energy provided to cover all user requirements. Since we require satisfaction of all user energy needs, the corresponding capacity values P_j^{cap} would be infeasible. We calculate E_j^{acu} as a function of P_j^{cap} as follows

$$E_j^{\mathrm{acu}}(P_j^{\mathrm{cap}})=E_{j-1}^{\mathrm{acu}} + \min(\min(P_j^{\mathrm{up}}, P_j^{\mathrm{cap}})\cdot\Delta T\cdot\eta, C_j^{\mathrm{up}}), \forall j. \quad (7)$$

For a robust service formulation, P_j^{d} must always be smaller than P_j^{cap}, and as a result it is necessary that this condition is met for all EV scenarios. Finally, if the capacity limitations only cover some time periods of the day, then a sufficiently large value can be assigned to P_j^{cap} for the remaining time steps to make the limitation inactive. We applied three different capacity limits $\mathbf{P^{cap}}$ of 500, 300 and 130 kW from 08.00 to 17.00 for two different days and calculated $\mathbf{E^{acu}}$. In Fig. 3 the results are shown, where it can be seen that a capacity limit of $\mathbf{P^{cap}} = 130$ kW is feasible for the first case (upper subplot)

but infeasible for the second case (lower subplot), as the lower energy limit is violated, which would result in user disutility.
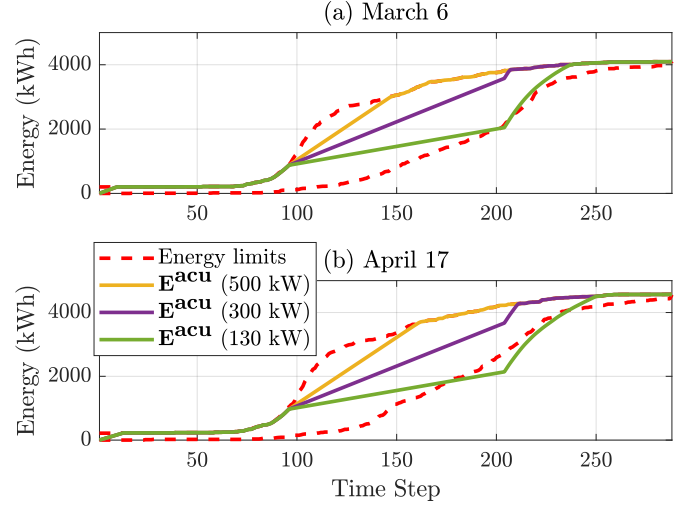

Fig. 3: Energy limits and E_j^{acu} as a function of three different $\mathbf{P^{cap}}$ levels (i.e. 500, 300 and 130 kW) for two different sample days in 2013.

We introduce $P_d^{\mathrm{cap},*}$ to denote the minimum value of $\mathbf{P^{cap}}$, which guarantees that $\mathbf{E^{acu}}(P_d^{\mathrm{cap},*}) \geq \mathbf{C^d}$ for a given day d. Note that in this work we consider that the DSO asks for a capacity limit whose value is the same for the whole period and thus $P_d^{\mathrm{cap},*}$ is scalar. If this period was divided in n subperiods, then $P_d^{\mathrm{cap},*}$ would be expressed as an $n-$dimensional feasible region. The advantage of using $P_d^{\mathrm{cap},*}$, instead of employing a robust formulation of (6), is that a capacity limit profile which satisfies this condition guarantees that both user needs and capacity limitation requirements are met, since all parameters are considered via (7). In Fig. 4 the value of $P_d^{\mathrm{cap},*}$ corresponding to a capacity limit from 08.00 to 17.00 is shown for all working days of 2013. The gradual increase of $P_d^{\mathrm{cap},*}$ can be seen, which reflects the increasing chargers utilization over year 2013. In the rest of the paper we will use 2013 EV data as if it corresponded to year 2017, since more recent EV data was not available.

V. EV AGGREGATOR'S OFFERING STRATEGY

In this section, a strategy for estimating an aggregator's opportunity cost for different capacity limit values is proposed. The goal of this paper is to propose a strategy for calculating this cost for varying capacity limit values. By utilizing this knowledge, an aggregator may bid in a strategic manner. However, strategic bidding (i.e. treating $\mathbf{P^{cap}}$ as a variable instead of a parameter) would require a game-theoretical model, and necessitate the aggregator to have knowledge and experience from market operation, which is outside the scope of this paper. In subsection V-A we describe how the aggregator's opportunity cost, incurred by providing a capacity limitation service in a given period, is calculated. In subsection V-B we propose a method to forecast this cost during an upcoming period with unknown electricity prices and EV uncertainty realizations.
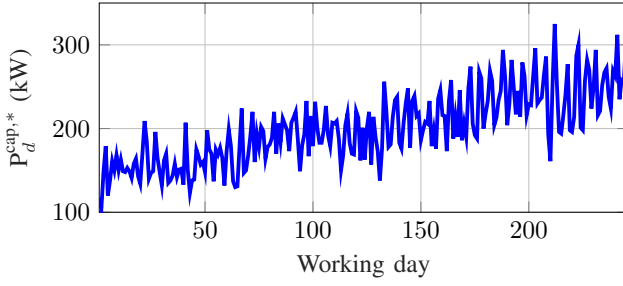
Fig. 4: Daily value of $P_d^{\text{cap},*}$ for all working days of 2013 and a capacity limit imposed from 08.00 to 17.00.

A. Opportunity Cost Calculation

Our goal is to calculate the aggregator's opportunity cost during the contracted period as a result of the capacity limitation service, instead of the actual operational cost. To obtain the opportunity cost for each predefined $\mathbf{P}^{\text{cap}}$ profile, we subtract the operational cost that corresponds to the solution of (6) from the unconstrained cost, i.e., the cost obtained by removing (6f). By repeating this process for the whole contracted period, we can calculate the total opportunity cost as a function of $\mathbf{P}^{\text{cap}}$.

We first use a set of scenarios W to obtain the DA schedule by solving (6) for each contracted day and $\mathbf{P}^{\text{cap}}$ profile, as described in subsection III-B. Afterwards, for each $\mathbf{P}^{\text{cap}}$ profile we solve the deterministic variant of (6) using the out-of-sample realized RT prices and EV uncertainty. We use a set of randomly chosen historical RT prices and past EV realizations to construct W. Once we have calculated past opportunity cost values, we can use forecasting methods to estimate the cost of an upcoming period. The computational time required for calculating past opportunity cost values is comparatively low, due to the linear structure of (6).

B. Opportunity Cost Forecast

1) Cost factors decomposition: We introduce $Q_{\mathbf{P}^{\text{cap}},d}$ to denote the actual opportunity cost for day d and capacity limit $\mathbf{P}^{\text{cap}}$. Opportunity cost depends on both the unknown EV realizations and electricity prices for an upcoming period $[d_1, d_2]$. We use superscript MA to denote the moving average and $\widehat{(\cdot)}$ a forecasted quantity. Since the service is offered over several days, we are interested in predicting the cost's moving average (MA) over t_{MA} days, given by

$$Q_{\mathbf{P}^{\text{cap}},d}^{\text{MA}} = \sum_{i=d-t_{\text{MA}}+1}^{i=d} Q_{\mathbf{P}^{\text{cap}},i}/t_{\text{MA}}. \qquad (8)$$

Even though past electricity prices are available for several years, our EV data covers one year. We decompose the effect of EV realizations and prices to use N_{p} years of prices without the corresponding EV data. We use $U_{\mathbf{P}^{\text{cap}},t}^r$ to denote the price component of opportunity cost, obtained by averaging the result of (6) for the realized prices of day t and the last N_{e} EV realizations prior to r. Note that t indexes over all days with available prices, whereas d over days with available EV data and $t = 245 \cdot N_{\text{p}} + d$; for the following example we use $N_{\text{p}} = 0$

and thus d and t coincide. The MA of the price component $U_{\mathbf{P}^{\text{cap}},t}^r$ is calculated as

$$U_{\mathbf{P}^{\text{cap}},d}^{\text{MA}} = \sum_{i=d-t_{\text{MA}}+1}^{i=d} U_{\mathbf{P}^{\text{cap}},i}^{d-t_{\text{MA}}+1}/t_{\text{MA}}. \qquad (9)$$

Adjustment factor $Y_{\mathbf{P}^{\text{cap}},d} = Q_{\mathbf{P}^{\text{cap}},d}^{\text{MA}} - U_{\mathbf{P}^{\text{cap}},d}^{\text{MA}}$ represents the error of $Q_{\mathbf{P}^{\text{cap}},d}^{\text{MA}}$ by using N_e EV realizations prior to $d - t_{\text{MA}}$ instead of the actual ones. In Fig. 5 the mean average error (MAE) of the adjustment factor for different N_e values is shown; $N_e = 5$ results in the smallest error values and we use this value for the rest of the paper. The role of the cost factors decomposition and the use of past electricity prices will be more evident in the forecasting evaluation, and the reduction of the prediction intervals (PIs).
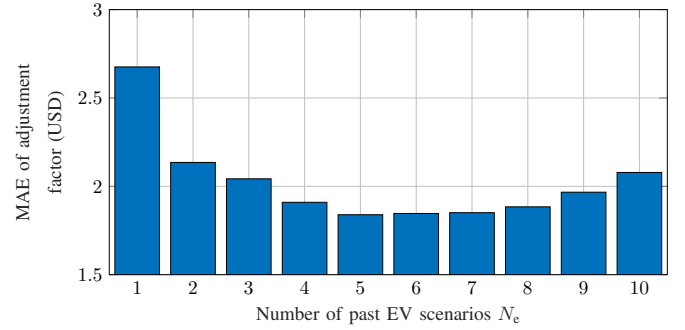

Fig. 5: MAE of the adjustment factor for different N_e values.

2) Forecasting: The first step is to identify the minimum capacity limit ($P_d^{\text{cap},*}$, as introduced in Section IV), which the aggregator can guarantee for the contracted period (equal to 20 working days in our study). We choose to train an Autoregressive Integrated Moving Average (ARIMA) model on the available $P^{\text{cap},*}$ values preceding the contracted period, but other forecasting methods can be used as well. We used an ARIMA model because it is an established, easy to implement technique, suitable for our application. A comparison between different techniques is outside the scope of this paper, but is an interesting path for future research. The residual analysis showed that the normality assumption is a good approximation. We forecast $P^{\text{cap},*}$ for 20 steps ahead, as well as the 99 % PI. The results for days $81 - 100$ are shown in Fig. 6, where the predicted maximum $P^{\text{cap},*}$ value is equal to 250 kW with 99 % probability.
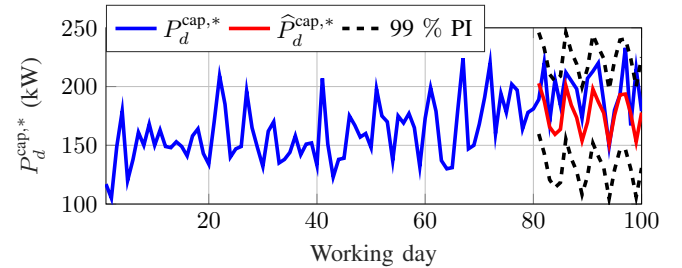

Fig. 6: ARIMA forecast of $P^{\text{cap},*}$ for days $81 - 100$.

We denote by $U_{\mathbf{P}^{\text{cap}},d}^{\text{MA},z}$ the cost where $d - t_{\text{MA}}$ is replaced in (9) by a fixed day z, which corresponds to the start of

the forecasting horizon (day d_1). For illustrative purposes, we forecast $U_{\mathbf{P^{cap}},t}^{\mathrm{MA},z}$ for days $81 - 100$ ($d_1 = 81$), a capacity limit of 500 kW and $N_p = 2$, resulting in 570 training data samples. $U_{\mathbf{500},t}^{\mathrm{MA},81}$ corresponds to the MA calculated by using prices of day t and the average cost for EV realizations from days $76 - 80$. We fitted an ARIMA model on the available 570 data samples to forecast $\widehat{U}_{\mathbf{500},t}^{\mathrm{MA},81}$ for 20 steps ahead, along with the 95 % PI. The results are shown in Fig. 7. The PI is obtained by assuming normally distributed residuals, which was found to be a good approximation.
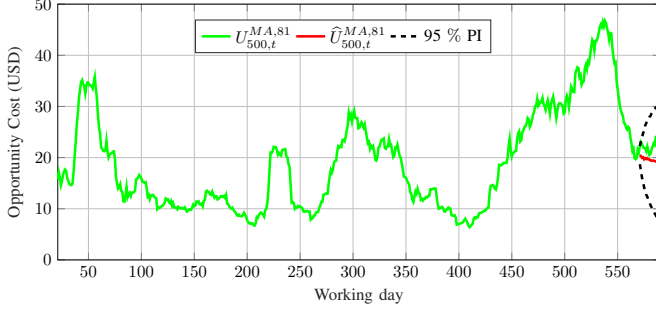

Fig. 7: ARIMA forecast of cost price component $U_{\mathbf{500},t}^{\mathrm{MA},81}$.

This forecast method does not require any direct DA/RT price forecasting, which would need much more complicated models and information which may not be available (such as weather data, renewable production data and possibly network topology or status of conventional generation among others). Even in that case, there is always significant uncertainty especially in the RT prices, which consequently cannot be accurately predicted. Instead, we propose a simpler method which relies on a direct forecast of opportunity cost, bypassing the need for modeling the DA/RT prices. Next, we forecast adjustment factor $Y_{\mathbf{500},d}$ for days $81 - 100$ to capture the effect of the time-evolving EV realizations. We calculated $Y_{\mathbf{500},d}$ as explained in the previous subsection and trained an ARIMA model to use for the prediction. The results are shown in Fig. 8. Similar to the previous forecast model the normality of the residual distribution was found to be a good approximation.
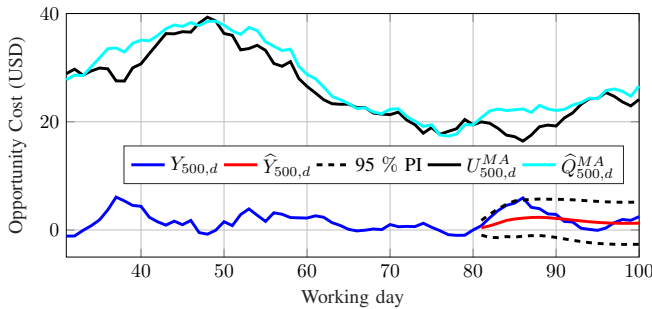

Fig. 8: ARIMA forecast of the adjustment factor $Y_{\mathbf{500},d}^{\mathrm{MA}}$.

3) Strategy Summary: In Fig. 9, a flowchart summarizing the steps required to construct an offering curve are shown. For simplicity we present the case where $\mathbf{P^{cap}}$ is scalar, but it is straightforward to generalize the process for multidimensional capacity limits. First, for a given period $[d_1, d_2]$ the maximum $P^{\mathrm{cap},*}$ value is forecasted, and is initially used as $\mathbf{P^{cap}}$. Next,
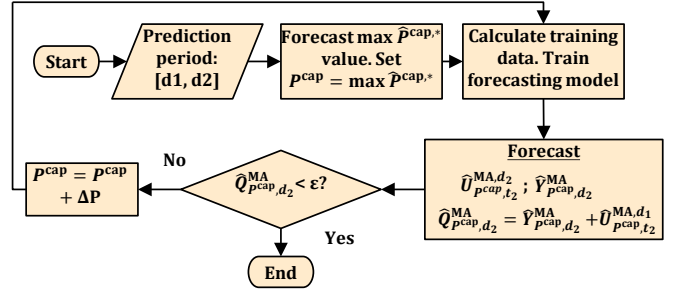

Fig. 9: Flowchart describing the process of constructing an offering curve for an upcoming service period.

the training data corresponding to the two cost components is calculated. This data is used to train the models and forecast $\widehat{Q}_{\mathbf{P^{cap}},d_2}^{\mathrm{MA}} = \widehat{U}_{\mathbf{P^{cap}},t_2}^{\mathrm{MA},d_1} + \widehat{Y}_{\mathbf{P^{cap}},d_2}$, where $t_2 = 245 \cdot N_\mathrm{p} + d_2$. The process is repeated by increasing $\mathbf{P^{cap}}$, until the forecasted cost becomes smaller than a value ε, indicating that $\mathbf{P^{cap}}$ is not a binding constraint. This results in an offering curve with opportunity cost expressed as a function of $\mathbf{P^{cap}}$. Note that steps ΔP, by which $\mathbf{P^{cap}}$ is increased, can be variable. More specifically, for values close to the maximum capacity limit the step could be small, and gradually increase, depending on the sensitivity of the forecasted values on $\mathbf{P^{cap}}$.

VI. CASE STUDY

In this section we evaluate the offering strategy and show how an aggregator can construct offering curves to participate in capacity limit auctions. The service covers a period from 8.00 am to 17.00 pm in each working day. Before constructing an offering curve, the minimum value of $P^{\mathrm{cap},*}$ for the service period must be forecasted. In Fig. 6 we showed an ARIMA-based forecast of the minimum $P^{\mathrm{cap},*}$ for a horizon equal to 20 days. The 99th percentile $\tilde{P}_d^{\mathrm{cap},*}$ is used as a forecast, and the accuracy of the model J_d is calculated as

$$J_d = \max(\tilde{P}_{d-t_{\mathrm{MA}}+1}^{\mathrm{cap},*}, \ldots, \tilde{P}_d^{\mathrm{cap},*}) - \max(P_{d-t_{\mathrm{MA}}+1}^{\mathrm{cap},*}, \ldots, P_d^{\mathrm{cap},*}). \tag{10}$$

The results for 150 days are shown in Fig. 10. The forecast errors are always smaller than 50 kW, and decrease with time. After $d = 130$ the average forecast error is 10 kW, and in the few cases where the limit is underestimated, this is limited to an error of $5 - 15$ kW. A very conservative estimate of $P^{\mathrm{cap},*}$ would result in the aggregator not bidding for small capacity limits. As we will show next, this is important because of the exponential increase of the opportunity cost as the capacity limit decreases. A good forecast of $P^{\mathrm{cap},*}$ thus allows the aggregator to minimize the potential loss of revenue.

Before calculating an offering curve, we will elaborate on how this is constructed based on the time-series forecasts described in Section V. The first model predicts opportunity cost by considering the known and lagged EV realizations; the second model predicts the required cost adjustment caused by the changes in EV patterns. The summation of the two predictions gives the opportunity cost forecast of the upcoming period. A total of 100 scenarios were used when solving (6), created by the joint realization of five EV scenarios and 20 RT prices scenarios. Since the residuals of the models are

This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/TSG.2019.2921402, IEEE Transactions on Smart Grid
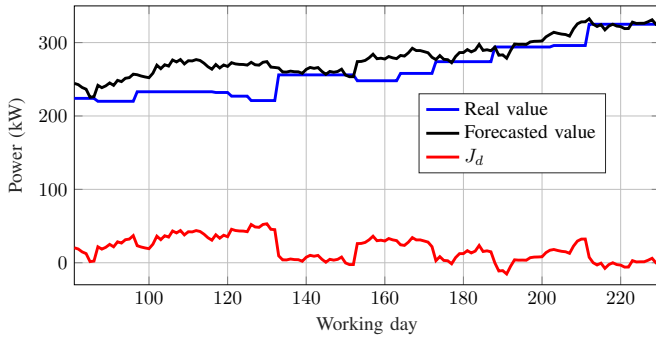
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Fig. 10: Accuracy of the forecasting model for the minimum capacity limit for a forecast horizon equal to 20 days.

normally distributed, we used the obtained expected values and standard deviations to create sample values for the forecasts. In Fig. 11, an illustrative example of these forecasts is shown for a period covering days $181 - 200$; electricity prices and EV realization data are available until that day. The sum of the generated samples produces the distribution of the prediction for the opportunity cost. From this distribution we calculated the expected value, along with the 2.5th and 97.5th percentiles to derive the 95 % PI. For the optimization problems MAT-LAB and the YALMIP toolbox [29] were used, with Gurobi 8.0 [30] as the solver. The computational requirements of the proposed strategy are relatively low due to the linear nature of (6), with most of the computational time devoted to calculating training data.
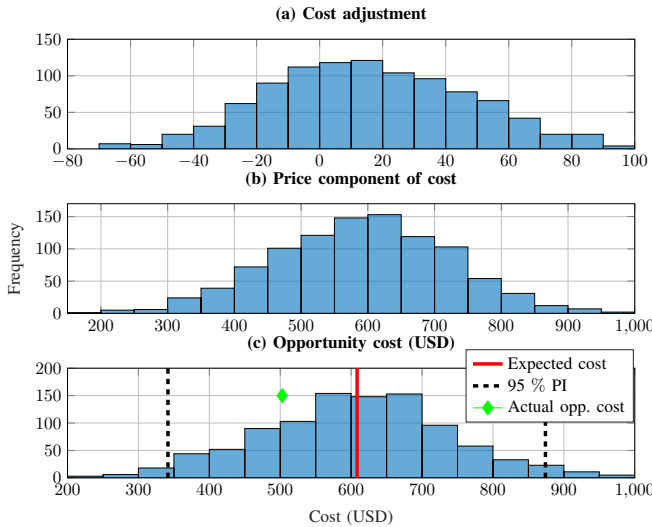

Fig. 11: Forecasts for a capacity limit of 500 kW and a period covering days $181 - 200$.

This process is repeated for a range of capacity limits to obtain an offering curve. Figure 12 shows such a curve for the considered period. A first observation is that both the forecasts and the actual opportunity cost exhibit an exponential behavior. This means that for relatively high capacity limits the opportunity cost of such a service is low, but increases significantly as the capacity limit takes values close to the physical delivery limitations. Another observation is that the

PIs significantly increase as the capacity limit decreases, reflecting the higher cost uncertainty for an aggregator managing a portfolio closer to its physical power limits. Finally, the accuracy of the prediction deteriorates as the capacity limit decreases. This happens because the variability of the opportunity cost is larger for smaller capacity limits.
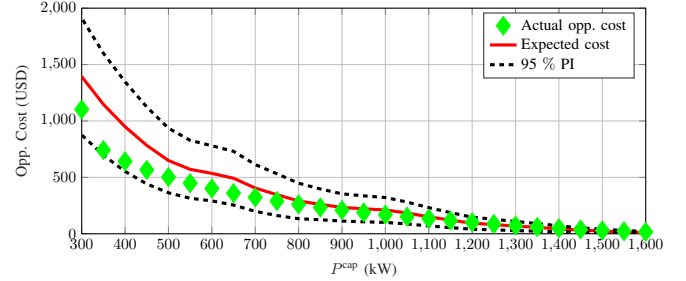

Fig. 12: Aggregator's offering curve for a period covering days $181 - 200$.

The accuracy of the forecast depends on the time of the prediction. It is very hard to forecast large increases or decreases in opportunity cost, because these are caused by rare scenarios of the DA/RT electricity prices. For example, days with strongly negative RT electricity prices result in a large increase of opportunity costs, but such events are hard to predict. The accuracy of the forecasting model was evaluated by making new predictions every day for a capacity limit of 500 kW and a service duration of 20 days. In each day d, the actual and the predicted opportunity cost correspond to a service period covering days $d - 19, \ldots, d$, with EV and price data being progressively available. More specifically, data until, and including, day $d - 20$ is available when forecasting costs for day d.

To reduce the PIs of the forecasts, we utilize past electricity prices data. One can observe from Fig. 7 that the price component of the opportunity cost is confined within a range of values. We use the 97.5th percentile of the price component of the first two years of the training dataset as an upper bound for the PI, and the 2.5th percentile as a lower bound. In other words, if the ARIMA model's 97.5th percentile prediction is larger than the 97.5th percentile from the first two years of the dataset, it is capped to this value. Similarly, the historical 2.5th percentile serves as a lower limit for the predictions. The forecasting results are shown in Fig. 13.
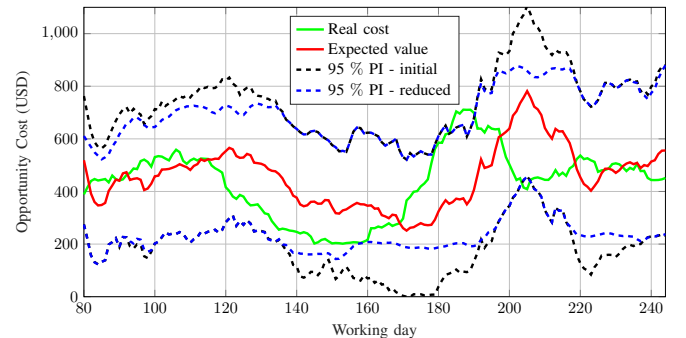

Fig. 13: Forecasting accuracy for 165 days and a capacity limit of 500 kW.

The accuracy of the prediction is acceptable, without resulting in a bias over 165 predictions (the average forecasting error is less than 25 USD), and with a MAE of less than 120 USD. As already mentioned, large changes in the opportunity cost cannot be predicted by the model because these do not exhibit a seasonal pattern and are rather determined by rare scenarios in the RT prices. The 95 % PIs were significantly reduced by utilizing the training dataset obtained from the cost factors decomposition. Thus, the precision of the forecasting was considerably improved, with 9 violations of the PIs, which is roughly equal to 5 % of the samples.

The presented analysis was conducted by considering a risk-neutral participation of the aggregator in the DA and RT markets. To reduce risk exposure, the aggregator can use a risk-averse strategy by including conditional value at risk (CVaR) when solving the two-stage stochastic optimization problem. The CVaR formulation of (6) is given in the Appendix. The simulations were repeated by setting the CVaR confidence level $\alpha = 0.95$, and using two different values for weighting parameter β: 1 and 10 (the outcome for $\beta = 0$ corresponds to the risk-neutral case). Parameter β introduces a trade-off between the expected cost and the risk for the aggregator, with higher values resulting in a more risk-averse behavior. The average daily cost under different values for β are shown in Table I, for both the unconstrained operation and the case where a limit of 500 kW is set. As expected, higher values of β result in an increase of the average cost for the aggregator, but also limit the very high cost values, by considerably reducing the 95-percentile values.

	Unconstrained Operation		$P^{\mathrm{cap}} = 500$ kW	
β	Average daily cost	95-percentile of daily cost	Average daily cost	95-percentile of daily cost
0	40.5	211.5	64.5	249.6
1	45.6	180.8	70.2	208.3
10	54.6	156.7	76.5	170.3

TABLE I: Average and $95-$percentile values of the actual daily costs in USD for different β values.

Next, the offering curve covering the same period as the one in Fig. 12 was constructed, with $\beta = 10$. The offering curves for both $\beta = 0$ and $\beta = 10$ are shown in Fig. 14.
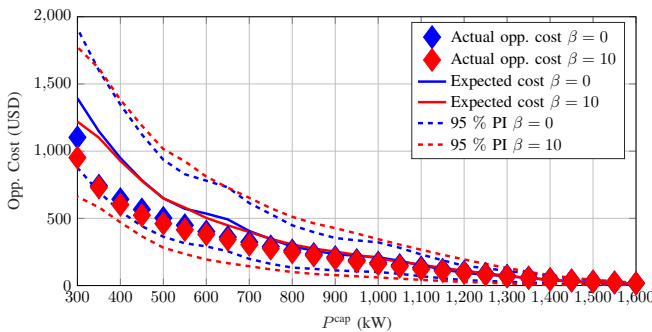

Fig. 14: Aggregator's offering curve for a period covering days $181 - 200$ with $\beta = 10$.

In Table II the average and $95-$percentile values of the actual opportunity costs are shown. A parameter β equal to 10 reduces the average value of the opportunity cost by approximately 7 % (for $\beta = 1$ the average value is almost equal to the risk-neutral case). Interestingly, the effect on the $95-$percentile values is much more pronounced, with a considerable increase in the risk-averse cases. This behavior occurs because costs in (6) are highly dependent on the out-of-sample realized RT prices and EV uncertainty, which are not included in the uncertainty set W. A more conservative DA schedule may occasionally result in high losses in RT, and thus in a higher volatility in the opportunity costs.

The results of Table II refer to daily opportunity costs, and are not directly transferable to the 20-days average values used in the offering curves. As seen in Fig. 14, the actual opportunity costs for the examined time period were indeed smaller for $\beta = 10$. The higher $95-$percentile values of the opportunity costs for the risk-averse case (as reported in Table II) also result in larger PIs. However, the actual opportunity costs and the predictions show a similar (exponential) behavior for the risk-averse cases, whereas larger β seems to result (on expectation) in lower but more volatile opportunity costs. It is interesting to note that a risk-averse strategy reduces the extreme cost values (on a daily basis) for the aggregator, but it has the opposite effect on opportunity cost. This is to a large extent offset by the mid-term nature of the market and the averaging of opportunity costs.

β	Average daily opportunity cost	95-percentile of daily opportunity cost
0	23.5	56.2
1	23.8	65.7
10	21.8	68.2

TABLE II: Average and $95-$percentile values of the actual daily opportunity costs in USD for different β values and $P^{\mathrm{cap}} = 500$ kW.

VII. Conclusion

In this paper we investigated how an aggregator can construct mid-term capacity limit offering curves, considering participation in the DA and RT markets. These curves reflect the aggregator's opportunity cost in the DA/RT markets, when offering such a DSO service. We proposed a practical and straightforward method, which does not require explicit forecasting of the evolving EV charging scenarios or electricity prices. The opportunity cost forecasting method decomposes the effect of electricity prices and EV realizations, thus accounting for evolving EV patterns and enabling the use of past electricity price data. The presented approach can be used for other DERs, such as thermal loads, with weather scenarios replacing the EV uncertainty. However, since weather data exhibits a strong seasonal behavior and historical data is more readily available, the cost decomposition part can be omitted.

Our results, based on real data from a large number of commercial EV chargers, showed that the opportunity cost of an aggregator can be forecasted with reasonable accuracy. Historical data can be used to achieve a significant improvement in the model's precision. However, as capacity limits decrease, opportunity costs and PIs show an exponential increase, and the range of the PIs increases considerably. Our results indicate that such a simple mechanism could provide

operational guarantees to DSOs and avoid overloading with a relatively low cost, as long as the capacity limits are not close to the physical limitations of the DERs.

As potential future work, it is of interest to investigate how the participation of DERs in the ancillary service market can be included in the opportunity cost forecasting, and how this would affect the shape of the offering curves. Moreover, the performance of different forecasting techniques needs to be compared. Finally, we intend to evaluate how such a capacity service can be used as an alternative to grid reinforcement, from a social welfare maximization perspective.

APPENDIX

Let $f(w)$ denote the aggregator's cost under scenario realization w:

$$f(w) = \sum_{m=1}^{N_{\mathrm{DA}}} P_m^{\mathrm{DA}} \cdot \lambda_m^{\mathrm{DA}} + \sum_{j=1}^{N_{\mathrm{RT}}} P_{j,w}^{\mathrm{RT}} \cdot \lambda_{j,w}^{\mathrm{RT}} \cdot \Delta T. \qquad (11)$$

Following [31], [32], CVaR is incorporated into (6) as:

$$\min_{\mathbf{U}, \boldsymbol{\eta}, \zeta} \quad \sum_{w \in W} \pi_w f(w) - \beta \big[\zeta - \frac{1}{1-\alpha} \sum_{w \in W} \pi_w \eta_w \big] \qquad (12a)$$

$$\text{s.t.} \quad (6b) - (6f) \qquad (12b)$$

$$\zeta + f(w) \le \eta_w, \ \forall \ w \qquad (12c)$$

$$\eta_w \ge 0, \ \forall \ w. \qquad (12d)$$

ACKNOWLEDGEMENT

REFERENCES

[1] R. A. Verzijlbergh, L. J. De Vries, and Z. Lukszo, "Renewable energy sources and responsive demand. Do we need congestion management in the distribution grid?," *IEEE Trans. Power Syst.*, vol. 29, no. 5, pp. 2119–2128, 2014.

[2] "Ecogrid 2.0 [online]." Available: http://www.ecogrid.dk/en/home_uk. Accessed: 07/31/2018.

[3] S. Huang, Q. Wu, Z. Liu, and A. H. Nielsen, "Review of congestion management methods for distribution networks with high penetration of distributed energy resources," *IEEE PES ISGT Europe*, pp. 1–6, 2014.

[4] R. Li, Q. Wu, and S. S. Oren, "Distribution locational marginal pricing for optimal electric vehicle charging management," *IEEE Trans. Power Syst.*, vol. 29, no. 1, pp. 203–211, 2014.

[5] N. O'Connell, Q. Wu, J. Østergaard, A. H. Nielsen, S. T. Cha, and Y. Ding, "Day-ahead tariffs for the alleviation of distribution grid congestion from electric vehicles," *Elect. Power Syst. Res.*, vol. 92, pp. 106–114, 2012.

[6] S. Huang, Q. Wu, S. S. Oren, R. Li, and Z. Liu, "Distribution locational marginal pricing through quadratic programming for congestion management in distribution networks," *IEEE Trans. Power Syst.*, vol. 30, no. 4, pp. 2170–2178, 2015.

[7] S. Hanif, T. Massier, H. Gooi, T. Hamacher, and T. Reindl, "Cost optimal integration of flexible buildings in congested distribution grids," *IEEE Trans. Power Syst.*, vol. 32, no. 3, pp. 2254–2266, 2017.

[8] S. Hanif, H. B. Gooi, T. Massier, T. Hamacher, and T. Reindl, "Distributed congestion management of distribution grids under robust flexible buildings operations," *IEEE Trans. Power Syst.*, vol. 32, no. 6, pp. 4600–4613, 2017.

[9] S. Huang, Q. Wu, L. Cheng, Z. Liu, and H. Zhao, "Uncertainty management of dynamic tariff method for congestion management in distribution networks," *IEEE Trans. Power Syst.*, vol. 31, no. 6, pp. 4340–4347, 2016.

[10] R. D. S. Ferreira, L. A. Barroso, P. R. Lino, M. M. Carvalho, and P. Valenzuela, "Time-of-use tariff design under uncertainty in price-elasticities of electricity demand: A stochastic optimization approach," *IEEE Trans. on Smart Grid*, vol. 4, no. 4, pp. 2285–2295, 2013.

[11] B. Zhou, R. Yang, C. Li, Y. Cao, Q. Wang, and J. Liu, "Multiobjective model of time-of-use and stepwise power tariff for residential consumers in regulated power markets," *IEEE Syst. J.*, vol. 12, no. 3, pp. 2676–2687, 2018.

[12] P. Olivella-Rosell *et al.*, "Optimization problem for meeting distribution system operator requests in local flexibility markets with distributed energy resources," *Appl. Energy*, vol. 210, pp. 881–895, 2018.

[13] S. S. Torbaghan, N. Blaauwbroek, P. Nguyen, and M. Gibescu, "Local market framework for exploiting flexibility from the end users," *International Conference on the European Energy Market, EEM*, 2016.

[14] K. Heussen, D. E. M. Bondy, J. Hu, O. Gehrke, and L. H. Hansen, "A clearinghouse concept for distribution-level flexibility services," in *IEEE PES ISGT Europe*, pp. 1–5, 2013.

[15] J. Villar, R. J. Bessa, and M. Matos, "Flexibility products and markets: Literature review," *Elect. Power Syst. Res.*, vol. 154, pp. 329–340, 2018.

[16] D. B. Nguyen, J. M. A. Scherpen, F. Bliek, W. Kramer, and G. K. H. Larsen, "Distributed optimal control and congestion management in the universal smart energy framework," in *European Control Conference (ECC)*, pp. 910–915, 2016.

[17] R. Philipsen, M. de Weerdt, and L. de Vries, "Auctions for congestion management in distribution grids," in *13th International Conference on the European Energy Market (EEM)*, pp. 1–5, 2016.

[18] N. Li, L. Chen, and M. A. Dahleh, "Demand response using linear supply function bidding," *IEEE Trans. on Smart Grid*, vol. 6, no. 4, pp. 1–12, 2015.

[19] Y. Xu, N. Li, and S. H. Low, "Demand response with capacity constrained supply function bidding," *IEEE Trans. Power Syst.*, vol. 31, no. 2, pp. 1377–1394, 2016.

[20] Y. K. Renani, M. Ehsan, and M. Shahidehpour, "Optimal transactive market operations with distribution system operators," *IEEE Trans. Smart Grid*, vol. 9, no. 6, pp. 6692–6701, 2018.

[21] M. N. Faqiry, L. Edmonds, H. Zhang, A. Khodaei, and H. Wu, "Transactive-market-based operation of distributed electrical energy storage with grid constraints," *Energies*, vol. 10, no. 11, pp. 1–17, 2017.

[22] D. P. Chassin and D. Rondeau, "Aggregate modeling of fast-acting demand response and control under real-time pricing," *Appl. Energy*, vol. 181, pp. 288–298, 2016.

[23] M. G. Vayá and G. Andersson, "Optimal bidding strategy of a plug-in electric vehicle aggregator in day-ahead electricity markets under uncertainty," *IEEE Trans. Power Syst.*, vol. 30, no. 5, pp. 2375–2385, 2015.

[24] M. G. Vayá and G. Andersson, "Self scheduling of plug-in electric vehicle aggregator to provide balancing services for wind power," *IEEE Trans. on Sustainable Energy*, vol. 7, no. 2, pp. 886–899, 2016.

[25] L. Baringo and R. Sánchez Amaro, "A stochastic robust optimization approach for the bidding strategy of an electric vehicle aggregator," *Elect. Power Syst. Res.*, vol. 146, pp. 362–370, 2017.

[26] Z. Liu, Q. Wu, K. Ma, M. Shahidehpour, Y. Xue, and S. Huang, "Two-stage optimal scheduling of electric vehicle charging based on transactive control," *IEEE Trans. on Smart Grid*, vol. 10, no. 3, pp. 2948–2958, 2019.

[27] K. Margellos and S. Oren, "Capacity controlled demand side management: A stochastic pricing analysis," *IEEE Trans. Power Syst.*, vol. 31, no. 1, pp. 706–717, 2016.

[28] R. Jiang, J. Wang, and Y. Guan, "Robust unit commitment with wind power and pumped storage hydro," *IEEE Trans. Power Syst.*, vol. 27, pp. 800–810, May 2012.

[29] J. Lofberg, "Yalmip : A toolbox for modeling and optimization in matlab," 2004.

[30] L. Gurobi Optimization, "Gurobi optimizer reference manual," 2018.

[31] R. T. Rockafellar and S. Uryasev, "Optimization of conditional value-at-risk," *Journal of Risk*, vol. 2, pp. 21–41, 2000.

[32] R. T. Rockafellar and S. Uryasev, "Conditional value-at-risk for general loss distributions," *Journal of Banking and Finance*, vol. 26, no. 7, pp. 1443–1471, 2002.

This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/TSG.2019.2921402, IEEE Transactions on Smart Grid

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