Cost Optimization of Energy Purchase for EV Fleets based on a Markovian EV Charging Model

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Abstract

This work analyses potential energy purchase strategies for an ICT-enabled and active charge management of a large fleet of electric vehicles in order to minimize applicable costs for the purchase of energy at Day-Ahead or Intraday spot markets. The optimization potential for energy purchase is leveraged through a Markovian electric vehicle charging model and on the basis of empirical data for mobility patterns of vehicles as well as actual spot market data. Two scenarios with different charging characteristics of the EV fleet are investigated. In a commuter scenario, where the fleet of EVs charges during daytime (7:00AM-3:30PM), we found that volatility in spot market prices from Q4/2011 - Q3/2012 may have allowed for cost optimization of up to 13% compared to entirely unmanaged charging. In a parcel delivery service scenario, the fleet of EVs charges during nighttime (6:00PM-6:00AM), which allows for cost optimization of up to 34% based on the same period for spot market data.

Keywords: EV Fleet Management, Energy Purchase, EV Charging Model, Markov

1 Introduction

In this work it is evaluated what value could be gained from an ICT-enabled, active charge management for a fleet of EVs considering the energy purchase at Day-Ahead and Intraday spot markets. We assume a large fleet of EVs being under contract of one Fleet Manager, who is at the same time the E-Mobility Provider (EMP) authorizing the charging processes of the EVs within the fleet. Depending on the fleet's underlying mobility patterns, it is in the interest of the EMP to:

1. Satisfy his customers by providing a good Quality of Service (QoS),

2. Control charging processes respecting actual grid constraints in order to ensure long-time system robustness,

3. Optimize his energy purchase strategy minimizing applicable energy consumption costs.

The underlying system model for this work is introduced in section 2. In order to derive realistic demand profiles for a whole fleet of EVs, it is necessary to study their mobility patterns in detail. Hence in section 3 we introduce two scenarios based on empirical and statistically relevant data, which are the basis for our evaluation. In section 4 we introduce our discrete non-homogeneous Markovian EV charging model, which allows us to calculate EV demand profiles over time considering the impact of variable charging policies, e.g. through Service Level Agreements (SLAs), as well as respecting local grid constraints. In section 5 we discuss our evaluation results focusing on the Spot Market, which consists of the Intraday and Day-Ahead markets. In addition, requirements for participation at the control reserve market including Primary and Secondary Control Reserve Energy and the Minute Reserve are considered. We summarize our findings and provide an outlook on further research in the conclusions in section 6.

2 System Model Overview

The system model for this work embodies three main entities: An EV Fleet Manager, a Broker and the Energy Market Platforms. From a market perspective, the Fleet Manager is a large energy consumer who tries to optimize his energy purchase through a broker who directly participates at the market. An overview of this system model is shown in Figure 1.
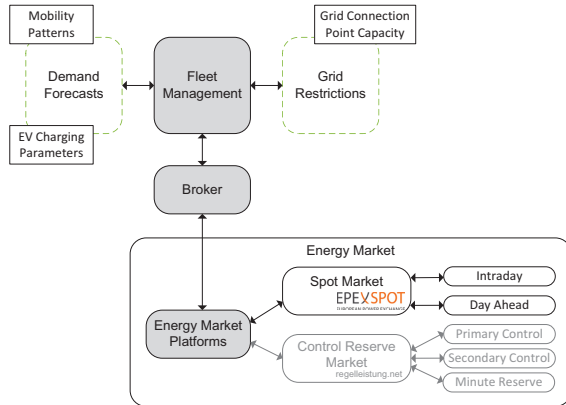

Figure 1: System Overview

For optimization of his purchase strategy the Fleet Manager needs detailed knowledge about the underlying fleet characteristics including its mobility patterns, EV charging parameters as well as grid limitations due to constrained capacity of Grid Connection Points (GCP). Technically this is implemented by extending already existing telemetry interfaces to the EV for the purpose of monitoring and controlling a charge process. Based upon this input data, the Fleet Manager can derive forecasts of the amount of energy needed at certain time intervals respecting local grid restrictions. The demand forecasts in this model heavily depend on average driven distances by the fleet participants and the time frame when EVs are connected to the grid (referred to as "connection time"). In this work, this data is based upon scenarios being defined in detail in section 3. The grid restrictions are defined by means of each GCP's capacity, which in turn is assumed as a constant constraint per GCP, similar to typical contracts for GCPs.

Taking into account the grid restrictions and the overall demand forecast for the fleet, the Fleet Management derives charging schedules over the connection time for the set of EVs. The degree of freedom for the charging schedules is adjustable through a QoS criteria which may be defined by the probability at which the entire EV fleet is successfully charged. The fleet's overall demand including an indication of its flexibility is forwarded to the Broker, who in turn takes part in the Energy Market (e.g. EPEX spot market) and tries to purchase the needed amount of energy for an optimal price.

3 Scenarios under Study

The evaluation scenarios in this work are based on large commercial/company fleet setups, where the charging of EVs is controlled by a Fleet Manager. In order to evaluate the impact of time at which charging takes place, two scenarios are investigated with varying time windows for charging:

- Commuter Daytime Scenario (7:00AM-3:30PM on weekdays, excluding weekends & holidays)

- Parcel Delivery Nighttime Scenario (6:00PM-6:00AM on weekdays, 6:00PM Friday-6:00AM Monday on weekends, holidays are handled according for the state North Rhine Westfalia in Germany)

Due to limited capacity of the Grid Connection Point (GCP), only a limited number of concurrently charging EVs are allowed per GCP which in turn results in the need for distributing the individual EV charging processes throughout the available connection time. Furthermore the Fleet Manager's interest is to distribute all charging processes in a way that results in minimum energy purchase costs. Hence, the following two sections describe in more detail how the resulting energy demand of the fleet and its energy purchase costs are derived in this work.

3.1 Estimation of Fleet Demand

A Fleet Manager may directly estimate and derive the energy demand of an entire fleet based upon the knowledge of nominal EV-specific consumption data and the average trip lengths for all participants of the fleet. In case of the commuter daytime scenario the information on average trip lengths were gathered from results of a representative traffic study [1], which was conducted in Germany during the year 2002. The evaluation of the study was limited to EV-friendly commuter traveling distances resulting in the distribution function according to Figure 2. In case of the parcel delivery nighttime scenario the distribution function was defined by the authors corresponding to an estimated parcel service use case also shown in Figure 2.

For simplicity reasons we assume a homogeneous fleet setup with the same type of EV for the entire fleet. Its specification data on driving range, battery capacity and driving consumption are derived as average from an exemplary set of available EVs shown in table 1. The average values are concluded as parametrization for the remainder of this work. In order to estimate the State of Charge (SoC) at arrival time the distribution function on travel distances according to Figure 2 is applied to all EVs within the fleet for both scenarios. From these results and the EV parametrization according to table 1 the expected demand during connection time (commuter daytime / parcel delivery nighttime scenario) can be derived for the entire fleet.

EV Model	Nominal Max. Distance [km]	Nominal Battery Capacity [kWh]	Nominal Consump. $[\frac{kWh}{100km}]$
Renault Kangoo Z.E.	170	22	12.9
Fluence Z.E.	185	22	11.9
Zoe Z.E.	160	22	13.8
Smart Fortwo	145	17.6	12.1
Ion	150	16	10.7
C-Zero	150	16	10.7
Leaf	175	22	12.6
I-Miev	150	16	10.7
Average	160.6	19.2	11.9

Table 1: EV Specification Data and derived input for EV Charging Model

Due to the assumption on rather homogeneous fleet mobility characteristics in terms of arrival and departure times, the *connection time* is defined by contract and therefore set by the Fleet Manager for the entire fleet. The *connection time* indicates in which time frame price optimized charging is supported by the underlying service of the Fleet Manager and the Broker. Hence, it defines the time frame where a large subset of the fleet is connected with a certain probability. It may be adapted from time to time by the Fleet Manager, who continuously observes the fleet's mobility characteristics. According to this definition the *connection time* does not necessarily refer to the actual arrival and departure time for each individual EV.

Other than varying traveling distance distribution functions for both scenarios, the commuter daytime scenario also implements a scenario-specific Service Level Agreement (SLA) defining that each EV with less than 50% SoC at plug-in time will start charging immediately until at least 50% SoC is reached. The Fleet Manager has to schedule charging processes accordingly and at the same time, while implementing this SLA, has to ensure that the nominated grid limitations are not violated. Continuation of charging
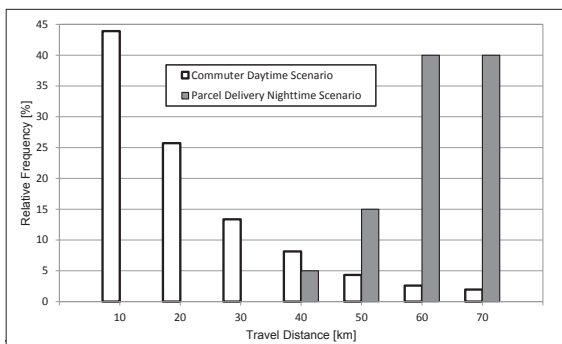

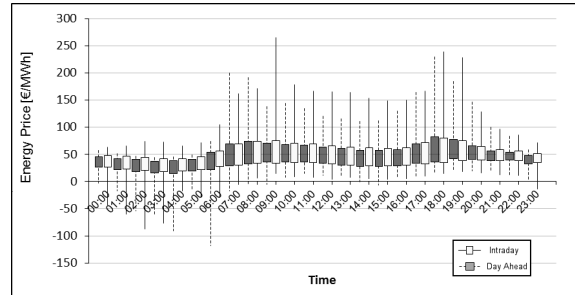Figure 2: Travel Distance Distribution for both Scenarios

Figure 3: EPEX Spot Mean Intraday and Day-Ahead Prices (Q4/2011-Q3/2012) derived from [2]

to a higher SoC than 50% is scheduled according the Fleet Manager's strategy until departure time. The idea behind this SLA is to provide a certain amount of flexibility to fleet users in case of any unplanned driving activity events even during the contractually agreed connection time. Such an SLA obviously increases the Quality of Service (QoS) from the EV user's perspective in situations where the EV is used spontaneously. On the other side it reduces the flexibility of the Fleet Manager for time-shifting the EV charging processes, which in turn could lead to reduced benefits of his energy purchase optimization.

3.2 Market Data Analysis

In order to correlate the demand for charging the EV fleet with Intraday and Day-Ahead spot market prices, actual EPEX Spot Intraday and Day Ahead market data for the time period between Q4/2011 and Q3/2012 were considered based on [2]. The corresponding results of this analysis are shown in Figure 3. It details the statistic distribution function of daily average Intraday and Day-Ahead prices including min. and max. values and mean added symmetric standard deviation.

For the parcel delivery nighttime scenario Figure 3 clearly shows a decrease of mean Intraday and Day-Ahead prices during connection time (6:00PM-6:00AM), whereas for the commuter daytime scenario (7:00AM-3:30PM) mean Intraday prices remain on higher levels, however also with higher standard deviations. In general it is shown, that Intraday prices are more volatile than Day-Ahead prices and Day-Ahead prices especially at night are lower than Intraday prices. Lowest energy mean prices can be found between 3:00AM and 4:00AM with 31€/MWh at the Intraday Market and 29€/MWh at the Day-Ahead market. Highest prices are studied at 6:00PM in the evening with 57€/MWh at the Intraday Market and 58€/MWh at the Day-Ahead market. This corresponds to a spread of 26€/MWh for the Intraday market prices and 29€/MWh for the Day-Ahead prices respectively. Since the maximum spread is located inside the connection time period of the parcel delivery nighttime scenario, we can immediately assume that a price optimization will have a larger impact in this scenario.
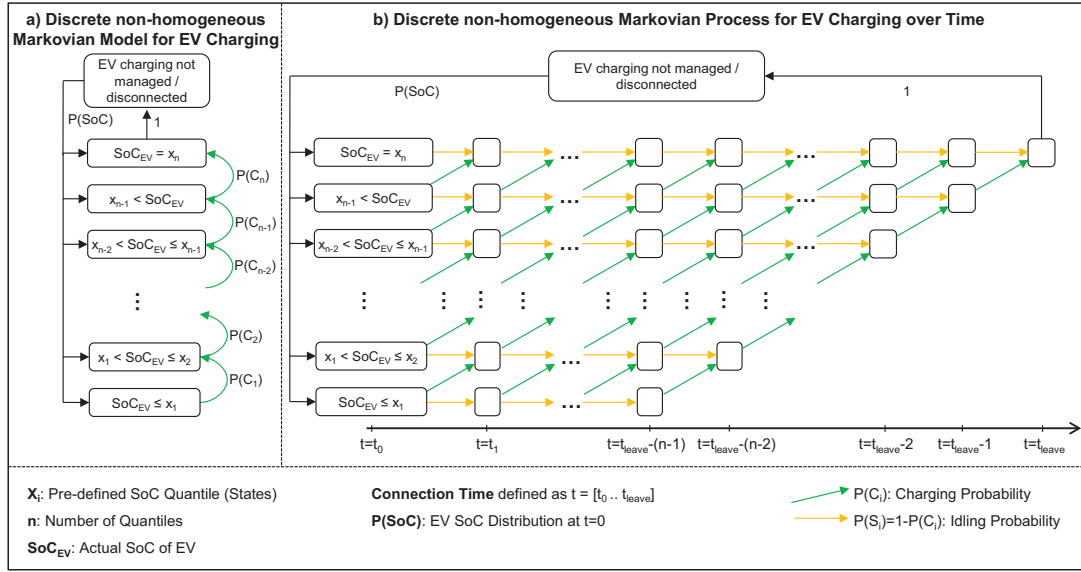
Figure 4: Discrete non-homogeneous Markovian EV Charging Model

4 Markovian Electric Vehicle Charging Model

In the context of this work, the Fleet Manager needs an analytical model of the EV charging process, which allows him to benchmark different charging scenarios. It is supposed to provide means for calculating optimized charging schedules of individual EV fleet participants in a way that their aggregate results in a price-optimized fleet schedule according to the energy market data defined in section 3.2. Hence, inspired by [3] an analytical charging model is proposed, which defines a discrete model for an EV charging process offering the following means of parametrization:

- Definition of fleet size and connection time

- Configuration of SoC distribution function for initial EV states at the beginning of connection time

- EV specifications (charging rate / battery capacity / average consumption, charging efficiency)

- Consideration of a max. number of concurrently charging EVs for a GCP according to grid limitations

- Charging decision criteria based on max. price for energy purchase

- Configurable battery charging profiles

As a result the discrete non-homogenous Markovian model shown in Figure 4 a) was defined. Other than the linear model based approach described in [4] it describes the charging process as a discrete model with a unique set of SoC quantiles (states) connected through corresponding state transitions. Each state transition is assigned to a predefined amount of time (e.g. 15 minutes) which leads to the corresponding discrete non-homogeneous Markovian process (see Figure 4 b) defining all available state transitions within a set of time slots during connection time. This setup allows us to apply certain charging strategies and SLAs by influencing the state transitions (either `idling` or `charging`) through a charging decision criteria, e.g. by policy or maximum price for energy purchase etc., and to formally describe the resulting charging schedule for the EV. Applying this model on a scalable set of EVs allows to calculate the overall fleet's demand profile, composed by the aggregate of all individual EV charging schedules during connection time. The model furthermore provides a measure on grid limitations by assigning a subset of EVs to one GCP. With a given power capacity of the GCP only a limited number of EVs are allowed to charge concurrently. This situation is modeled by limiting the amount of EVs in the `charging` transition during one time slot.

In combination with the previously defined scenario data from section 3, this model allows us to determine potential benefits or drawbacks of any given charging policy with regards to the resulting energy purchase costs.

5 Findings and Results

The aim of the following evaluation is to estimate what value could be gained by the Fleet Manager and Broker through charge shifting according to two different purchase strategies for both previously described scenarios (see section 3). The first strategy, subsequently referred to as *Managed Intraday Purchase*, only acts upon price signals on the Intraday spot market, whereas the second purchase strategy, subsequently referred
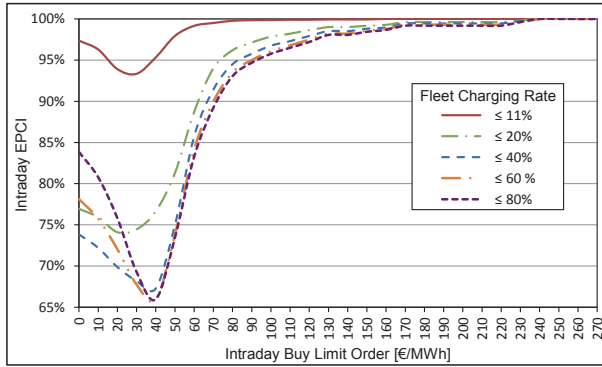
(a) Gain of Managed Intraday Purchases
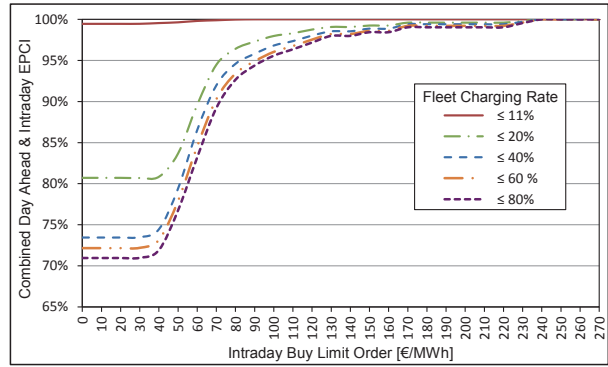
(b) Gain of Managed Day-Ahead and Intraday Purchases based on Phelix Day Index

Figure 5: Energy Purchase Strategy Evaluation for Parcel Delivery Nighttime Scenario

to as *Managed Day-Ahead & Intraday Purchase*, acts upon price signals on the Day-Ahead and Intraday spot market. In order to quantitatively describe the overall gained value, the *Energy Purchase Cost Indexes (EPCI)* are introduced for our evaluation:

- *Intraday EPCI* is defined as "resulting purchase costs in reference to an unmanaged Intraday-price based purchase policy with no use of charge shifting but consideration of max. available GCP capacity".

- *Combined Day-Ahead & Intraday EPCI* is defined as "resulting purchase costs in reference to a combined Day-Ahead and unmanaged Intraday-price based purchase policy with no use of charge shifting but consideration of max. available GCP capacity".

Both strategies are evaluated for a series of different *fleet charging rates* (indicated by the ratio of allowed number of concurrently charging EVs vs. overall number of EVs in the fleet which are considered during connection time) and depending on the *Intraday Buy Limit*. The *Intraday Buy Limit* is used as decision criteria whether to buy a certain amount of energy for one time slot or not. If the amount was not bought due to a higher price signal than defined by the *Intraday Buy Limit* it is delayed for a later slot. The *Intraday Buy Limits* start at 0€/MWh and develop in steps per 10€ up to 270€, whereby 270€ are higher than the maximum price at the Intraday market at the studied time period between Q4/2011 and Q3/2012.
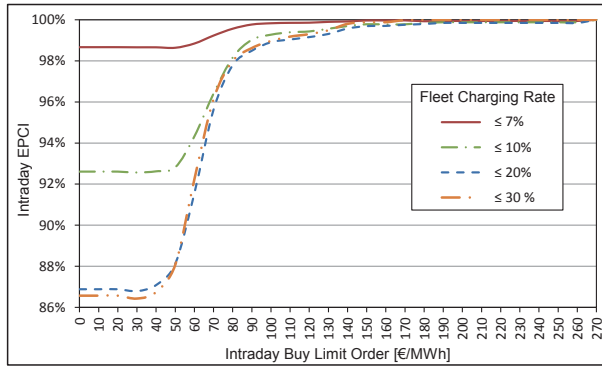
In case of the *Managed Day-Ahead & Intraday Purchase* strategy which also acts upon price signals on the Day-Ahead spot market, the *Day-Ahead Buy Limits* are determined by either the *Phelix Day Base* or the *Phelix Month Base*. The missing share of energy that is not bought on the Day-Ahead spot market must be bought Intraday according to the approach described above. The *Phelix Day Base* is the average price for all 24

one hour time slots of traded energy at the Day-Ahead energy market and published by the European Energy Exchange (EEX) the day before. The *Phelix Month Base* on the other side is calculated as average price of last month's *Phelix Day Base*. Subsequently they are referred to as *Phelix Day Index* and *Phelix Month Index*, respectively. The applicable amount of energy for purchase is determined by the EV charging model based on the SoC distribution at t=0 and is recalculated for each time slot. The previously introduced EV model (see section 4) assures that all EVs are charged until the end of connection time (even if that means that a set of EVs is forced to be charged towards the end of the connection time at suboptimal prices, see Figure 4b). It furthermore always considers the constraints defined by the *fleet charging rate*.

To find the optimum parameter set for each purchase strategy and estimate its gain for the parcel delivery nighttime and the commuter daytime scenario both purchase strategies are studied referring to their own reference values (see definition of *Energy Purchase Cost Index*). Furthermore in section 5.3 both purchase strategies are compared with each other, so that the optimum purchase policy can be derived.

5.1 Parcel Delivery Nighttime Scenario

The results of the parcel delivery nighttime scenario evaluation are shown in Figure 5. On the left the resulting *Intraday EPCI* is shown for the *Managed Intraday Purchase* strategy whereas on the right the *Combined Day-Ahead & Intraday EPCI* for the *Managed Day-Ahead & Intraday Purchase* strategy is shown. In case of the *Managed Day-Ahead & Intraday Purchase* strategy only the *Phelix Day Index* based result is shown, since differences compared to the Phelix Month Index-based approach were marginal. In case energy is ordered already on the Day-Ahead market (price is beneath the Buy Limit Order set by the *Phelix Day Index*), resulting energy purchase costs are not as volatile as in case of *Managed Intraday Purchase* strategy. Since missing en-

(a) Gain of Managed Intraday Purchases
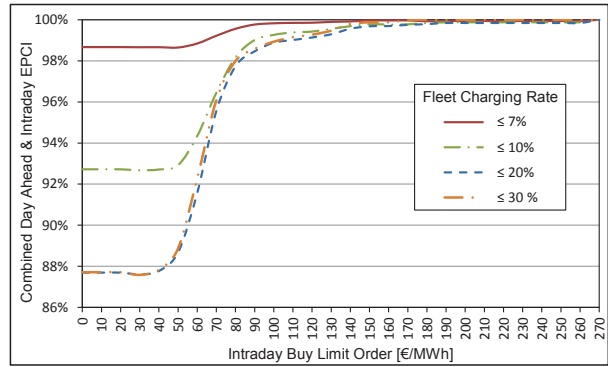
(b) Gain of Managed Day-Ahead and Intraday Purchases based on Phelix Day Index

Figure 6: Energy Purchase Strategy Evaluation for Commuter Daytime Scenario

ergy must be ordered in this strategy on the Intraday market as well, resulting energy consumption costs vary referring to increasing Intraday Buy Limit Orders. In contrast to the *Managed Intraday Purchase* strategy, costs do not decrease from 0€/MWh up to 30€/MWh. Such limits at the Intraday market often lead to no purchase success because average prices are higher, so that energy is forced to be purchased at the end of the *connection time*. In case energy is ordered Day-Ahead, such forced purchases are reduced, so that costs in case of additional Day-Ahead purchase do not decrease from 0€/MWh up to 30€/MWh as in the *Managed Intraday Purchase* strategy. Starting at 30€ with increasing Intraday Buy Limit Orders the resulting energy purchase costs increase as well, since now energy is purchased at the Intraday market at no optimum prices, because price reduction during the course of *connection time* cannot be used best.

What can be seen for the *Managed Intraday Purchase* strategy at the parcel delivery nighttime scenario is that an Intraday Buy Limit Order of around 30€/MWh to 40€/MWh would have resulted in the best purchase strategy based on the EPEX spot market data for time frame Q4/11 – Q3/12. The optimum costs are at about 66% of the reference for more than approximately 40% concurrently charging EVs. Almost no further cost optimization is feasible by providing higher *fleet charging rates*. In the less volatile *Managed Day-Ahead & Intraday Purchase* strategy with a maximum charging rate of 40%, costs can be decreased up to about 73.5%, so that maximum savings of 26.5% are possible. Starting at this point savings start to saturate for higher *fleet charging rates*.
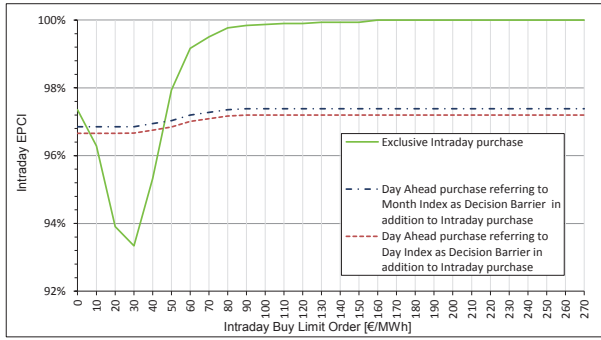
5.2 Commuter Daytime Scenario

Unlike in the parcel delivery nighttime scenario, almost no differences between *Managed Intraday* and *Managed Day-Ahead & Intraday Purchase* strategies are recognized in the commuter daytime scenario. Again, no noteworthy differ-

ences between both Buy Limit Order approaches for the *Managed Day-Ahead & Intraday Purchase* strategy can be observed, so that only a Phelix Day Index based approach is shown on the right in Figure 6 next to the *Managed Intraday Purchase* strategy on the left. For all evaluated policies costs are nearly steadily increasing considering increasing Buy Limit Orders. Referring to Figure 3, this is caused by the fact, that energy prices at daytime are in average higher than at nighttime, so that energy during daytime is not as often purchased Day-Ahead as during nighttime. Minimum resulting energy consumption costs are reached at an Intraday Buy Limit order of about 30€/MWh with savings up to 13%.
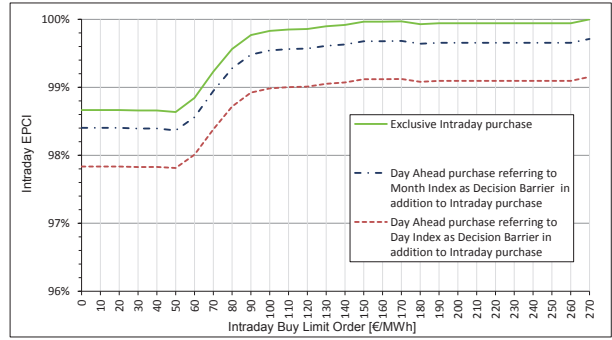
5.3 Comparison of Scenarios

In the previous two sections best parameters for the *fleet charging rate* as well as for the Buy Limit Order for each purchase strategy in both scenarios were derived for the given set of input parameters. In this section the performance of the *Managed Intraday Purchase* strategy and the *Managed Day Ahead & Intraday Purchase* strategy are directly compared. In this comparison the *Intraday EPCI* is used as reference measure. Hence, an unmanaged Intraday purchase policy without charge shifting is set as reference as 100% in Figure 7. The comparison of both scenarios is furthermore based on using minimum installed capacity of the GCP, to minimize installation costs as well. In general the resulting EPCI plots show the same overall characteristics as the corresponding curves in previous sections (Figures 5 and 6) with minimum *fleet charging rates*.

The direct comparison shows, that in the parcel delivery nighttime scenario the *Managed Intraday Purchase* strategy with Intraday Buy Limit Orders between 10€/MWh and 40€/MWh is even better than the *Managed Day-Ahead & Intraday Purchase* strategy, although in average prices at the Day-Ahead market are typically slightly lower than at the Intraday market. The

(a) Gain of Energy Purchase Strategies for Parcel Delivery Nighttime Scenario at minimum GCP Capacity

(b) Gain of Energy Purchase Strategies for Commuter Daytime Scenario at minimum GCP Capacity

Figure 7: Comparison of Commuter and Parcel Delivery Scenarios at minimum GCP Capacities

commuter daytime scenario on the other hand shows the expected characteristics, where the *Managed Intraday Purchase* strategy is more expensive than the *Managed Day-Ahead & Intraday Purchase* strategy. The results in Figure 7 also show the comparison of Phelix Day Index and Phelix Month Index based Buy Limit Orders for Day-Ahead purchase in case of the *Managed Day-Ahead & Intraday Purchase* strategy. In both scenarios overall costs are lower when the Phelix Day Index is used as purchase decision barrier. Savings of almost 7% in the parcel delivery nighttime and only 2% in the commuter daytime scenario are caused by the fact, that during the parcel delivery nighttime scenario a higher charge shift potential is available due to longer connection times (see section 3) and higher energy demands in accordance with the travel distribution (see section 3.1).

In the end the results show that the proposed model in combination with existing market data provides a meaningful toolbox for Fleet Managers or EMPs to determine their Intraday Buy Limits per time slot if they are planning to participate at the spot market. The same applies for brokering bodies who participate at the market representing Fleet Managers or EMPs.

5.4 Application to Control Reserve Energy Markets

Next to the quantitative study of spot market participation the qualitative access to control reserve markets through fleets of EVs is considered in this work. Therefore, underlying requirements of the German market are taken into account, to examine what type of participation may be feasible based on actual market conditions. Three kinds of control reserve energy are used: Primary Control Reserve, Secondary Control Reserve, as well as Minute Reserve. An overview on all requirements for participation as well as the underlying processes were gathered and are summarized in table 2.

From our findings participation at the Primary Control Reserve market is quite ambitious be-

cause 1MW positive and negative power has to be offered at the same time by the fleet of EVs for weekly time slices. Positive control reserve may be provided either by reducing the fleet's demand or by discharging support for EVs. But ensuring the capability of provisioning at least 1MW of positive or negative control reserve at any time during a full week is considered a very ambitious requirement. For the Secondary Control Reserve, negative or positive power of 5 MW is needed, that has to be offered for a whole week in two possible time slices. To guarantee the availability of such an amount of power at all times defined by the offer's time slices during a whole week with an exclusive EV fleet, may also cause problems. For example in case of a commuter fleet scenario the requirements of Secondary Control Reserve energy would not be satisfied, because EVs are charged at company grounds only during working hours on weekdays. The third kind of reserve control energy is the Minute Reserve, which can be offered daily for time slices of 4 hours. The minute reserve fits best, but with a minimum amount of power of 5MW guaranteed over 4 hour time slices. Nevertheless a huge number of EVs and charge spots is needed and a certain reserve of EVs needs to be considered since connection times may not be fulfilled by each fleet participant. From this first qualitative review our recommendation would be to use EVs only as an optional portfolio advancement for an already established source for control reserve energy, e.g. based on a *Virtual Power Plant (VPP)* concept utilizing a set of heterogeneous types of *Distributed Energy Resources (DER)*.

6 Conclusions and Outlook

This work proposes a toolbox for Fleet Managers and EMPs based on a Markovian EV Charging Model to calculate and optimize their energy demand costs for charging a fleet of EVs based on past EPEX market data. Two independent scenarios were investigated with different energy consumption profiles (parcel delivery nighttime vs. commuter daytime scenario). For these cases

Evaluation Criteria	Primary Control	Secondary Control	Minute Reserve
Offer Invitation Cycle	weekly	weekly	daily
Offer deadline	Tuesday 15:00 for next week starting on Monday 0:00	Wednesday 15:00 for next week starting on Monday 0:00	10:00 day before delivery (Auctions, which would be on a Saturday, Sunday or a holiday have to be established on the last working day before one of these days.)
Auction result publishing	Tuesday 16:00 for next week starting on Monday 0:00	Wednesday 16:00 for next week starting on Monday 0:00	11:00 day before delivery (Opens oportunity to take part in EPEX Day-Ahead market.)
Tradeable Time Slices	no slices	2 slices; Prime time: 8:00 - 20:00; Secondary Time: 0:00 - 8:00 & 20:00 - 24:00 (Whole Saturdays, Sundays and Holidays belong to secondary time)	6 equal slices, starting at 0:00 with a duration of 4 hours (0:00 - 4:00, 4:00 - 8:00, 8:00 - 12:00, 12:00 - 16:00, 16:00 - 20:00, 20:00 - 24:00)
Auction decision criterion	capacity charge / demand charge (Ger. "Leistungspreis") [€/MW] (in case of equal prices first bid wins)	capacity charge / demand charge (Ger. "Leistungspreis") [€/MW]	capacity charge / demand charge (Ger. "Leistungspreis") [€/MW]
Call order	automatic activation by plant controller (basic prices / energy price (Ger. "Arbeitspreise") [€/MWh] are included in capacity / demand charges and are not paid on top)	Merit order by basic prices / energy prices (Ger. "Arbeitspreise") [€/MWh]	Merit order by basic prices / energy prices (Ger. "Arbeitspreise") [€/MWh]
Minimum amount	1 MW (positive AND negative)	5 MW (positive OR negative not XOR)	5 MW (positive OR negative not XOR)
Pooling (Aggregation)	Units in a pool may be changed every time. Units shall be mapped to the pool before the beginning of every 15 minute slot.	Units in a pool may be changed every time. Units shall be mapped to the pool before the beginning of every 15 minute slot.	Units in a pool may be changed every time. Units shall be mapped to the pool before the beginning of every 15 minute slot.
Pre-Qualification	Primary control has to be activated automatically in a 'constant' way in case of frequency deviations of +/- 200 mHz in 30 seconds and must be able to be active for at least 15 min. [Transmission Code 2003 Anhang D1]	Test run, which shows that unit can be activated and shut down within 5 minutes with a maximum overshoots of 10%. [Transmission Code 2007 Anhang D2]	Test run, which shows that unit can be activated and shut down within 15 minutes. [Transmission Code 2007 Anhang D3]
Pre-Qualification Simplification	Third party's pre-qualification can be used, if units are not offered in control reserve market.	Third party's pre qualification can be used, if units are not offered in control reserve market.	Third party's pre qualification can be used, if units are not offered in control reserve market.
Availability Factor	100% [Transmission Code 2003 Anhang D1]	>95% [Transmission Code 2007 Anhang D2]	100% [Transmission Code 2007 Anhang D3]
Sources	Bundesnetzagentur Beschluss Az: BK6-10-097	Bundesnetzagentur Beschluss Az: BK6-10-098	Bundesnetzagentur Beschluss Az: BK6-10-099
Pros / Cons for EV Fleet Participation	(-) 1 week allocation not very suitable (-) bound to capability of offering positive AND negative control reserve (-) timing requirements are hard to meet for highly distributed scalable systems	(-) 1 week allocation not very suitable	(+) 4 hours time slices more suitable (-) 5 MW minimum amount

Table 2: Requirements for different Types of Control Reserve in Germany

our results show, that it cannot be claimed, that early Day-Ahead energy purchase strategies are always economically better than exclusive Intraday purchase strategies. It is shown, that in the parcel delivery nighttime scenario purchase costs with exclusive participation at the Intraday market (*Managed Intraday Purchase* strategy) can be lower than those with additional Day-Ahead purchases. Since the Intraday market is more volatile compared to the Day-Ahead market, such purchase strategies come along with additional risks, but may offer better absolute optimums for reducing energy consumption costs of a fleet of EVs. The study of application to the control reserve market shows, that in future work the minute reserve could be considered as well, so that additional savings may be possible. In addition to the extension to control reserve energy, direct trading between balancing areas will be studied, as well as flexible arrivals and departure times of EVs. Another future aspect is the economical assessment of providing V2G support based on market data using benefits at high price time periods.

Acknowledgments

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