Aggregator-Controlled EV Charging in Pay-As-Bid Reserve Markets with Strict Delivery Constraints

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***Abstract*—Electric Vehicles (EVs), similar to other types of flexible loads, can be controlled to provide additional flexibility to power system operators, which is needed to transition from primarily fossil fuel based electricity generation to more renewable generation. Existing electricity markets already provide economic incentives to offer flexibility. So-called aggregators in charge of controlling EV charging could take advantage of these incentives. However, random driving behavior and area-specific market rules complicate the market participation of EV aggregators in energy and reserve markets. The goal of this paper is to investigate the design and performance of a system that would enable EV aggregators to participate in wholesale electricity markets. We consider a certain type of market environment, which includes an intraday energy market and pay-as-bid reserve markets that require exact reserve delivery and have long operating intervals. We therefore propose a novel approach for concurrent market participation that can deal with these constraints, even when faced with highly uncertain reserve activation and EV behavior.**

***Index Terms*—Energy management, electric vehicles, electricity markets, optimization methods, scheduling algorithms.**

NOMENCLATURE

i	EV ID.
k	Bid ID.
n	Number of EVs.
t	Variable to denote time.
d	Variable to denote duration.
l	Variable to denote EV battery state of charge.
Δ	Variable to denote change of EV battery state of charge.
p	Variable to denote power.
e	Variable to denote energy.
t_{now}	Current simulation time.
$\bar{t}_{fore}$	Forecasted EV departure time contained in parking period statement **PPS**.
$\bar{t}_{actual}$	Actual EV departure time, as compared to forecasted departure time $\bar{t}_{fore}$ contained in **PPS**.
d_{oi}^M	Duration of operating interval on market M.
d_{bd}^M	Minimum duration between bid placement and start of operating interval on market M.
d_{sched}	Discretization duration interval for optimization.
d_{act}^M	Activation duration on reserve market M.
d_{tot}	Total available EV charging duration contained in a resource availability statement **RAS**.
l_s	EV battery state of charge at beginning of parking period contained in parking period statement **PPS**.
l_{now}	State of charge of an EV battery at current simulation time.
$\underline{l}_i$	Minimum state of charge of EV i's battery.
$\bar{l}_i$	Maximum state of charge of EV i's battery.
p_{min}^M	Minimum reserve bid size on market M.
p_{inc}^M	Minimum reserve bid size increment on market M.
$\underline{p}_i$	Nominal charging power of EV i.
e_{min}^M	Minimum energy market bid size on market M.
e_{inc}^M	Minimum energy market bid size increment on market M.
ϵ_M	Dispatch tolerance of market M.
σ_{fore}	Standard deviation of departure time forecasting error.
r_i	Charging rate of EV i at nominal charging power.
R	Variable indicating repair mode.
$avail$	Variable indicating that EV is connected to charging station.
N	Set containing all EVs.
L	Data set describing state of energy gap **L** with content $\boldsymbol{S}^P$.
$\mathbf{EV}_i$	Data set describing state of EV i with content l_{now}, $avail$, **PPS**, $\boldsymbol{S}^C$, $\boldsymbol{S}^P$.
PPS	Parking period statement with content $\underline{t}$, $\bar{t}_{fore}$, and l_s.
F	Schedule fragment with parameters $i, k, \underline{t}, \bar{t}, p$.
$\boldsymbol{S}$	Schedule with content $\mathbf{F}_1, \mathbf{F}_2, ...$
P	Power level with parameters $\underline{t}, \bar{t}, p$.
$\boldsymbol{P}$	Power profile with content $\mathbf{P}_1, \mathbf{P}_2, ...$
AI	Availability interval with parameters $\underline{t}, \bar{t}$.
AIS	Set of availability intervals with content $\mathbf{AI}_1, \mathbf{AI}_2, ...$
RAS	Resource availability statement with parameters $i, d_{tot}, \boldsymbol{AIS}$.
RASS	Set of resource availability statements with content $\mathbf{RAS}_1, \mathbf{RAS}_2, ...$

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I. INTRODUCTION

The ongoing integration of renewable energy generation from wind and solar requires a paradigm shift from demand-following supply to supply-following load. The concept of demand response, which initially focused on reducing the cost of peak power supply by thermal generators, has thus recently evolved into a more general concept with the goal of continuously adjusting demand to match the random power supplied by renewables [1]. From a capital investment perspective, demand response can be very efficient: In contrast to dedicated energy storage, flexible loads already exist, e.g., thermal loads such as heating and cooling systems in buildings.

Several recent research papers have demonstrated the potential of flexible loads for balancing power supply and demand [1], [2], [3], [4]. However, controlling many small resources connected on the power distribution level instead of dispatching several large generators on the transmission grid level poses new challenges for operational control. The complexity of this control task is further increased by the uncertain behavior of many loads: Their energy consumption is driven by random user behavior and environmental conditions that are hard to predict.

In many regions of the world, centrally managed electricity markets or energy exchanges have been established [5]. Although a large share of the total electric energy consumed is still traded bilaterally between large producers and consumers, the share of energy traded on exchanges is increasing steadily. The goal of electricity markets is to match electricity supply and demand in the most efficient way possible. Electricity market systems are usually organized as a cascade of independent auction markets that allow participants to trade different products across multiple time scales [5]. This enables a stepwise power balancing process that allocates decreasing amounts of energy in ever shorter time intervals while the time of physical power delivery approaches. In addition to energy markets, markets for reserve are becoming commonplace. Reserves are required to close the gap between the previously scheduled supply and forecasted demand [4]. They are dispatched upon short notice to keep the power grid in a secure state. The use of reserve markets allows power system operators to cover their demand for reserves at the lowest possible cost.

The advent of electric vehicles (EVs) introduces a new type of distributed flexible load into existing power systems. Their primary purpose is to provide mobility to their owners, which determines the times during which they are connected to the power grid and their energy demand during these periods. Unfortunately, parking periods and energy demands are uncertain and hard to predict accurately. On the one hand, this uncertainty makes wholesale market sourcing of EV charging energy challenging since it is difficult to provide just the right amount of energy without incurring prohibitive penalties. On the other hand, controlling the charging behavior of many EVs in almost real time would enable aggregators to sharply increase or decrease their power demand almost instantaneously, matching even highly volatile renewable supply or reserve activation signals issued by system operators, which is a clear advantage over slowly ramping generators.

If flexible loads are not controlled by the system operator, but by so-called aggregators who participate in the electricity markets, the corresponding market rules further limit charging control. Electricity markets differ substantially across different control regions (cf. [6], [7]), therefore it is essential to consider market operation details when proposing resource aggregation schemes.

Several papers have addressed the problem of bringing flexible loads, such as EVs, to multiple markets, in particular energy and reserve markets [8], [9], [10]. However, these publications consider reserve markets typical for the U.S. with one hour long operating intervals[1], uniform pricing[2], proportional reserve activation[3], and fixed or predictable deviation penalties[4] for energy and reserve bids. Unfortunately, the methods proposed in the related literature cannot be applied to all market contexts, in particular those existing in several European countries including Germany. In contrast to the market context typical for the U.S., which these publications refer to, they feature *pay-as-bid*[5] reserve markets that require *mandatory reserve delivery* without the possibility to deviate, and have *relatively long operating intervals* (4-12 hours). Energy market bid deviations are possible in these markets, as well, but penalties are based on the actual cost of the system operator to balance out the resulting deviations. In contrast to U.S. reserve markets, these costs are *highly dynamic and uncertain*, which is eventually again due to the way the reserve markets are organized.

The major differences between the two market contexts outlined above have important consequences for the possible degree of explicit profit maximization when uncertain resources like EVs are controlled to participate in reserve and energy markets. Taken together, the relevant features of the current German reserve and energy market design render the price-based optimization based on forecasts and opportunistic bidding proposed in previous work intractable in this market context. To address these challenges, we propose a novel market participation approach that is not based on buying energy day-ahead and later trade-off revenues from reserve delivery against deviation penalties as proposed in [8], [9], [10], but instead allows aggregators to promise reserve that they can fully deliver and use the intraday spot market as backup without causing additional reserve activation and corresponding penalties. Although our approach does not allow for explicit profit maximization based on price forecasts, it *implicitly maximizes market revenues* by allowing aggregators to offer as much reserve as possible to generate a stable income from flexible EV charging. This approach could also be applied in other jurisdictions, such as the ones addressed in the related literature. However, it would be less attractive compared to tailor-made approaches that are able to exploit their features for explicit profit maximization. Our approach also considers detailed market rules, in particular minimum bid sizes and bid size increments. It features a fast schedule repair mechanism that enables reserve delivery despite the randomness of reserve activation and EV behavior. Based on the results of stochastic simulations using various parameter

[1] Operating intervals define the time for which bids can be submitted, i.e., if they are one hour long, a market participant can place different bids (quantity and price) for each future hour in the considered range.

[2] If a uniform price is determined, all participants receive the same market price, irrespective of the price they have bid.

[3] If reserve is traded at uniform prices, it is usually activated proportionally, i.e., the amount of reserve being delivered by each market participant is determined by multiplying the amount of required reserve in the corresponding time interval by the relative share of the total provisioned reserve of that participant.

[4] Deviation penalties result if market participants do not deliver the energy they promised.

[5] Pay-as-bid means that each market participant receives exactly the bid price it has asked for, which implies the activation of reserve in merit order, i.e., in ascending order of bid price.

settings, we find that the proposed method achieves market-conformity without affecting EVs and is computationally feasible within the required time frames.

In the following Section II, we review related work. In Section III, we propose new abstractions for managing EV charging schedules under uncertainty. In Section IV, we describe an effective method for approximating solutions of the corresponding NP-hard optimization problems and propose an algorithm that repairs existing charging schedules. In Section V, we evaluate the proposed features based on a dual market use case, in which the aggregator controls the charging behavior of a large fleet of EVs to offer as much negative reserve as possible. We discuss our results and contributions in Section VI. Section VII provides conclusions and practical implications.

II. Related Work

Leveraging the ability of EVs to defer charging or even charge power back into the grid has attracted significant attention in the research community [11], [1], [12], [13], [14]. Although EVs represent a new load on the grid, this flexibility could help to achieve another high-priority goal, namely the integration of the steadily increasing power generation from wind and solar, which poses serious challenges for power system operators due to uncertain output that is hard to predict [15].

One major part of the available studies focuses on safety aspects, i.e., investigates how intelligent control of EV charging can prevent overloading distribution grids and therefore also help to defer investments into the power grid infrastructure (e.g., [16], [17]).

A second part investigates how fleets of EVs can be controlled to support load leveling efforts [18], [2], to charge at times of low wholesale energy prices [19], or to achieve a direct coupling with renewable energy supply [20], [3], [21]. Some authors have also investigated the potential of EVs to provide reserves [12], [4], however with a focus on scenarios where the system operator controls EV charging.

A third part, which this paper belongs to, considers market participation of EV aggregators. The authors of [8], [9], and [10] consider aggregators that participate in day-ahead energy and reserve markets operated by the PJM, ERCOT, and the Spanish system operators, respectively.[6] These markets use hourly operating intervals for both energy and reserve, determine uniform hourly prices, and allow for (penalized) deviations or short-time adjustments of the submitted reserve and energy bids. The works of [8], [9], and [10] propose different technical approaches for participating in such markets and evaluate them based on different assumptions regarding prices and EV behavior. However, their common idea is to use day-ahead predictions of EV energy demand and co-optimize energy and reserve bids based on predicted prices. This approach also allows for providing positive reserve without having to discharge EV batteries, since EVs can be instructed to deviate downwards from the day-ahead energy bids and thus intentionally incur the corresponding penalties. An ancillary problem that all these papers have to deal with is the various forecasting errors (several price trajectories, EV energy demand, reserve utilization), which lead to random deviations from energy and reserve bids and corresponding financial penalties.

The authors of [8] propose a two-stage stochastic linear programming method for co-optimizing energy and reserve market bidding on the PJM market. Apart from the day-ahead energy and reserve markets, they also take the possibility of limited hour-ahead adjustments of reserve and energy bids into account, i.e., their optimization has to be repeated in hourly intervals. A key strength of their approach is that it takes deviation penalties explicitly into account, they even compare different penalty regimes. However, while the authors include real-time market prices and the demand for reserve as stochastic variables into their optimization problem, they assume that EV behavior and market prices are known with certainty day-ahead. Under these assumptions, the stochastic program achieves an optimal trade-off between incurring deviation penalties and obtaining revenue from providing reserve in the PJM market setting.

The approach presented in [9] considers the ERCOT market. They propose to solve a deterministic optimization problem every hour to update the following decision variables: The capacity of each EV to provide different types of reserve (regulation up capacity, regulation down capacity, and responsive reserve) as well as their scheduled hourly power trajectories. The daily EV charging schedule can thus be adjusted every hour to respond to updated forecasts of future reserve activation, market prices, and EV behavior. A strength of their approach is the consideration of uncertain EV behavior, which needs to be predicted day-ahead. However, they do not consider deviation penalties.

The authors of [10] consider the Iberian electricity market environment. They also propose price-based charging cost minimization by co-optimizing day-ahead energy market and reserve bids based on forecasts. Thus, similar to [8] and [9], their approach relies on accurate day-ahead forecasting of several variables, in particular EV availability, charging requirements, hourly reserve participation factors, hourly reserve capacity prices, hourly reserve utilization prices, and hourly reserve activation. They propose to first solve the full day-ahead cost minimization problem based on a unique set of forecasted values for all variables. Since the results of this optimization cannot be directly applied in the operating hour due to forecasting errors, they in a second step solve an optimization problem to minimize total energy deviations. In their evaluation, the authors conduct an excellent analysis of the impact of forecasting accuracy on aggregator profits by comparing clairvoyance with persistence forecasting.

The purpose of [22] is to gauge the business value of vehicle-to-grid reserves in Germany. Their paper considers similar reserve market properties as we do in this paper, in particular hard constraints on reserve delivery and long reserve market operating intervals. However, their focus is more on vehicle-to-grid (V2G) based provision of reserve, which we do not consider, and they do not consider concurrent participation in energy and reserve markets as we do in this paper.

[6] PJM and ERCOT are located in the U.S.

Instead of maximizing reserve provision using mathematical optimization, they divide the expected EV charging energy at a given time by a fixed duration of 1-4 hours, taking the minimum of the resulting values during night times as the maximum level of reserve that the EVs can provide.

The authors of [23] propose an EV aggregation approach that considers the risk of deviating from day-ahead energy market bids and incurring balancing charges. They do this by including a value-at-risk term in the objective function, which allows for risk-averse profit maximization. Their evaluation features an excellent statistical analysis of day-ahead market prices and balancing charges, which they simulate based on fitted ARIMA models. Similar to [8], [9], [10], they consider day-ahead energy sourcing using price forecasts and applying stochastic optimization. However, they do not consider participation in reserve markets, which distinguishes their contribution from our paper and the contributions reviewed above.

In contrast to [8], [9], and [10], whose contributions are outlined above, our paper considers a *different market environment* that exists in several European countries [6], among others Germany, which has the following features:

- In these market environments, reserve markets rely on *pay-as-bid* auction mechanisms, i.e., in contrast to the uniform price auctions used in other market contexts, the participants of the reserve market considered in our paper receive exactly the payments they ask for when submitting their bids, provided the system operator accepts their bid. This also means that the system operator activates reserve in ascending order of bid delivery prices, i.e., the reserve contribution per time unit is *not proportional* to the total activated reserve. As a consequence, our market context establishes an explicit dependency of quoted bid prices on the fraction of reserve demand to be covered by individual market participants, which render forecasts of revenues from activated reserve, as well as the individual reserve contributions over time, highly inaccurate.
- Reserve market operating intervals are *significantly longer* than one hour (4-12 hours), which leaves less room for optimization compared to markets where reserve can be provided in hourly time slices.
- Deviations from reserve bids are *not possible*. Aggregators thus always have to be ready to deliver the promised amount of reserve and therefore cannot apply opportunistic reserve market bidding, i.e., take advantage of the possibility to deviate from promised reserve amounts for the sake of profit maximization as proposed in the literature cited above.[7]
- Deviation penalties for energy market bids in Germany are not fixed, but depend on reserve activation and are therefore *highly uncertain*.[8]

In summary, the differences between the market environment addressed in this paper and those addressed in the literature that also propose concrete solutions for the EV charging problem are substantial and, unfortunately, render the proposed solutions inapplicable to our context. In this paper, we therefore explore a completely different approach to multi-market sourcing of EV charging energy compared to [8], [9], and [10]: Instead of trading off the cost of energy bid deviations against the benefit of providing reserve, we propose to provide a maximum amount of negative reserve in subsequent operating intervals of the reserve market and use the intraday energy market as backup source for charging energy. Based on historical market outcomes, we demonstrate the business rationale of this approach, even if it does not allow for explicit profit maximization due to the restrictions resulting from the chosen market context. Uncertain EV departure times are then dealt with using a fast schedule repair mechanism, which, as we show, can guarantee reserve delivery as required in the chosen market environment. We also show that our approach allows for almost eliminating deviations from energy market bids, thus avoiding the problem of uncertain penalties. In addition to reducing the aggregator's exposure to the corresponding financial risk, the approach has the advantage of reliably absorbing reserve requirements instead of implicitly causing new ones, which is an advantage in any market context.

III. Models

A. Electricity Markets

The current market rules in the Germany require that bids placed on wholesale electricity markets (both energy and reserve) adhere to certain minimum sizes and size increments [24], [25]. Bids have to be placed before certain deadlines before the corresponding auctions take place and cannot be canceled once placed. If committed reserve is activated, or cleared energy market bids are physically settled, the aggregate power/energy profiles have to adhere to certain energy delivery rules. In the case of reserves, the promised power level has to be reached within a certain time period ranging from seconds to several minutes, depending on the corresponding type of reserve [25]. Furthermore, the reserve power consumed or generated has to remain at the target level during the entire activation time period with minor tolerance. The delivery

[7] While deviations from reserve market bids are not possible in our market context, deviations from energy market bids are possible, but can result in financial penalties.

[8] If participants of the energy markets (day-ahead or intraday energy market) deviate from their executed bids, they have to contribute the proportional share to a financial compensation scheme, called reBAP. The money collected via the reBAP scheme is used to partially cover the total cost of reserve provision. This compensation can be positive or negative, based on whether the type of deviation led to the activation of reserve or prevented it. Thus, neither are deviation penalties fixed as in other markets, nor can they be predicted by market participants, which exposes them to financial risk. The remaining reserve provision cost is socialized, i.e., it is part of what end users have to pay for their electricity. Recent regulatory changes to the reBAP scheme have increased deviation penalties and thereby increased the incentives to participate in the intraday market instead of incurring potential compensation charges. In summary, despite the fact that intraday market participants could systematically deviate from their promised quantities, they (i) are subject to unpredictable and potentially significant deviation penalties, and, (ii), would eventually increase end-consumer costs.

rules on the energy markets are less strict compared to the reserve markets. In particular, energy market rules only require that a certain amount of energy is generated or consumed within the corresponding operating interval while power levels may change over time. Furthermore, market participants are allowed to deviate from their energy bids, i.e., the energy they actually generate or consume may differ from what they have previously promised. However, in this case, they are subject to deviation penalties (cf. our explanations provided in Section II).

In the following, we formalize these market constraints in a general way, i.e., our formalization describes the constraints of any type of reserve or energy market M. In the case of reserve markets, the participants have to commit to a power level, p_{target}, whereas in the case of energy markets, they have to commit to a certain amount of energy, e_{target}.

- If a market participant wants to buy/sell energy or sell reserve on market M during the operating interval $\left[\underline{t}^M, \underline{t}^M + d_{oi}^M\right]$, it has to place the bid before the corresponding bidding deadline $t_{dl} = \underline{t}^M - d_{bd}^M$. Duration d_{oi}^M denotes the standardized length of operating intervals on market M and duration d_{bd}^M denotes the minimum time span between the bidding deadline and the start of the corresponding operating interval.
- The bid size $\{p, e\}^M$ submitted to the market operator before time t_{dl} has to adhere to the bid size constraints of market M, i.e., $\{p, e\}^M = \{p, e\}_{min}^M + \alpha\{p, e\}_{inc}^M$, where $\{p, e\}_{min}^M$ is the minimum bid size, $\{p, e\}_{inc}^M$ is the allowed bid size increment, and $\alpha \in \mathbb{N}$.
- The total reserve power p_{actual}^M delivered during the operating interval $\left[\underline{t}^M, \underline{t}^M + d_{oi}^M\right]$, must not deviate from the committed amount p_{target}^M by more than a market-specific error, ϵ_M, i.e., $p_{actual} \in \left[p_{target}^M - \epsilon_M, p_{target}^M + \epsilon_M\right]$.
- The total energy e_{actual}^M delivered during the operating interval $\left[\underline{t}^M, \underline{t}^M + d_{oi}^M\right]$, can deviate from the committed amount e_{target}^M, but then causes proportional financial penalties.

B. Computation of Resource Availability Statements

In the following, we assume the existence of an information system that enables two-way communication between the EV aggregator and the EVs. This information system maintains a set of *virtual* EVs $i \in \mathbf{N}$ and corresponding *resource schedules* that are updated in response to market participation events or resource events. In the following, we abbreviate the set of data that the information system stores for virtual EV i with $\mathbf{EV}_i$. Generally, we write $X.y$ to denote the value of variable y in data set X. A *market event* takes place when a resource is scheduled to stand by for providing reserve power, deliver reserve, or supply/consume energy. A *resource event* occurs, for example, when a resource becomes available or unavailable, if communication between the service and the physical resource gets interrupted, or if the physical resource sends new status data to the information system backend.

While an EV i is connected to a charging station, a corresponding tracking variable, $\mathbf{EV}_i.avail$ is set to $true$, otherwise it is equal to $false$. If the EV arrives at a charging station and connects to the power grid for recharging, the information system creates a corresponding *parking period statement* $\mathbf{EV}_i.\mathbf{PPS}$ containing the arrival time $\underline{t}$, a forecasted departure time $\bar{t}_{fore}$, and the EV battery's state of charge upon arrival l_s, i.e., $\mathbf{PPS} = \left[\underline{t}, \bar{t}_{fore}, l_s\right]$. Based on these values, the information system can determine the time t_{must} within the parking period when the EV needs to start charging *at the latest* to still charge as much energy as possible into its battery. Thus, if the departure time forecast $\bar{t}_{fore}$ was accurate and EV charging started at time t_{must}, the EV's electric range would not be affected by deferred charging at all, i.e., the energy level of the EV's battery would equal the level it would have reached had it started to charge upon arrival. Time t_{must} can be computed according to Equation 1, where r denotes the change of the state of charge per time unit. The state of charge refers to the usable range of the battery's total energy capacity and is expressed as fraction. The value of r therefore takes charging efficiency into account. Parameter $\bar{l}$ denotes the maximum state of charge.

$$t_{must} = \bar{t}_{fore} - min\left\{max\left\{\bar{t}_{fore} - \underline{t}, 0\right\}, \frac{\bar{l} - l_s}{r}\right\} \qquad (1)$$

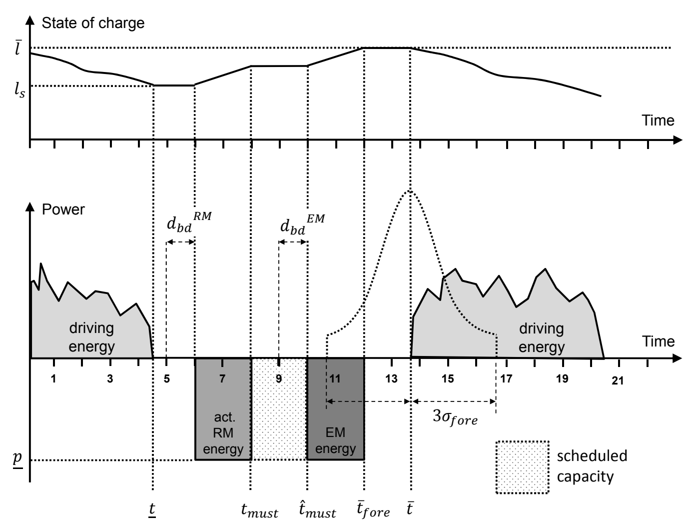


Fig. 1. Scheduling of EV charging.

Figure 1 shows an exemplary situation where an EV arrives at time $\underline{t} = 4.5$ with a total charging duration requirement of 4 time units, taking a fixed charging power $\underline{p}$ as given. The system expects it to leave at $\bar{t}_{fore} = 12$, which, according to Equation 1, yields an initial must start charging time of $t_{must} = 8$. On time before the next bidding deadline $t_{dl}^{RM} = 5$ of reserve market RM, the information system schedules the provision of 4 hours of reserve by the EV between times 6 and 10. The system activates the EV's contribution to reserve from time 6 to 8, which increases t_{must} from 8 to $\hat{t}_{must} = 10$. At time 9, the system has to schedule the remaining EV charging time such that the remaining charging energy can still be considered for the EM operating interval starting at time 10. Thus, in this example, half of the charging energy is sourced on the reserve market and the other half is sourced on the energy spot market.

Each virtual $\mathbf{EV}_i$ has two schedules, one power schedule, $\mathbf{EV}_i.\boldsymbol{S}^P$, and one capacity schedule, $\mathbf{EV}_i.\boldsymbol{S}^C$. If the information system schedules a certain resource to consume power in the future, the power schedule of this resource is modified accordingly. If a resource is committed to stand by for participating in the provision of reserve, its capacity schedule is modified. If the reserve is activated, again the power schedule is updated.

Schedules are stored as lists of *schedule fragments*. Each schedule fragment $\mathbf{F}$ contains the identifier of the corresponding virtual EV, i, a bid identifier k that associates the fragment with a previously placed bid, a start time $\underline{t}$, a stop time $\overline{t}$, and a power level p, i.e., $\mathbf{F} = [i, k, \underline{t}, \overline{t}, p]$. *Power profiles* can be obtained from a list of schedule fragments by superposition (method sup) of individual schedule fragments. We define a power profile $\boldsymbol{P}$ as an ordered list of time intervals with corresponding power levels, i.e., $\boldsymbol{P} = \{\mathbf{P}_1, \mathbf{P}_2, ...\}$, where $\mathbf{P}_j = [\underline{t}_j, \overline{t}_j, p_j]$ and $\overline{t}_j = \underline{t}_{j+1}$.

The aggregator can query the set of resource schedules to obtain sets of *resource availability statements*, $\boldsymbol{RASS} = \{\mathbf{RAS}_1, \mathbf{RAS}_2, ...\}$, where the resource availability statement of EV i, $\mathbf{RAS}_i$, consists of a resource identifier i, a charging power level p, the total available charging duration d_{tot}, and a set of *availability intervals* $\boldsymbol{AIS} = \{\mathbf{AI}_1, \mathbf{AI}_2, ...\}$ with $\mathbf{AI}_j = [\underline{t}_j, \overline{t}_j]$ indicating when resources can be activated. A resource availability statement can thus be described formally as $\mathbf{RAS} = [i, p, d_{tot}, \boldsymbol{AIS}]$. This definition allows for representing intermittent availability for charging: The variable d_{tot} specifies the total duration that the EV can charge at nominal power p, but charging can only take place within the time intervals provided in $\boldsymbol{AIS}$. This formulation is required to realize concurrent market participation, i.e., allocating energy consumption from the same EVs to multiple market bids that are allowed to overlap in time, as well as the schedule repair mechanism that reallocates energy from schedules that have become infeasible to available EVs.

To obtain a set of availability statements from the EV fleet, the aggregator needs to know the start time $\underline{t}$ and the stop time $\overline{t}$ of the targeted market operating interval. Furthermore, the aggregator needs to specify whether the query is for reserve or energy capacity. The corresponding query parameter is denoted by $type = \{reserve, energy\}$.

Before describing these procedures formally, we introduce some ancillary methods and notations: Method $X.next()$ returns the next data item contained in the ordered data set X, starting with the first value. Method $X.add(y)$ adds value y to set X. Methods $min\{x, y\}$ and $max\{x, y\}$ return the minimum and maximum of two numeric values x and y.

1: Inputs: $\mathbf{EV}_i, \underline{t}, \overline{t}, type$
2: $\boldsymbol{AIS} \leftarrow \varnothing$; $d_{tot} \leftarrow 0$; $p \leftarrow \underline{p}_i$
3: **if** $type = energy$ **then**
4: $\underline{t} \leftarrow max\{\mathbf{EV}_i.\mathbf{PPS}.t_{must}, \underline{t}\}$; $\overline{t} \leftarrow min\{\mathbf{EV}_i.\mathbf{PPS}.\overline{t}_{fore}, \overline{t}\}$
5: **else if** $type = reserve$ **then**
6: $\underline{t} \leftarrow max\{t_{now}, \underline{t}\}$; $\overline{t} \leftarrow min\{\mathbf{EV}_i.\mathbf{PPS}.t_{must}, \overline{t}\}$
7: **if** $\underline{t} < \overline{t}$ **then**
8: $\boldsymbol{P}^C \leftarrow sup(\mathbf{EV}_i.\boldsymbol{S}^C)$; $\boldsymbol{P}^P \leftarrow sup(\mathbf{EV}_i.\boldsymbol{S}^P)$
9: $\Delta_{cur} \leftarrow getMax\Delta(\mathbf{EV}_i)$
10: $cont \leftarrow true$
11: $\mathbf{P}^C_{cur} \leftarrow \boldsymbol{P}^C.next()$; $\mathbf{P}^P_{cur} \leftarrow \boldsymbol{P}^P.next()$
12: $\underline{t}_{cur} \leftarrow \underline{t}$; $\overline{t}_{cur} \leftarrow min\{\mathbf{P}^C_{cur}.\overline{t}, \mathbf{P}^P_{cur}.\overline{t}\}$
13: **while** $cont$ **do**
14: **if** $\mathbf{P}^C_{cur}.p = 0 \wedge \mathbf{P}^P_{cur}.p = 0 \wedge \overline{t}_{cur} > \underline{t} \wedge \underline{t}_{cur} < \overline{t}$ **then**
15: $\underline{t}_{new} \leftarrow max\{\underline{t}_{cur}, \underline{t}\}$; $\overline{t}_{new} \leftarrow min\{\overline{t}_{cur}, \overline{t}\}$
16: $\Delta_{new} \leftarrow min\{\Delta_{cur}, (\overline{t}_{new} - \underline{t}_{new})r_i\}$
17: $d_{new} \leftarrow \frac{\Delta_{new}}{r_i}$
18: $\boldsymbol{AIS}.add([\underline{t}_{new}, \overline{t}_{new}])$
19: $d_{tot} \leftarrow d_{tot} + d_{new}$
20: $\Delta_{cur} \leftarrow \Delta_{cur} - \Delta_{new}$
21: **if** $\overline{t}_{cur} \geq \overline{t}$ **then**
22: $cont \leftarrow false$
23: **else**
24: **if** $\overline{t}_{cur} = \mathbf{P}^C_{cur}.\overline{t}$ **then**
25: $\mathbf{P}^C_{cur} \leftarrow \boldsymbol{P}^C.next()$
26: **if** $\overline{t}_{cur} = \mathbf{P}^P_{cur}.\overline{t}$ **then**
27: $\mathbf{P}^P_{cur} \leftarrow \boldsymbol{P}^P.next()$
28: $\underline{t}_{cur} \leftarrow \overline{t}_{cur}$; $\overline{t}_{cur} \leftarrow min\{\mathbf{P}^C_{cur}.\overline{t}, \mathbf{P}^P_{cur}.\overline{t}\}$
29: **return** $[i, p, d_{tot}, \boldsymbol{AIS}]$

Fig. 2. Algorithm specification for method $getRAS$.

Figure 2 lists the algorithm of method $getRAS(i, \underline{t}, \overline{t}, type)$, which yields the resource availability statement for EV i valid for the time interval $[\underline{t}, \overline{t}]$. The method $getRAS$ can only be invoked for a virtual resource i representing an EV if the information system currently stores a corresponding parking period statement $\mathbf{EV}_i.\mathbf{PPS}$. The variables t_{now}, $\mathbf{EV}_i.l_{now}$, and r_i denote the current time, the current energy level of EV i, and the charging rate in terms of energy level increase per time unit of EV i.

The algorithm of $getRAS$ first adjusts the search interval by constraining it to the time interval $[t_{must}, \overline{t}_{fore}]$ if the aggregator searches for resource availability statements for the computation of an energy market bid (lines 3&4), and to the interval $[t_{now}, \overline{t}_{fore}]$ if it searches for statements for computing reserve market bids (lines 5&6). If it finds a valid search interval, i.e., if the updated interval start and stop times still differ (line 7), it begins with the actual computation of the resource availability statement. First it builds power profiles from the resource schedules (line 8). Then it computes by how much EV i's energy level can still be increased during the parking period by invoking method $getMax\Delta(\mathbf{EV}_i)$ (line 9). Having obtained the available energy level change, the algorithm of $getRAS$ continues by traversing the power profiles searching for time intervals during which it can still schedule battery charging (line 14). This is the case if both, the current level of the power profile derived from the capacity schedule ($\mathbf{P}^C_{cur}$) and the current level of the power profile derived from the power schedule ($\mathbf{P}^P_{cur}$) are zero, and if in addition the currently selected time interval, $[\underline{t}_{cur}, \overline{t}_{cur}]$ overlaps with the search time interval $[\underline{t}, \overline{t}]$. When it finds such intervals, it computes the actual boundaries of the availability interval $[\underline{t}_{new}, \overline{t}_{new}]$ (line 15), the state of charge difference that can be achieved by scheduling consumption during this interval Δ_{new} (line 16), and the corresponding charging duration d_{new}. In line 18&19, the latest availability interval is added to the list $\boldsymbol{AIS}$ and the total duration is updated with the charging duration computed for this availability interval. The remaining lines 21-28 update the local variables $cont$, $\mathbf{P}^P_{cur}$, $\mathbf{P}^C_{cur}$, $\underline{t}_{new}$, and $\overline{t}_{new}$ for the next loop iteration.

IV. Optimization and Scheduling

A. Reserve Market Bids

To schedule reserve, the information system has to approximate solutions of two types of optimization problems, denoted by A and B, respectively. Feasible solutions of optimization problem A indicate the maximum bid size for a particular operating interval. Feasible solutions of optimization problem B prescribe EV charging schedules taking a feasible power level as given.

In the following, we propose a heuristic method based on integer programming, which can be applied to perform this task. The time-related variables of the set of resource availability statements provided as input to the optimization method are discretized into small time intervals of length d_{sched}. In the following specifications, time indexes are normalized relative to the value of $\underline{t}$ used to retrieve resource availability statements (cf. method $getRAS$ specified in Figure 2), i.e., time index $t = 1$ refers to time interval $[\underline{t}, \underline{t} + d_{sched}]$.

The objective of optimization A is to maximize the level of negative reserve power that can be maintained by a fleet of resources during time interval $\left[\underline{t}, \overline{t}\right]$ based on the information available at time t_{now} when the optimization is performed. The result is the maximum reserve bid size p^*_{max}. The integer time horizon h used in the following is then equal to $(\overline{t} - \underline{t})/d_{sched}$. The integer variable m denotes the number of retrieved resource availability statements at time t_{now}, i.e., $m = |\boldsymbol{RASS}|$. The Boolean decision variable $u_{i,t}$ indicates that EV i charges at a fixed rate r_i during time interval t. Equations 2 provide a formal definition of optimization problem A.

$$\max_{u_{i,1}} \quad \sum_{i=1}^{m} -u_{i,1}\mathbf{RAS}_i.p \tag{2a}$$

$$\begin{aligned} \text{s.t.} \quad & \sum_{i=1}^{m} u_{i,t}\mathbf{RAS}_i.p \\ & \in \left[\sum_{i=1}^{m} u_{i,1}\mathbf{RAS}_i.p - \epsilon_{RM}, \sum_{i=1}^{m} u_{i,1}\mathbf{RAS}_i.p + \epsilon_{RM}\right]; \\ & \quad t = 1, ..., h \end{aligned} \tag{2b}$$

$$u_{i,t} \in \{0, 1\}; i = 1, ..., m; t = 1, ..., h \tag{2c}$$

$$0 \leq \sum_{t=1}^{h} u_{i,t}d_{sched} \leq \mathbf{RAS}_i.d_{tot}; i = 1, ..., m \tag{2d}$$

$$\begin{aligned} & u_{i,t} = 0; \forall \mathbf{AI}_j \in \mathbf{RAS}_i.\boldsymbol{AIS} : t < \mathbf{AI}_j.\underline{t} \vee t \geq \mathbf{AI}_j.\overline{t}; \\ & \quad i = 1, ..., m \end{aligned} \tag{2e}$$

Constraint 2b makes sure that the total power level over the optimization horizon does not differ by more than $2\epsilon_{RM}$ between any two scheduling intervals. Constraint 2c defines the admissible value ranges of the decision variables. Constraint 2d assures that no resource is scheduled to consumes more energy than it can based on the maximum charging durations from the resource availability statements. Constraint 2e makes sure that a resource is only activated within the time periods during which it is available, based on the availability time intervals obtained from the resource availability statements.

The maximum bid size p^*_{max} resulting from optimization A will most likely not conform to the bid size constraints of the target reserve market. However, one can show that if $\max_i |\mathbf{EV}_i.p| \leq \epsilon_{RM}$, every power level $p^{RM} \in [p^*_{max}, 0]$ can be satisfied within tolerance ϵ_{RM} using the same set of resource availability statements $\boldsymbol{RASS}$ as input to optimization A.

The objective of optimization B is to determine feasible EV charging schedules to reach a given power level $p^{RM} \in [p^*_{max}, 0]$. Furthermore, it allows for specifying an arbitrary objective that can be used to prioritize charging of certain resources. The function $prio(\mathbf{RAS})$ returns a higher value the higher the priority of including EV i into the schedule is. Equations 3a-3e formally describe optimization problem B.

$$\max_{u_{i,t}} \quad \sum_{i=1}^{m}\sum_{t=1}^{h} u_{i,t}prio(\mathbf{RAS}_i) \tag{3a}$$

$$\begin{aligned} \text{s.t.} \quad & \sum_{i=1}^{m} u_{i,t}\mathbf{RAS}_i.p \in \left[p^{RM} - \epsilon_{RM}, p^{RM} + \epsilon_{RM}\right]; \\ & \quad t = 1, ..., h \end{aligned} \tag{3b}$$

$$u_{i,t} \in \{0, 1\}; i = 1, ..., m; t = 1, ..., h \tag{3c}$$

$$0 \leq \sum_{t=1}^{h} u_{i,t}d_{sched} \leq \mathbf{RAS}_i.d_{tot}; i = 1, ..., m \tag{3d}$$

$$\begin{aligned} & u_{i,t} = 0; \forall \mathbf{AI}_j \in \mathbf{RAS}_i.\boldsymbol{AIS} : t < \mathbf{AI}_j.\underline{t} \vee t \geq \mathbf{AI}_j.\overline{t}; \\ & \quad i = 1, ..., m \end{aligned} \tag{3e}$$

The objective function (Equation 3a) considers the priority of the available resource availability statements: It makes sure that EVs contribute to reserve in descending order of the specified priority. The function $prio$, which maps resource availability statements to a numeric value, can be specified arbitrarily based on the content of these statements or other EV status information. For instance, the information system can prioritize EVs with a lower state of battery charge at reserve commitment time. Constraint 3b assures that the EV fleet can sustain the target power level p^{RM} during the time interval $\left[\underline{t}, \overline{t}\right]$ within tolerance $\pm\epsilon_{RM}$. The remaining constraints 3c - 3e correspond with constraints 2c - 2e of optimization problem A.

Optimization problems A and B have linear objective functions and integer decision variables. Therefore they are linear integer programs which are NP-hard [26]. Solutions of such problems can be approximated using state-of-the-art solvers. These solvers apply heuristics (e.g., branch and bound, branch and cut, linear relaxation) to yield feasible, but not necessarily optimal solutions, in polynomial time.

B. Energy Market Bids

Since the objective of the aggregator is to maximize the electric range of each EV under its control, its information system automatically places bids on the energy market to cover the remaining energy demand of all EVs before the last chance to do so has passed (cf. time 9 in the example shown in Figure 1). This means that the approach does not place energy market bids selectively (e.g., based on forecasted prices), but to guarantee maximum charging levels, which we define as a strict constraint in this work. Resource availability statements that correspond with this remaining energy demand can then be obtained from each virtual EV i by invoking the $getRAS$ method in energy bid mode, i.e., $getRAS\left(i, \underline{t}, \overline{t}, energy\right)$. Equation 4 yields the *total* energy e_{must} that the aggregator should purchase on energy market EM based on a set of corresponding resource availability statements ***RASS*** computed at time $t_{now} < \underline{t} - d_{bd}^{EM}$.

$$e_{must} = \sum_{\mathbf{RAS} \in \boldsymbol{RASS}} \mathbf{RAS}.p \times \mathbf{RAS}.d_{tot} \tag{4}$$

This amount of energy may not adhere to the bid size rules of market EM. Thus, an energy gap between e_{must} and the next feasible bid size e^{EM} may result. The aggregator can either close this gap by dispatching additional resources, or incur the financial penalties resulting from this energy deviation. In the following, we denote the energy gap by $\mathbf{L}$ and treat it like a controllable resource with its own power schedule. The power schedule of $\mathbf{L}$ is denoted by $\mathbf{L}.\boldsymbol{S}^P$. We also assume, without loss of generality, that the power level p of all schedule fragments $\mathbf{F} \in \mathbf{L}.\boldsymbol{S}^P$ are equal to a certain small amount of power, $p_{\mathbf{L}}$. This property will become important when replacing scheduled power consumption of $\mathbf{L}$ with available EV charging energy (cf. Section IV-C).

C. Schedule Repair

In this section, we describe a schedule repair mechanism that achieves a reallocation of schedule fragments that have become infeasible due to EVs that leave the charging stations sooner than expected. Since actual EV departure times cannot be predicted exactly, the forecasted departure time of an EV, $\overline{t}_{fore}$, will either be greater or smaller than the *actual* departure time $\overline{t}_{actual}$.

For each parking period statement, two cases have to be considered: $\overline{t}_{fore} \leq \overline{t}_{actual}$ and $\overline{t}_{fore} > \overline{t}_{actual}$.

If $\overline{t}_{fore} \leq \overline{t}_{actual}$, the scheduled charging duration may not suffice to reach the theoretically possible EV state of charge before the beginning of the next trip. However, all schedules committed by the information system during the EV's parking time remain feasible (cf. Figure 1). Therefore no schedule repair has to be performed in this case.

If $\overline{t}_{fore} > \overline{t}_{actual}$, the system may have scheduled the EV to stand by for providing reserve or to consume energy that will later be purchased on the energy market, although the EV is no longer there to charge. In the following, we refer to schedule fragments of EVs that have left soon than predicted as *dropped* fragments. In both cases, the consumption shortfall can be compensated to avoid that the aggregator deviates from contractual obligations, in the case of reserve bids it has to be compensated, in the case of energy bids it should be compensated. This can either be achieved by controlling a sufficiently large electrical load in real time, or by accessing EVs that still have room for absorbing energy.

EVs with need to charge arrive continuously. Their capacity to provide reserve is only used when the information system commits them so that the aggregator can place a corresponding reserve market bid. This happens only in rather large time intervals, namely each time the deadline for reserve market bidding approaches. Furthermore, the proposed approach for computing reserve market bids (cf. IV-A) often leads to a situation where the capacity of certain EVs to provide reserve is not fully used. This happens either because only a part of their capacity was scheduled for reserve bids, or they were not considered at all due to the market bid size constraints (usually $p^*_{max} > p^{RM}$).

To achieve a continuous reallocation of EV schedule fragments that form part of either a reserve or energy market bid, we propose an algorithm referred to by the method name $reallocateFrags$, which can be invoked in very short time intervals, or every time an EV leaves unexpectedly. In essence, the method first collects all dropped schedule fragments including the entire schedule of the energy gap $\mathbf{L}.\boldsymbol{S}^P$ into two sets, one for capacity and one for power fragments. If the repair mode is set to on, the method applies an efficient algorithm referred to by the method name $match$, that identifies the capacity of available EVs using method $getRAS$ and then attempts to integrate each dropped capacity or power schedule fragment into the corresponding schedule of an available EV. The remaining dropped power schedule fragments are added to the schedule of the power gap. The algorithm of $match$ greedily reallocates schedule fragments while traversing the total time period during which shortfalls will occur starting at the current time. This assures that dropped fragments have a maximum chance to get reallocated to other EVs upon repeated executions of $reallocateFrags$. If the repair mode is switched off, all dropped power schedule fragments are included into the schedule of the energy gap, i.e., in this case $\mathbf{L}$ "delivers" all activated reserve and "consumes" all purchased spot market energy that was originally assigned to EVs that have left sooner than expected.

The time criticality of executing the schedule repair algorithm is very high. Its purpose is to prevent that the aggregator fails to deliver the reserve it has committed to. Thus, schedule replacements for the energy contribution of EVs wanting to leave sooner than the system expects should be found before the corresponding EVs actually leave. To account for this issue, the system can impose a mandatory waiting time on these EVs, which should remain within reasonable bounds to leave drivers unaffected. The run time of the schedule repair algorithm therefore determines how long an EV driver has to wait until leaving a charging station in case the system has predicted a later departure time. Section V-C presents quantitative results about the performance of these algorithms, in particular how long they take to execute.

V. Simulation Study

A. Use Case

We consider a multi-market use case where the EV aggregator concurrently participates in a market for negative reserve RM and an energy spot market EM. The aggregator's objective is to offer as much reserve as possible on market RM, which allows it to obtain revenue from consuming energy.

This objective is realized by committing to the highest possible negative reserve levels in subsequent operating intervals of the reserve market. The spot market is used to source all remaining charging energy required for maximizing an EV's state of charge before the next trip. Energy market bids are placed automatically based on the procedure described in Section IV-B.

The aggregator controls the charging behavior of n EVs. To obtain realistic behavior for a large fleet of EVs, we use the following data-driven approach based on representative driving patterns from official German survey data [27]. The collected data set is publicly available and contains trip data reported by more than 50,000 German households. To obtain the subset of the data we are interested in, we applied a number of selection and data quality criteria. After all criteria had been applied, we obtained a total number of 15,910 daily driving profiles of uniquely identified cars that could be replaced by EVs. We randomly sampled daily driving profiles from this database to generate sufficiently long individual driving profiles. For this study, we generated a total number of 10,000 such driving profiles. During simulations, the charging rates and requirements are generated based on the specifications of the BMW i3 electric car: An average electric range of 150 km and a mean full recharging time at standard charging power (230 V, 20 A, 4.6 kW) of 7 hours [28]. EVs generally only use a certain fraction of their actual battery capacity to extend their life time, usually between 80 and 90%. Until this state of charge, the charging power remains approximately at a constant level, even if applying the constant current to constant voltage (CC-CV) charging scheme commonly used for lithium ion batteries (cf. the results presented in [29]). In this article, we assume that the nominal charging power is the same for all EVs, i.e., $\underline{p}_i = \underline{p}_j$ for all EVs $i, j \in \mathbf{N}$. This assumption is backed by the existence of standards for EV charging equipment.

We assume that the aggregator service is able to forecast EV departure times once a vehicle arrives at a charging station. The actual departure time, $\bar{t}_{actual}$, can be obtained from the data set. During simulations, the forecasted departure time $\bar{t}_{fore}$ is generated by drawing a random number from a truncated Normal distribution with mean $\bar{t}_{actual}$ and standard deviation σ_{fore}.[9] On the left side, the distribution is truncated at $max\left\{\underline{t}, \bar{t}_{actual} - 3\sigma_{fore}\right\}$, on the right side it is truncated at $\bar{t}_{actual} + 3\sigma_{fore}$. Since reliable departure time prediction accuracies do not exist in the literature, we conduct a sensitivity study on how prediction accuracy, expressed via different values of σ_{fore}, affects our results (cf. Section V-C).

In our use case, we defined the prioritization function $prio(\mathbf{RAS})$ used in optimization problem B to assign priority values such that $prio(\mathbf{RAS}_i) > prio(\mathbf{RAS}_j)$ if $\mathbf{EV}_i.l_{now} < \mathbf{EV}_j.l_{now}$. Thus, according to the objective function of optimization problem B, the information system will attempt to consider EVs with a lower state of battery charge upon arrival with higher priority when computing final reserve market bids. This in turn increases the chance that these EVs get charged before their must charge time t_{must} via reserve activation, and will therefore less likely run out of battery charge on the following trip if it leaves sooner than expected.

B. Setup

We assume that the aggregator offers the maximum negative reserve in each operating interval of RM. To cover the residual energy demand, it places corresponding bids on the intraday energy spot market. Furthermore, we assume that all bids placed get matched by the respective market operator.[10] We also assume that single intervals of reserve activation last for d^{RM}_{act} and that the entire reserve power is activated.[11]

Reserve activation is simulated using independent random numbers x_j drawn from a Bernoulli distribution $X(\gamma^{RM}_{act})$.[12] The simulation time increment is set to $d_{inc} = 1$ minute, which is sufficient to capture the full detail of the simulation dynamics. The total time horizon of our simulation is 30 days, which is sufficient to collect informative distributions of relevant output variables (cf. Section V-C). At the beginning of each simulation run, the state of charge of all EVs i, $\mathbf{EV}_i.l_{now}$, is set to the respective maximum $\bar{l}_i$ and the simulated time t_{now} is set to zero.

In each simulated time step, the following actions are performed in the given order:

1) Increment simulation time t_{now} by d_{inc}.
2) Execute $reallocateFrags$ (cf. Section IV-C).
3) If $t_{now} \mod d^{RM}_{act} = 0$, activate committed reserve according to x_j drawn from $X(\gamma^{RM}_{act})$.
4) If $(t_{now} + d^{RM}_{bd}) \mod d^{RM}_{oi} = 0$, compute maximum feasible reserve bid and submit it to market RM (cf. Section IV-A).
5) If $(t_{now} + d^{EM}_{bd}) \mod d^{EM}_{oi} = 0$, compute feasible energy bid and submit it to market EM (cf. Section IV-B).
6) Advance state of all resources by d_{inc}.
7) Update metrics based on simulated actions during time interval $[t_{now} - d_{inc}, t_{now}]$.

Table I contains the parameter values we used in different simulation runs. We selected these values to match the European Power Exchange (EPEX) rules, which apply to several European countries, including Germany. EPEX runs an intraday spot market that clears continuously and closes 45 minutes before each 15 minutes long operating interval [24]. In contrast to other market environments, participation in the EPEX intraday market is possible without having previously

[9]Since we are simulating forecast errors, we are assuming the existence of a forecasting method. Such a method should produce normally distributed residuals if correctly fitted, which is why we are using a Normal distribution to generate the forecasts.

[10]This assumption implies that the EV aggregator always bids prices lower than the highest price bids that still get chosen by the system operator in the case of reserve, and that it always bids prices higher than the lowest price bids that still get matched on the energy market.

[11]This is a realistic assumption: Since TSOs usually activate reserve in ascending order of delivery prices, it is most likely that single providers of reserve, especially if they are rather small market players, have to provide their entire capacity instead of only a fraction of it. This only applies to pay-as-bid markets. In markets where a uniform price for reserve is determined, reserve is usually activated according to a corresponding contract-to-delivery ratio.

[12]This assumption allows us to assess the impact of random activation without having to restrict the evaluation to a specific market situation.

placed a bid for the same time period on the day-ahead market (cf. [30]). The minimum amount of energy that can be traded on the intraday energy market is 0.5 MWh per hour, i.e., 0.125 MWh per 15 minute long time slot. The primary and secondary reserve markets in Germany currently clear on a weekly basis, the markets for tertiary or minute reserve clear once per day [25]. Primary and secondary reserve operation intervals are currently 12 hours, tertiary reserve operating intervals are currently 4 hours long. Minimum bid sizes for primary reserve are 1 MW, and 5 MW both for secondary and tertiary reserve. Bid size increments are currently 1 MW each. Thus, while our model captures the current constraints of participating in the energy spot market, our assumptions anticipate a situation where reserve markets are more flexible with respect to bid sizing and allow for more frequent participation. This additional flexibility has been repeatedly proposed, most recently in a position paper of the German government [31]. We therefore expect reserve market rules to change in the near future, in particular, the clearing frequency could be increased without major effort. We also used different bid increments and operating intervals because it facilitates revealing the impact of changes of these parameters on the performance metrics of the proposed system components.

TABLE I
MODEL PARAMETERS (* INDICATES DEFAULT VALUES)

Parameter	Values	Description
n	1,000; ...; 10,000	Number of EVs
d_{sched}	5 min	Duration of optimization time intervals
d_{oi}^{RM}	2; 4*; 6 h	Duration of RM operating intervals
d_{bd}^{RM}	1 h	Time between RM bidding deadline and start of operating interval
p_{min}^{RM}	0.25; 0.5*; 0.75 MW	Minimum RM bid size
p_{inc}^{RM}	0.25; 0.5*; 0.75 MW	Minimum RM bid size increment
γ_{act}^{RM}	0.3; 0.4*; 0.5	Probability of reserve calls
d_{oi}^{EM}	15 min	Duration of EM operating interval
d_{bd}^{EM}	1 h	Time between EM bidding deadline and start of operating interval
e_{min}^{EM}	0.125 MWh	Minimum EM bid size
e_{inc}^{EM}	0.125 MWh	Minimum EM bid size increment
R	on, off	Schedule repair mode switch
σ_{fore}	1; 2*; 3 h	Standard deviation of departure time forecast

The simulation was implemented as a single-threaded Java program. Schedule fragments, schedules, resource availability statements, and virtual resources were all implemented as Java classes. During code execution, all required Java objects were kept in main memory. All necessary data selections, insertions, and updates were also performed on data stored in main memory, i.e., there were no delays resulting from accessing the hard drive. The performance results presented in the following section can thus be considered as a realistic preview of how an actual system would perform without memory bottlenecks. All integer programs were solved using IBM ILOG CPLEX version 12.5 [32], which was invoked via its Java interface. The optimality gap was set to 10%. This rather high value was chosen since additional experiments for smaller optimality gaps revealed no major optimality improvements and exponentially increasing solving times. The observed behavior most likely results from CPLEX heuristics that are able to find good solutions relatively quickly, but, due to the combinatorial nature of our integer programming problems, take much longer to significantly improve these solutions. Simulation programs were run on a server equipped with an Intel Xeon E5-2650 CPU (2.0 GHz). We allocated 5 GB of main memory to each program, which was sufficient even for the large instances.

Time measurements were carried out using native Java methods, which are sufficiently accurate given the relevant time scales (milliseconds to seconds). The simulation code was run on a dedicated server making sure that each program could use exactly one core at full capacity and was able to access ample main memory. We measured the time of entire method executions, e.g., the time it takes to compute the maximum reserve bid size for a future time interval, to account for all necessary data processing.

C. Results

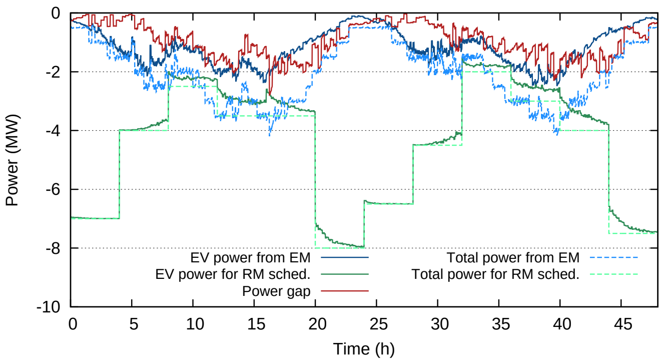
In this section, we report the results obtained using the simulations setup described in Section V-B. Figures showing the sensitivity of metrics with respect to changes of the fleet size n, i.e., Figures 4(a), 4(b), and 6, are based on the default parameters listed in Table I. All remaining figures show the case of $n = 10,000$.

Table II lists the parameter configurations we use in the evaluation in detail. In particular, we use the configuration labels in the figures featured in this section.

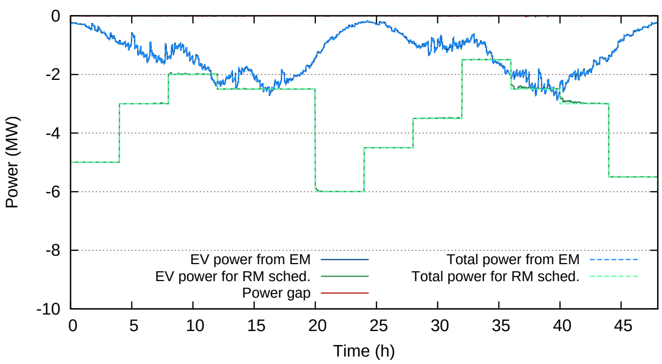
TABLE II
CONFIGURATIONS (k = 1,000; FIG. = VALUE SPECIFIED IN FIGURE)

Conf.	n	R	d_{oi}^{RM}	p_{min}^{RM}	p_{inc}^{RM}	γ_{act}^{RM}	σ_{fore}
Ax	xk	off	4 h	0.5 MW	0.5 MW	0.4	2
Bx	xk	on	4 h	0.5 MW	0.5 MW	0.4	2
C	10k	fig.	4 h	0.5 MW	0.5 MW	0.4	2
D	10k	fig.	2 h	0.5 MW	0.5 MW	0.4	2
E	10k	fig.	6 h	0.5 MW	0.5 MW	0.4	2
F	10k	fig.	4 h	0.25 MW	0.25 MW	0.4	2
G	10k	fig.	4 h	0.75 MW	0.75 MW	0.4	2
H	10k	fig.	4 h	0.5 MW	0.5 MW	0.3	2
I	10k	fig.	4 h	0.5 MW	0.5 MW	0.5	2
J	10k	fig.	4 h	0.5 MW	0.5 MW	0.4	1
K	10k	fig.	4 h	0.5 MW	0.5 MW	0.4	3

Figure 3 serves to illustrate the dynamics of the power sourcing processes. We plotted two days worth of data for the default parameter configuration if schedule repair is disabled and enabled, respectively. One can see that with $n = 10,000$ EVs in the controlled EV pool, the differences between the EV power and the power scheduled for the reserve and energy market are significant if schedule repair is deactivated. The gap power (represented by the red line) then needs to be constantly absorbed, either by a fully controllable ancillary load, or via counter-bidding on the energy market and incurring corresponding deviation penalties. If schedule repair is activated,



(a) Power for configuration C with R=off



(b) Power for configuration C with R=on

Fig. 3. Power dynamics during 2 simulated days.

however, EV power almost coincides with the corresponding market schedules and almost no deviations occur.

Figure 4(a) shows for increasing fleet sizes how much energy the aggregator purchased on the energy spot market, how much (potential) energy it committed to on the reserve market, how much reserve energy was actually delivered, and how large the energy gap becomes. If schedule repair is not used (configurations A1-10), more reserve gets committed and used. However, this causes the energy gap to increase, as well. If schedules get repaired (configurations B1-10), the gap almost disappears, while approximately 65% of reserve compared to the no repair configuration can be provided. The different energy metrics increase linearly with the number of EVs under the control of the aggregator. The amount of reserve provided relative to the energy sourced from the spot market increases with the size of the fleet, both with and without schedule repair.

Figure 4(b) shows the maximum power gap observed in the simulations. This metric is important because it determines the necessary size of a potential ancillary load, irrespective of how much it is actually utilized over time. One can observe that, with schedule repair disabled, it increases approximately linearly at a rate of roughly 0.3 MW per 1,000 EVs. If schedules are repaired, the maximum gap is relatively small and is independent of the numbers of controlled EVs. The proposed schedule repair algorithm is therefore highly effective.

Figure 4(c) illustrates how the maximum energy gap changes if the simulation parameters are changed. These results reveal that longer operating intervals of the reserve market would lead to higher maximum power gaps (configurations D vs. E). The same applies to higher forecast inaccuracy (configurations J vs. K). Both of these results are intuitive, since the corresponding parameters have a direct effect on the occurance of unexpected vehicle departure during reserve market operating intervals. The results shown in Figure 4(c) also demonstrate that the effectiveness of the proposed schedule repair mechanism remains very high, even in circumstances that would lead to greater deviations without repair.

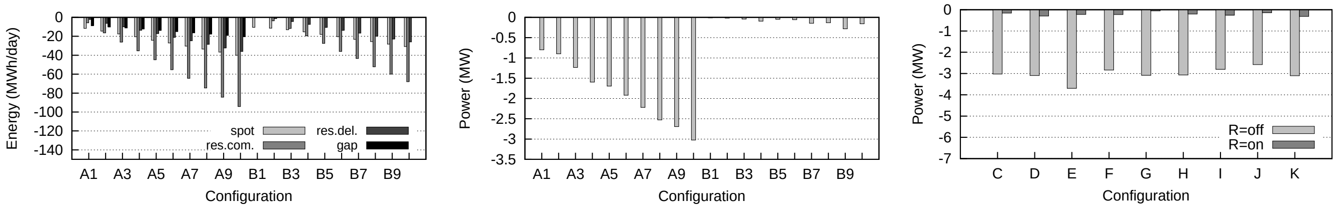
Figures 5(a) and 5(b) reveal the effect of sensitivity parameter changes on the reserve that the aggregator commits and the energy it has to purchase on the spot market, respectively. The impact of the reserve operating interval size d_{oi}^{RM} showing in the comparison between configurations D and E is intuitive: The longer this duration is, the less energy can be committed in total and the more energy the aggregator has to buy on the spot market as a consequence. The activation probability of reserve also has a visible impact on committed reserve and spot market energy purchased: Lower probabilities lead to more committed reserve and result in less energy that needs to be sourced on the spot market (cf. configurations H vs. I).

Figure 5(c) demonstrates how changes of key simulation parameters affect the average electric mileage of the EV fleet. One can see that approximately 93% of the total distance traveled can be covered electrically if the charging energy is sourced from the reserve and spot market using our approach. For comparison, we also included the maximum electric mileage that could theoretically be achieved via greedy charging, i.e., if the EVs started to charge right upon arrival. This percentage is approximately 94%. Thus, the aggregator's interference slightly increases the percentage distance traveled using the range extender. It is important to note here that most of the mileage that cannot be traveled electrically results from long trips that could not be completed without the use of the range extender anyways. If EVs are taken on such long trips, they may be recharged at fast charging stations along the way, which is not considered in our simulations. Therefore the observed 1% decrease of the electric mileage due to market-based EV charging could completely disappear provided the existence of fast recharging stations that are currently being rolled out in Germany.

Figures 6(a)-7(c) provide an overview of how fast the system is able to respond to market and resource events.

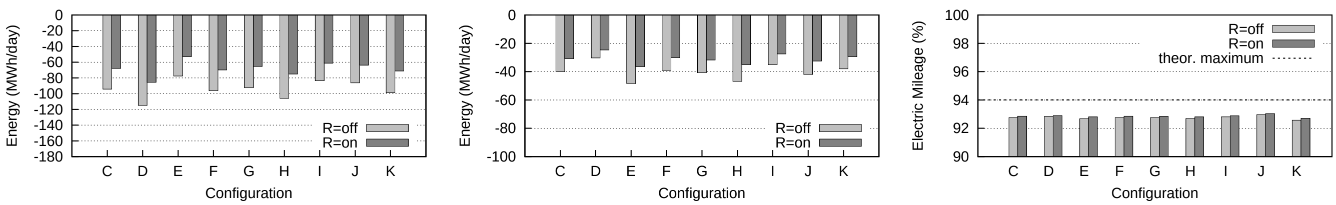
At least up to the considered fleet size, both the time to respond to maximum reserve bid requests (cf. Figure 6(a)) and reserve commitment requests (cf. Figure 6(b)) increases approximately linearly. It also becomes apparent that both, maximum reserve bid computation and reserve commitment, take less time if the repair mode is activated. This is due to the decreased availability of EV charging capacity in this case, which reduces the size of the corresponding optimization problems: The repair algorithm replaces dropped fragments with available charging capacity of other EVs. Once the replacing charging capacity has been committed, it is no longer available in the bid computation processes that follow.

Figure 6(c) shows how much time it takes to perform schedule repair. We also plotted the case where dropped fragments are not matched with available statements of other EVs, but only transferred to the schedule of the energy gap. We can observe a linear increase of the repair time at a rate



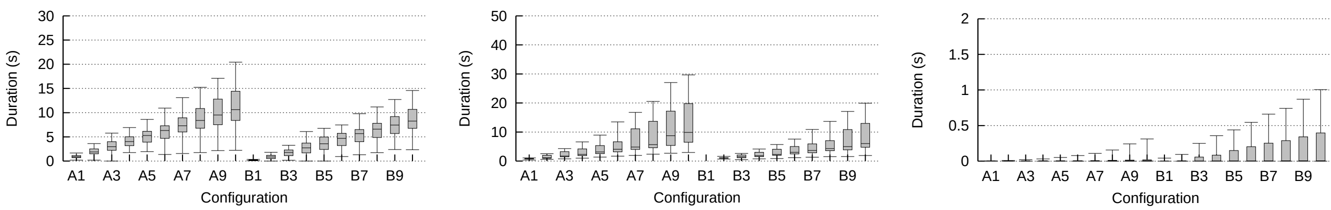
(a) Total energy brought to market (b) Maximum power gap (c) Sensitivity of maximum power gap

Fig. 4. Energy brought to market and power gap.



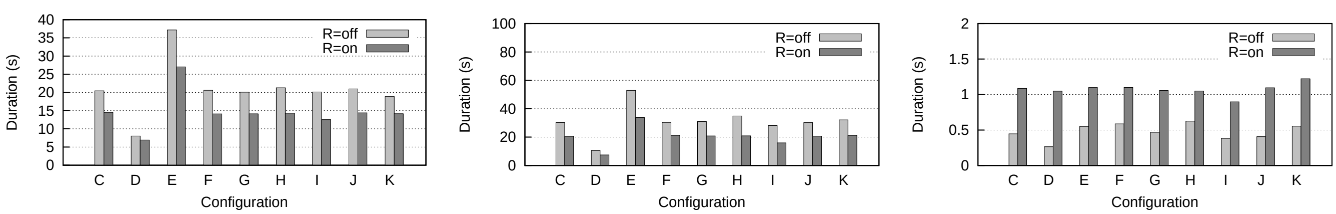
(a) Sensitivity of total committed reserve energy (b) Sensitivity of total energy purchased (c) Sensitivity of mean electric mileage

Fig. 5. Sensitivity of energy brought to market and electric mileage.



(a) Time to compute reserve market bids (b) Time to commit reserve market bids (c) Time to repair schedules

Fig. 6. Task execution durations based on default parameter values.



(a) Time to compute reserve market bids (b) Time to commit reserve market bids (c) Time to repair schedules

Fig. 7. Sensitivity of of 99.5th percentile task execution durations at $n = 10,000$.

of approximately 0.1 seconds per 1,000 EVs. Thus, at 10,000 EVs under the control of the aggregator, the system needs at most one second to respond to unforeseen departures.

Figures 7(a)-7(c) show the sensitivity of the time it takes to execute the different computational tasks of the information system.

As shown by Figure 7(a), the duration of the reserve market operating interval d_{oi}^{RM} has the strongest influence on the time to compute reserve market bids (configurations D vs. E). A lower reserve activation probability also increases the time to compute reserve market bids (configurations H vs. I). Similar to increasing the operating interval duration, a lower reserve activation probability increases the number of decision variables and corresponding constraints of the optimization problem solved, because the number and fragmentation of the resource availability statements provided as input to the optimization process increase in both cases.

Figure 7(b) shows how the different sensitivity parameters influence the time the systems needs to commit resources, i.e., to approximate a solution of optimization problem B. Apart from the fact that performing this task takes longer than computing maximum reserve market bids (optimization A), the results with respect to the main influencing factors are similar.

Figures 7(a) and 7(b) together show that both reserve market bid computation processes always take longer if EV charging power is not reallocated to other EVs, which again hints at the fact that switching the repair mode on decreases the availability of EV charging capacity (cf. the explanations provided above).

Figure 7(c) demonstrates that irrespective of the chosen parameter configuration of the simulation, the 99.5th percentile duration of schedule repair always stays in a range between 0.9 and 1.2 seconds. Parameters γ_{act}^{RM} and σ_{fore} have the strongest impact on this metric (configurations H vs. I, and J vs. K): Smaller reserve activation probabilities lead to larger bids and therefore increase the probability of unexpected EV departures that the repair algorithm has to cope with. Lower forecasting accuracy also increases this probability and therefore has the same effect.

VI. Discussion

A. Summary of Contributions

The approach for managing charging control for EVs presented in this article allows aggregators to concurrently participate in several wholesale electricity markets, both reserve and energy spot markets, while taking the strict constraints regarding the time and amount of reserve committed and delivered existing in several European market environments into account. It is able to cope with the random behavior of vehicles using a combination of proactive and reactive scheduling techniques, which allows for making decisions in the available time frames while minimizing energy deviations. It therefore almost eliminates financial penalties or the need for ancillary power provided by additional energy resources. Our approach maximizes the electric mileage of EVs and does not require discharge of EV batteries. We therefore argue that the aggregator's control will have no effect on EV mobility or lifetime. We have evaluated our technique using realistic market scenarios and vehicle usage data.

B. Business Case

Our results have shown that the primary use of EVs, i.e., the total electric mobility they provide, is only marginally affected by the control of the aggregator: Based on the relatively short contemporary electric range, such as the one offered by the BMW i3, only drivers who travel long distances would notice the impact of the aggregator's control via decreased electric range. However, these long distance drivers will either not use EVs for these trips, or take advantage of fast charging services currently being installed along highways so that they do not have to make excessive use of range extenders. Since we do not consider vehicle to grid capability or deviations from nominal charging power in this work, the lifetime of EV batteries under aggregator charging control would be equal to the lifetime resulting from greedy, i.e., uncontrolled charging. Thus, EV owners would not experience a reduction of their return on investing into electric mobility. However, we believe that if remote charging control is not implemented by default in EV chargers in the future, aggregators would have to provide additional economic incentives to EV owners for being allowed to control charging. How high these incentives would have to be is unclear, but the upper bound of retail rebates such that offering controlled charging to customers is still profitable for aggregators will be estimated in the following.

In the presented use case, the aggregator attempts to maximize the provision of negative reserve. It only accesses the spot market as backup energy source to limit the impact of reserve market participation on electric mobility. This strategy implies that it is more profitable to provide reserve than to take advantage of varying spot energy market prices for charging cost minimization. Although our goal in this article is not to propose financially optimal market participation strategies, we offer the following calculation to economically back our choice.

All figures used in the following are based on market data collected over the course of two years (2012&2013), which is publicly available at [25] and [24]. The prices on the intraday spot market in Germany range between approximately zero and 100 EUR/MWh (99% confidence interval). The average spot market price of energy is approximately 43 EUR/MWh on the day-ahead and 44 EUR/MWh on the intraday market [33]. Typical daily minimum and maximum prices range between approximately 20 and 80 EUR/MWh, respectively.

The results shown in Figure 4(a) indicate that the total daily average charging energy of an EV fleet consisting of 10,000 BMW i3s is 57 MWh (31 MWh purchased on the energy spot market, 26 MWh being supplied via activated negative reserve). If it was possible to source the entire energy demand via the energy spot market during the lowest price time period (best case), this energy would cost the aggregator a total of $57 \times 20 = 1,140$ EUR/day. The average cost of sourcing the EV charging energy on the day-ahead energy would amount to $57 \times 43 = 2,451$ EUR/day.

The average price of negative secondary reserve, i.e., the price paid to market participants for offering reserve capacity, is approximately 11.5 EUR/MWh.[13] The reserve energy price, i.e., the price paid when reserve gets activated, ranges between zero up to 821 EUR/MWh, but only starts to rise above zero at activation levels of more than 1,000 MW, which only happens approximately 5% of the time. Thus, the revenue the aggregator could gain via activation fees is very small and we therefore neglect it in this calculation. Based on our results, the aggregator could commit to a daily average of 68 MWh of reserve, which would result in an average of $68 \times 11.5 = 782$ EUR/day. The average cost of energy sourced via the intraday energy market equals $31 \times 44 = 1,364$ EUR/day. Thus, if the aggregator used our approach, it would incur an average cost of $1,364 - 782 = 582$ EUR/day compared to incurring a regular cost of $2,451$ EUR/day, or $1,140$ EUR/day in a highly optimistic energy market sourcing case with load shifting. Overall, even if we make conservative assumptions regarding the revenue potential of the proposed dual market strategy and the most optimistic assumptions regarding the revenue potential of the alternative single market charging control strategy, the proposed strategy investigated in our use case is still superior.

End-consumer electricity prices in Germany, which currently amount to 0.2459 EUR/kWh excluding the value-added tax (VAT) equal to 19%, are currently comprised of 0.1747 EUR/kWh for grid utilization and other taxes, and 0.0712 EUR/kWh remaining as revenue for the retailer, which it has to use to cover its current wholesale electricity sourcing costs of 43 EUR/MWh [35]. Thus, the retail rebate including VAT that the aggregator could offer to EV owners without lowering

[13]The average auction prices of negative secondary reserve actually range between 660 and 1,284 EUR/MW (weekly auctions for two time slices), which results in a per MWh price range from 8 to 15 EUR/MWh. The low and high average prices refer to the averages across all lowest bids and highest bids placed in the course of the years 2012 and 2013, respectively. More details can be found in [25], [34].

its retail margin would be equal to $1.19 \times (2,451 - 582)/(57 \times 1.000) \approx 0.033$ EUR/kWh, which translates to a percentage reduction of 11.4% compared to the current retail electricity cost of 0.2926 EUR/kWh. The average yearly cost saving per EV would then be $(57 \times 365 \times 1,000 \times 0.033)/10,000 \approx 69$ EUR.

C. Limitations and Future Work

We have not considered implementation details regarding the required two-way communication between the information system backend and the EV fleet. However, two-way communication between remote backends and EV on board systems is already available today (cf. [36], [37]) and it should therefore be possible to transmit the small amounts of charging control data required to realize our approach in the given time frames.

In this article, we assume that EVs always charge at fixed nominal power. This could represent a limitation of our contribution since EV chargers can theoretically be controlled at continuum rates. However, as the objective functions of the optimization problems that need to be solved for computing reserve bids indicate (cf. Equations 2a and 3a), continuum controllability of EV charging power is not necessary in the considered use case: Since the individual nominal charging power (4.6 kW for the BMW i3) is small compared to the reserve market bid sizes that are feasible in our use case (up to 12 MW) and the optimization goal is to maximize total charging power, even enabling continuous optimization would result in selecting the nominal charging power. Otherwise, as recent research on EV charging behavior suggests [29], an approximately constant charging power in the typical state of charge range (20-90%) is a valid assumption, even if the common constant current to constant voltage (CC-CV) charging scheme for lithium ion batteries is applied. Although our evaluations presented in Section V are limited to level-2 charging, our approach can also be applied if the discrete charging levels vary depending on charging location. We picked level-2 charging because it is the most common charging level that can be delivered everywhere via wall-mounted charging equipment at home and at public charging poles. Level-1 charging is very slow and would only be used at locations with no charging equipment. Level-3 charging causes very high currents (125 A per EV) that may not be feasible at many locations and leads to accelerated battery aging.

The evaluation of the proposed approach could be extended to more sophisticated bidding strategies and also to other types of deferrable loads with random behavior, e.g., thermal loads. Regarding bidding strategies, aggregators may want to minimize sourcing cost explicitly, e.g., by forecasting market prices and bid more selectively based on their expectation of reserve and energy market prices. In particular, participation in more reserve markets, e.g., the market for primary or negative tertiary reserve, could be of interest to the aggregator. However, based on current market prices and reserve activation probabilities, the market for negative secondary reserve seems to be most attractive (cf. [22]). The methods provided in this article provide a necessary starting point for implementing other strategies, as well.

The computational approach used to approximate feasible maximal reserve bids scales approximately linearly with the size of the EV fleet, although this is an NP-hard problem. The maximum time to compute approximate solutions of problems A and B sequentially was 1 minute for 10,000 EVs, which is sufficient to participate even in markets that clear hourly. Furthermore, scalability could be provided via parallelization, i.e., the same approach could scaled to millions of EVs provided access to compute clusters. However, there is certainly room for improvement regarding the proposed integer programming based solution method, e.g., heuristics that make use of the problem's unique characteristics to speed up computation while delivering comparable results. We defer such efforts to future research.

The reserve market design we focus on in this paper has been criticized in several recent publications [38], [39]. In particular, the authors of [38], who have analyzed the current German market design, recommend uniform pricing for reserve markets. According to their theoretical analysis, this would result in higher market efficiency and transparency. The authors of [39] focus on the important link between renewable capacity growth and the demand for reserve, which is mediated by market design. They have analyzed historic data from the German reserve market to gain empirical insights. Although their analysis reveals that reserve prices have drastically declined over the last few years despite significant capacity growth of wind and solar generation during the same period, which can be interpreted as a sign of increasing competition and market efficiency, they also argue for the adoption of reserve market designs similar to the ones existing in North America. Based on the content of a recent strategy paper on future electricity market design released by the German government [31] such a radical redesign of reserve markets is not planned in the near future. However, the tendering rules of the current reserve markets, in particular the frequency of auctions, duration of operating intervals, and minimum bid sizes, have repeatedly changed in recent years and can be expected to do so in the coming years, which could lower the market entry barriers for renewable generators and aggregators further.

VII. Conclusions

In this article, we have described an approach for controlling large fleets of EVs such that aggregators can participate in reserve markets that are pay-as-bid, require guaranteed delivery of promised reserve, and have long operating intervals. In particular, our approach allows EV aggregators to maximize the provision of negative reserves while making sure that EVs do not have to sacrifice electric range. Our main technical contributions are effective abstractions for managing EV charging schedules, an integer programming based method for planning reserve provision, and a corresponding schedule repair mechanism that minimizes energy deviations.

Our work is useful input for start-up and established companies in the business of bringing flexible loads to market. It introduces new ideas for achieving market-conform control of flexible loads with uncertain behavior subject to restrictive reserve market rules. In our opinion, these ideas could also be useful in other market settings and for other types of distributed energy resources with uncertain availability. Our results stress the influence of market design decisions, such as minimum bid sizes and increments, timing constraints, and operating interval durations, on the revenue potential of the aggregator business: The more flexible these markets become, the more profitably aggregators can control EV charging.

REFERENCES

[1] D. Callaway and I. Hiskens, "Achieving Controllability of Electric Loads," *Proceedings of the IEEE*, vol. 99, no. 1, pp. 184–199, 2011.

[2] L. Gan, U. Topcu, and S. Low, "Optimal Decentralized Protocol for Electric Vehicle Charging," *IEEE Transactions on Power Systems*, vol. 28, no. 2, pp. 940–951, 2013.

[3] J. Rivera, P. Wolfrum, S. Hirche, C. Goebel, and H.-A. Jacobsen, "Alternating Direction Method of Multipliers for Decentralized Electric Vehicle Charging Control," in *52nd Conference on Decision and Control (CDC2013), Florence, Italy.*, 2013.

[4] C. Goebel and D. Callaway, "Using ICT-Controlled Plug-in Electric Vehicles to Supply Grid Regulation in California at Different Renewable Integration Levels," *IEEE Transactions on Smart Grid*, vol. 4, no. 2, pp. 729–740, 2013.

[5] D. Kirschen and G. Strbac, *Fundamentals of Power System Economics*. Wiley, 2004.

[6] E. Rivero, J. Barquin, and L. Rouco, "European Balancing Markets," in *8th International Conference on the European Energy Market (EEM)*, pp. 333–338, May 2011.

[7] J. F. Ellison, L. S. Tesfatsion, V. W. Loose, and R. H. Byrne, "Project Report: A Survey of Operating Reserve Markets in U.S. ISO/RTO-managed Electric Energy Regions," tech. rep., Sandia National Laboritories, 2012.

[8] S. Vagropoulos and A. Bakirtzis, "Optimal Bidding Strategy for Electric Vehicle Aggregators in Electricity Markets," *IEEE Transactions on Power Systems*, vol. 28, no. 4, pp. 4031–4041, 2013.

[9] E. Sortomme and M. El-Sharkawi, "Optimal Combined Bidding of Vehicle-to-Grid Ancillary Services," *IEEE Transactions on Smart Grid*, vol. 3, no. 1, pp. 70–79, 2012.

[10] R. Bessa, M. Matos, F. Soares, and J. Lopes, "Optimized Bidding of a EV Aggregation Agent in the Electricity Market," *IEEE Transactions on Smart Grid*, vol. 3, no. 1, pp. 443–452, 2012.

[11] W. Kempton and J. Tomic, "Vehicle-to-Grid Power Implementation: From Stabilizing the Grid to Supporting Large-Scale Renewable Energy," *Journal of Power Sources*, vol. 144, no. 1, pp. 280–294, 2005.

[12] M. Galus, S. Koch, and G. Andersson, "Provision of Load Frequency Control by PHEVs, Controllable Loads, and a Cogeneration Unit," *IEEE Transactions on Industrial Electronics*, vol. 58, no. 10, pp. 4568–4582, 2011.

[13] N. Rotering and M. Ilic, "Optimal charge control of plug-in hybrid electric vehicles in deregulated electricity markets," *IEEE Transactions on Power Systems*, vol. 26, no. 3, pp. 1021–1029, 2011.

[14] R. Sioshansi and P. Denholm, "The value of plug-in hybrid electric vehicles as grid resources," *Energy Journal*, vol. 31, no. 3, pp. 1–23, 2010.

[15] Y. Makarov, C. Loutan, J. Ma, and P. de Mello, "Operational Impacts of Wind Generation on California Power Systems," *IEEE Transactions on Power Systems*, vol. 24, pp. 1039–1050, May 2009.

[16] J. Lopes, F. Soares, and P. Almeida, "Integration of Electric Vehicles in the Electric Power System," *Proceedings of the IEEE*, vol. 99, pp. 168–183, Jan 2011.

[17] O. Ardakanian, C. Rosenberg, and S. Keshav, "Distributed Control of Electric Vehicle Charging," in *Proceedings of the Fourth International ACM Conference on Future Energy Systems*, (New York, NY, USA), pp. 101–112, ACM, 2013.

[18] V. del Razo, C. Goebel, and H.-A. Jacobsen, "Benchmarking a Car-Originated-Signal Approach for Real-Time Electric Vehicle Charging Control," in *5th PES Innovative Smart Grid Technologies Conference, Washington D.C., USA*, 2013.

[19] C. Goebel, "On the Business Value of ICT-controlled Plug-in Electric Vehicle Charging in California," *Energy Policy*, vol. 53, no. 3, pp. 1–10, 2013.

[20] A. Papavasiliou and S. S. Oren, "Large-Scale Integration of Deferrable Demand and Renewable Energy Sources," *IEEE Transactions on Power Systems*, vol. 29, no. 1, pp. 489–499, 2014.

[21] A. Subramanian, M. Garcia, D. Callaway, K. Poolla, and P. Varaiya, "Real-Time Scheduling of Distributed Resources," *IEEE Transactions on Smart Grid*, vol. 4, no. 4, pp. 2122–2130, 2013.

[22] D. Dallinger, D. Krampe, and M. Wietschel, "Vehicle-to-Grid Regulation Reserves Based on a Dynamic Simulation of Mobility Behavior," *IEEE Transactions on Smart Grid*, vol. 2, no. 2, pp. 302–313, 2011.

[23] I. Momber, A. Siddiqui, T. Gomez San Roman, and L. Soder, "Risk Averse Scheduling by a PEV Aggregator Under Uncertainty," *Power Systems, IEEE Transactions on*, vol. 30, pp. 882–891, March 2015.

[24] European Power Exchange (EPEX), "Intraday Market for Electric Energy." http://www.epexspot.com/en/product-info/Intraday/germany, 2013.

[25] regelleistung.net, "Rules for Reserve Tendering." https://www.regelleistung.net, 2014. Last accessed: 10 Mar 2014.

[26] L. Wolsey, *Integer Programming*. Wiley, 1998.

[27] Federal Ministry of Transport, Building and Urban Affairs, "Mobility in Germany." http://mobilitaet-in-deutschland.de/engl%202008/index.htm, 2008. Last accessed: 30 Jul 2015.

[28] BMW, "BMW i3 (Range Extender) Technical Data." http://www.bmw.com/com/en/newvehicles/i/i3/2013/showroom/technical_data.html?, May 2014. Last accessed: 29 May 2014.

[29] F. Marra, G. Y. Yang, C. Traholt, E. Larsen, C. Rasmussen, and S. You, "Demand Profile Study of Battery Electric Vehicle under Different Charging Options," in *2012 IEEE Power and Energy Society General Meeting*, pp. 1–7, 2012.

[30] European Power Exchange (EPEX), "EPEX Spot Operational Rules." http://www.epexspot.com/en/extras/download-center, Jul 2015. Last accessed: 28 Jul 2015.

[31] Federal Ministry for Economic Affairs and Energy, "An Electricity Market for Germany's Energy Transition," tech. rep., Federal Ministry for Economic Affairs and Energy, Germany, 2014.

[32] IBM ILOG, "CPLEX Version 12.5." http://www-01.ibm.com/software/commerce/optimization/cplex-optimizer/, 2013.

[33] Fraunhofer Institute for Solar Energy Systems ISE, "Electricity Spot Prices and Production Data in Germany 2013." http://www.ise.fraunhofer.de/de/downloads/pdf-files/aktuelles/boersenstrompreise-und-stromproduktion-2013.pdf, Jan 2014. Last accessed: 2 Aug 2015.

[34] consentec, "Description of Load-Frequency Control Concept and Market for Control Reserves." https://www.regelleistung.net/ip/action/downloadStaticFiles?download=&CSRFToken=c5f1ce79-c356-4850-a1fc-b9097801db0c&index=zF9H_cRXf9Y%3D, Feb 2014. Last accessed: 2 Aug 2015.

[35] eurostat, "Electricity Prices for Household Consumers." http://ec.europa.eu/eurostat/statistics-explained/index.php/File:Electricity_prices_for_household_consumers,_second_half_2014_%28%C2%B9%29_%28EUR_per_kWh%29_YB15.png, 2014. Last accessed: 29 Jul 2015.

[36] D. Rua, D. Issicaba, F. Soares, P. Almeida, R. J. Rei, and J. Peas Lopes, "Advanced Metering Infrastructure Functionalities for Electric Mobility," in *IEEE PES Innovative Smart Grid Technologies Conference Europe (ISGT Europe)*, pp. 1–7, Oct 2010.

[37] T. Markel, M. Kuss, and P. Denholm, "Communication and Control of Electric Drive Vehicles Supporting Renewables," in *IEEE Vehicle Power and Propulsion Conference, 2009. VPPC '09.*, pp. 27–34, Sept 2009.

[38] F. Müsgens, A. Ockenfels, and M. Peek, "Economics and Design of Balancing Power Markets in Germany," *International Journal of Electrical Power & Energy Systems*, vol. 55, pp. 392–401, 2014.

[39] L. Hirth and I. Ziegenhagen, "Balancing Power and Variable Renewables: Three Links," *Renewable and Sustainable Energy Reviews*, vol. 50, pp. 1035–1051, 2015.