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Leveraging Energy Flexibility with Electric Vehicles

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Executive Summary

In this paper, we present an implementation of price-optimized charging based on energy flexibility. Three fleet operators determine the energy demand needed to charge battery electric vehicles (BEVs) at a specific time and share this information as so-called power corridors with an energy aggregator. The aggregation system collects the predicted power corridors from the charging systems and calculates the flexible energy demand. A trading system receives the aggregated information and returns the power prices to the aggregation system. As a result, the aggregation system calculates and delivers charge plans for each site of the fleet operator with optimized power prices to the charging systems. This study can contribute to a new energy market communication system by providing insights on how to leverage the energy flexibility BEVs can offer for a data-driven energy system.

Keywords: BEV, energy, optimization, smart charging, market development, aggregator, flexibility

1 Introduction

In 2020, the road transport sector was responsible for 11.9 % of the worldwide greenhouse gas emissions [1]. To combat human-made climate change, a strong reduction of these emissions is urgently necessary. One possible strategy to reduce these emissions is the electrification of this sector, which will result in an energy demand of several hundred gigawatt hours by 2030 only in Europe [2]. Due to the generally high idle times of passenger cars, this total demand can be flexibly shifted. The charging processes can be scheduled when energy from volatile, renewable energy sources is available or when electricity prices are low. However, the question remains how this theoretical idea can be implemented in practice. A major challence is the determination of energy flexibility BEVs can offer and to optimize the charging process according to the objective. Current research shows that existing policies of many countries prevent innovative approaches for flexibility trading [3]. The aim of the TRADE EVs II project is to find a scalable solution for this challenge. The project with a duration of three years was initiated in 2021 by SAP, nextmove, EWS and FFE involving a fleet of more than 400 EVs from employees. The project builds on the experience gained from the predecessor project TRADE EVs I where an energy optimization heuristic to schedule charging processes has been deployed [4] and a charging system prototype based on Open E-Mobility [5] has been set up.

TRADE EVs II extends the setup with an energy-flexibility aggregation system to establish a demand side management (DMS) for charging.

The theoretical idea of smart charging, i.e., postponing charging processes to times when electricity prices are low or renewable energy is available, is not a new one. There are many publications that examine smart charging on a theoretical basis [6]–[8]. The authors in [7] predict a future saving potential of 200 €/BEV/year for smart charging with variable prices. Approaches to avoiding over-coordination and herding effects have been discussed in the literature on price-based BEV charging coordination. One such approach, proposed by [9] involves spatial price differentiation to effectively incorporate distribution grid limitations into charging schedules. Another study by [10] emphasizes the potential cost savings achieved through smart BEV charging and the ability to feed energy back into the power grid (V2G). There are some research projects that implemented the aggregation of vehicle fleets to charge them price optimized. For example, the projects BDL and Lama in Germany can be mentioned [11]. V2X Suisse is an example for a project from Suisse [12]. Away from research projects, various companies are working on the development of commercial solutions for smart charging. Octopus Energy, for example, has implemented smart charging with variable electricity prices for its customers in the UK via its platform Kraken [13]. Also, the company enel X developed a platform based solution for smart charging [14]. Tibber and aWATTar are further such companies from Europe. However, the aggregation process used by these companies is not transparent. Another problem with most of the solutions so far is that they are proprietary. Open systems are not in the focus of present work. This paper will therefore show how such an aggregation can be done and how it can be implemented independently from proprietary systems.

Improving the electrical fleet performance requires a clear objective and measurable variables. The concept of flexibility in general is considered domain-specific, and thus difficult to define. In the case when systems should adapt to an external environment, like in our case the BEV fleet to the availability of energy, they can adapt better if the variables include flexibility in one or more dimensions [15]. Energy flexibility in our paper is considerd as the possibility to shift the energy demand over time. Other definitions for energy flexibility are characterized by static approaches, considering the composition of parameters at a given time instant [4]. Approaches towards a dynamic flexibility function to control demand with penalty signals [16] are a common way to incentivize consumption behavior, and propagate the paradigm shift towards a demand control energy system. The critics are that penalty based flexibility indexes depend on the interpretation of the energy providers, who improve their objectives of CO_2 emmisions or real-time prices without considering the actual amount of energy demanded by the consumers immediatly. Our approach presented in this paper is in contrast to this based on a bidirectional communication between the consumers and the energy provider. The research goal is to improve the energy consumption with demand side management (DMS) processes, by considering a local charging system setup with BEVs, storages and renewable energy sources.

Data availability on a charging system level is the key enabler for effective DMS-processes and the basis for a level playing field for exchanging flexibility services between BEV fleet operators and energy providers. In the project we assessed two approaches for car data integration: hardware-based onboard units and software-based telematic services. With the in-car data, the charging system calculates the energy demand needed for the charging period. The data-points considered are the state-of-charge (SoC), the battery-model, and a charging priority of the cars.

TRADE EVs II as a project aims to address the following questions:

- How can e-mobility systems be optimized for different operation scenarios?
- How can our definition of flexible energy demand optimize energy consumption of BEV fleets?
- What are the processes and algorithms required to leverage energy flexibility of BEV fleets?
- What data needs to be available to feed the algorithms?
- How can our insights reshape the existing energy landscape?

In this paper, we present the project, by discussing the project methodology, the data processes, the developed system architecture and preliminary results of the research.

2 Background – Modeling of Energy Flexibility

In TRADE EVs II we assume that only unidirectional charging of BEVs is possible, hence the following assumptions apply power $P \geq 0$ and energy $E \geq 0$.

For the mathematical modeling, the specific terms power-corridor (flex-corridor) and flexible energy demand (energy demand over the flexible time range) are introduced. Figure 1 shows the timeline between a start time t_s when the car connects to the wallbox and an end time t_e when the car disconnects from the wallbox. Within this range the energy demand for charging can be consumed, this range we call energy segment. Because $P \geq 0$ apply, there is no negative power value, therefore bi-directional charging is not included in the model, however because $P = 0$ is possible, the case for pausing the charging sessions and turning of the base load for the assets of the charging system is included.

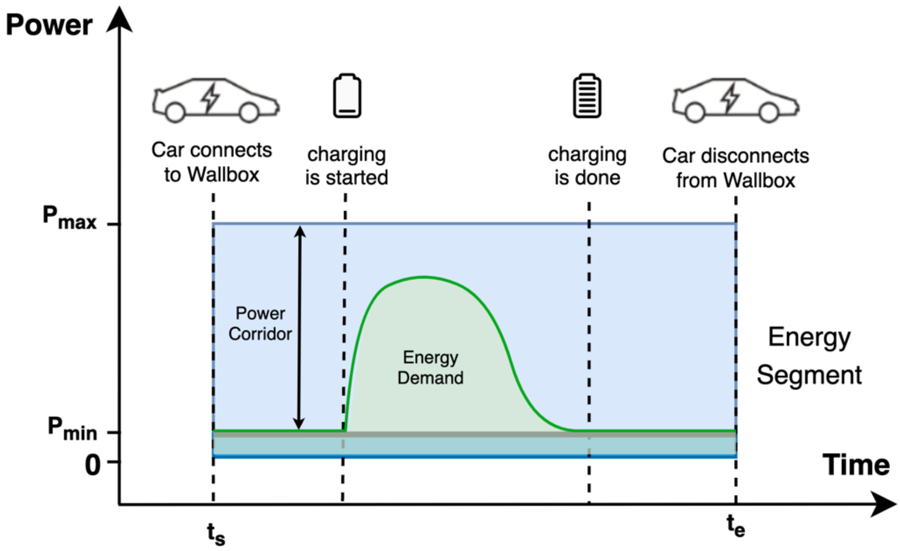

Figure 1: Energy demand and power corridor for a BEV charging process within an energy segment.

Each charging system C can serve $n + 1$ electrical vehicles $V\epsilon\{v_i, i = 1..n\}$ and can also manage $m + 1$ energy assets $A\epsilon\{a_j, j = 0..m\}$, for example energy storages or generators.

The power corridor ${P_C}^t$ of each charging system C is defined as the difference between the maximal consumption power ${P_{max}}^t$ and the minimum required power ${P_{min}}^t$ of the charging system for a specific point in time t (Equation 1). P_{max} is the maximum connected power which can be consumed by all vehicles and assets and is defined in Equation 2. P_{min} is the minimum power required by the charging system to operate the connected assets (Equation 3). Pausing the charging sessions is equal to $\sum_{i=0}^{n} {P_{v_i}}^t = 0kW$, if the consumption of $\sum_{j=0}^{m} {P_{a_j}}^t = 0kW$ then the assets either are off or being operated in "island mode" with local storage or generation.

$$ {P_C}^t = {P_{max}}^t - {P_{min}}^t \quad (1) $$

$$ {P_{max}}^t = \sum_{i=0}^{n} {P_{v_i}}^t + \sum_{j=0}^{m} {P_{a_j}}^t, \{\max(P_{v_i}^t); \max\left(P_{a_j}^t\right)\} \quad (2) $$

$$ {P_{min}}^t = \sum_{i=0}^{n} {P_{v_i}}^t + \sum_{j=0}^{m} {P_{a_j}}^t, \{min(P_{v_i}^t); min\left(P_{a_j}^t\right)\} \quad (3) $$

The power corridor over the time interval between a start time t_s and an end time t_e, is the flexible amount of energy E_f.

$$E_f = \int_{t_s}^{t_e} P_C{}^t dt \tag{4}$$

The energy demand is the consumption needed by the charging system over the time interval $[t_s, t_e]$ to ensure operations. It can be set by the charging system, but needs to comply with the assumptions.

$$E_D \geq \int_{t_s}^{t_e} P_{min}{}^t dt \text{ and } E_D \leq \int_{t_s}^{t_e} P_{max}{}^t dt \tag{5}$$

An energy segment E_S is defined as the maximum energy the grid could provide within an interval $[t_s, t_e]$ under the limit of the possible maximum connected load the infrastructure can absorb.

$$E_S = \int_{t_s}^{t_e} P_{max}{}^t dt \tag{6}$$

The relation in Equation 7 shows that the consumable energy demand E_D must lie between the flexible energy demand and the maximum energy possible due to the maximum connected load of the grid.

$$E_f \leq E_D \leq E_S \text{ for } [t_s, t_e] \tag{7}$$

Flexibility F is zero if the flexible amount of energy E_f is equal to the energy demand E_D in the same interval or if E_D is equal to the energy segment E_S.

$$E_f = E_D \vee E_D = E_S \longrightarrow F = 0 \text{ for } [t_s, t_e] \tag{8}$$

Flexibility is increasing, if:

$$E_f < E_D \wedge E_D < E_S \longrightarrow F > 0 \text{ for } [t_s, t_e] \tag{9}$$

Energy segments E_S forecasted with long timeframes, hence hold a larger flexibility potential than E_S with small timeframes and might be of substantial value for an energy provider DSM. The interface for exchanging this flexibility information is the precondition to create insights how charging can be improved to save costs by grid-friendly operation.

Above equations are valid under the conditions that $P \geq 0$ and $E \geq 0$. By including renewables and bidirectional charging there is also the negative flexibility case imaginable if the energy demand is $E_D < 0$.

$$E_f > E_D \wedge E_D > -E_S \longrightarrow F > 0 \text{ for } [t_s, t_e] \tag{10}$$

$$E_f = -E_D \vee E_D = -E_S \longrightarrow F = 0 \text{ for } [t_s, t_e] \tag{11}$$

$$E_f > E_D \wedge E_D > E_S \longrightarrow F > 0 \tag{12}$$

Other definitions for energy flexibility focus on the responsiveness of consumer behavior to signals like CO_2 intensity or the energy price. They define a dynamic flexibility function to evaluate the consumer behavior how they react to the real time energy situation. The calculated flexibility index can be used to apply penalties for unflexible behavior of the consumers [16]. Our approach in contrast, focuses on the transparent communication of energy demands and the flexible amount of energy the consumers are able to shift in time. This enables the energy provider to allocate and plan the consumption and allows the consumers to receive the demanded power and energy by adapting consumption plans within their self defined possibilities.

3 Project Methodology

3.1 Project Procedure

The project is divided into two main phases: concept and application, as shown in Figure 2. Beginning with the definition of use-cases for controlled charging. The focus was set on the use-case of spot-market-optimized charging, where the charging processes are influenced by the current electricity spot prices. Subsequently, the concept was extended for integration into the day-ahead markets, which resulted in the design of an aggregation algorithm and the interfaces required to establish a maket communication process.

The application-phase started with the collection of charging data from the participating BEVs. We developed a calculation method to determine the flexibility of the BEV fleet which we call the flex-corridor. Besides, we developed an algorithm to aggregate the demand data from different sites and communicate price signals. Hence, we use analysis to describe and publish our findings subsequently.

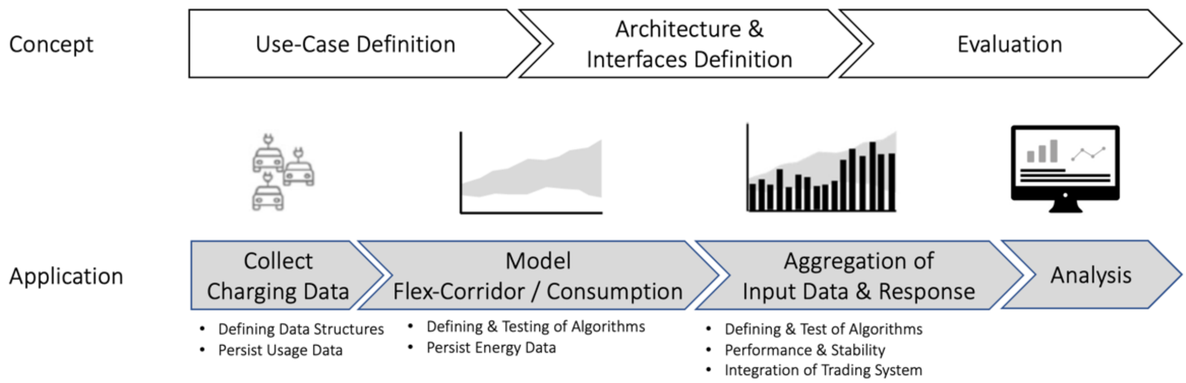

Figure 2: Sequence of project steps

3.2 Challenges

Besides difficulties in predicting the energy consumption, the forecasting of local energy supply – especially for renewable energies – beholds challenges as well. This is partly due to analog measuring technology and on the other hand due to static electricity tariffs like (40ct / kWh) which does not depict the share of renewables and therefore provides no trigger for sustainable charging behavior of self-interested chargepoint operators.

With our setup, participants need to specify the extent to which their power demand is flexible and whether it can be shifted. This holds another challenge because rational participants cannot be expected to prioritize the performance of the system over their own interests. Therefore, it is crucial to establish incentives that encourage the revelation and provision of flexibility among the participants. The incentive design must ensure that all are better off by disclosing their flexibility data, which means that they should receive benefits for revealing their information compared to withholding it. This allows the participants to align their behavior more flexible while maximizing their individual utility. Ultimately, to ensure everyones participation in the mechanism, it is essential to guarantee individual rationality, as well as the appropriate incentive and coordination mechanisms [15].

Data availability is the key to solve the problem, as seen in the manufacturing industry, where even minor process adjustments can generate substantial value [17]. Slight variations in the power system's flexibility can also have a significant impact on economic results. To make the most of this flexibility, it is essential to have a clear understanding of the available flexibility resources.

3.3 Functional Solution Approach

Addressing the challenges according to flexible energy demand, we evaluate three different controlling scenarios, one for each of the three fleet types, small company fleet, rental car fleet and big company fleet. All scenarios interact with the central aggregation system. The aggregator system transfers information between consumption facilities, generation facilities and authorized market partners to generate value by cognizant triggering of energy purchase decisions influnenced by the different interests of the actors, Figure 6 shows the scenario. The value is generated by the allocation of the forecasted energy demand within the flexible time range of the three consumers. With the incentive to charge when energy prices are low, the overall energy costs should be lowered.

In the first scenario we have a small fleet from the german energy provider EWS on a company parkingspace with ten AC charging stations. Each station is managed solely by its charging controller, which only communicates with the BEV. In this szenario, the total load is set by the consumption from the BEVs connected to the charging stations onsite. The forecast of the charging energy for the site is trained daily based on the actual consumption data from the BEV charging sessions. The prediction functions are refined continuously in the project to increase the overall accuracy of the charging forecasts. For example if new charging stations and BEVs get installed. BEV drivers are aware that the charging session can be shifted to different time-slots during the parking period to avoid charging during price peaks.

The second scenario is the load management scenario at Nextmove, which has implemented peak-shaving to operate more charge points in sequence than would be possible in parallel. The limitation of the connected load and local energy shortages are also considered. The Nextmove dataset is provided from a rental fleet and contains 420 BEVs from different usage types like business, private and test drives. Currently, the fleet consist of 245 midsize BEVs and 75 large BEVs. The journeys are planable and especially the business customers use the car for frequent traveling. Most drivers use the rental to test a BEV before buying it, which includes pushing it to its limits. For example, we observed that at the beginning of the rental period the SoC is much lower when the first charging session starts compared to the other charging sessions for rest of the rental period. Within this scenario, we conduct experiments with push notifications to suggest charging when energy prices are low. In return, the BEV drivers receive a discount per kWh for their charging session. Wherever possible in-car data is used for the charging estimates of an individual car. In the next step, this data is combined for several locations with Nextmove charging sites to calculate the energy demand for the day-ahead activities. The rental station charging sites are already operated with a load management system ensuring to follow the local grid limitations and the charging schedule from the aggregator.

The third scenario at SAP is a smart-grid scenario, which integrates information from the local grid to actively steer the total consumption of a charging system [5] serving 400 long-range employee BEVs with 81 installed charge points. This scenario integrates information from the local energy management system, which controls onsite photovoltaic (PV) and battery storages. Every 15 minutes an optimization of the local consumption is triggered, based on a heuristical programing model to minimize peak-demand, load imbalance and electricity costs [4]. The electricity cost minimization functionality is integrated so that it considers the onsite photovoltaic energy generation as complimentary energy but integrates no external energy prices yet. This function requires additional data for fine-grained energy prices from the aggregator, which is planned as a prospective feature. The entire site can offer a flexible energy potential from plus 20 percent to minus 20 percent from the planned consumption (limited by the maximum connected load of the site, 680kW). The total charging capacity of the charge points is 1020 kW, therefore the infrastructure is always operated below the total potential consumption of all charge points. Additional local PV generation of 80 kWp and a 150 kWh stationary battery offer additional flexibility. Figure 3 shows a single charging plan configuration, which is created by the optimizer to reduce the grid peak-load at the SAP site in Mougins.

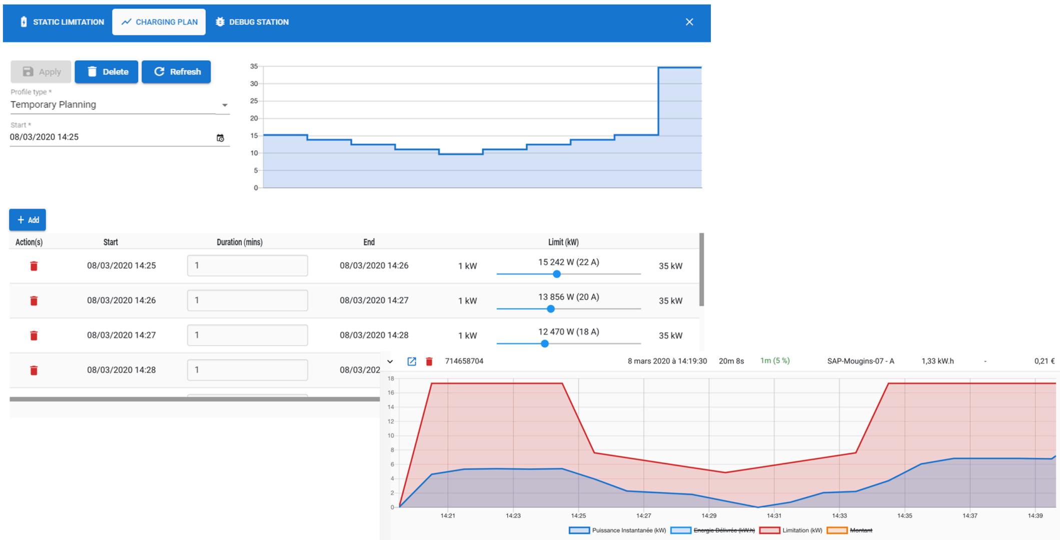

Figure 3: Definition of a charging plan based on the charging optimizer. The charging plan defines the power limit per charge point for every minute of the charging session.

3.4 Data access for Optimization Data

Three different interfaces have been used by the fleet operaters during the project to access realtime information from the charging sessions. Figure 4 shows the interfaces implemented for the charging system.

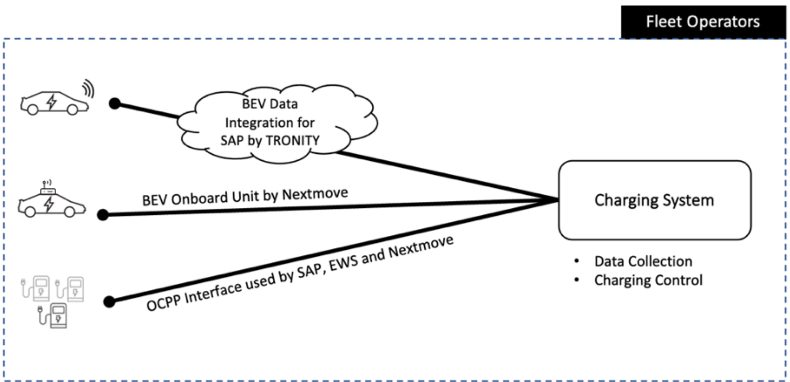

Figure 4: Interfaces for accessing realtime charging session information.

3.4.1 Operations based on Charge Point Data

All three scenarios use the open charge point protocol (OCPP) version 1.6. to exchange charging parameters for authentication, real-time charging session information, and to deploy charge plans. With data argmentation from a BEV database and a user database, heuristical optimization problems like prioritisation and load management of charging sessions are implemented in the charging system. The charge point data source is the basic data source for the charging systems in all three scenarios.

3.4.2 Hardware-Based Onboard Units for Real Time Data

The onboard unit used for the project consists of a transmitter module and an on-board-diagnose (OBD) plug using the standard connection to the BEV. Currently it supports 51 different BEV models from Nextmove for a real-time monitoring. The transmitter is capable to get over-the-air updates from the monitoring backend via its mobile connection. The price estimate for the developed onboard unit is approximately 450€ plus an additional data plan for connectivity. Due to firmware updates in the BEV regarding in-car energy management, it was already necessary to update during the project 300 units over-the-air. The availability of in-car real-time data depends on the car state to prevent potential vampire losses during parking periods.

3.4.3 Software-Based Telematic Services for Real Time Data

The enabling technology for software based BEV data access was realized with the TRONITY platform[1], providing integration into the cloud services of the BEV manufacturer for processing SoC information in real time. BEV drivers from the SAP site in Mougins provided their consent for charge optimization purposes. For a yearly fee of 60€ per car the service can be used without any hardware dependencies. Figure 5 shows a charging session with real time optimization considering the SoC provided by the TRONITY platform.

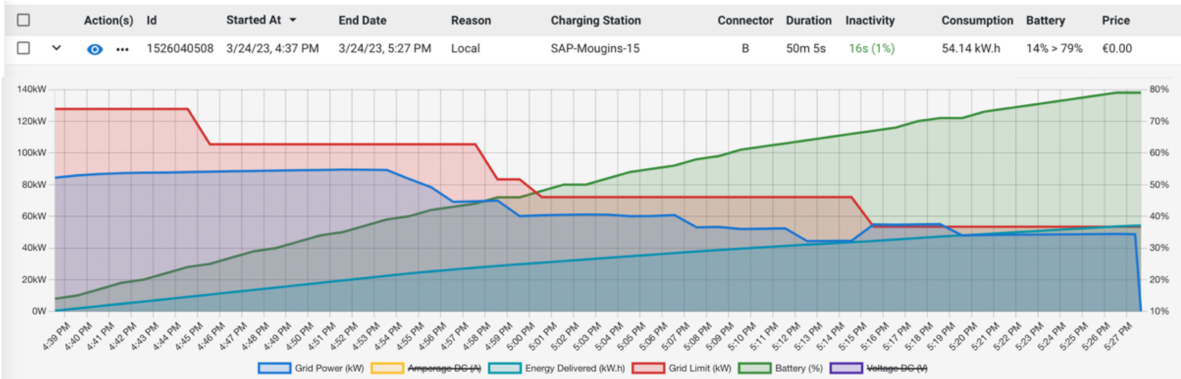

Figure 5: An increasing state of charge limits the power consumption, at eighty percent the charging session ends.

3.5 System Architecture

The system architecture identifies two domains which display the collaboration between fleet operators and the energy provider. Each domain has its responsibilities and tasks. The architecture of the demonstrator in Figure 6 shows the connected systems. Each fleet operator has a charging system to control the energy consumption based on the charging plan for the BEV fleet. The energy provider has an aggregation system and a trading system to interact with the fleet operators and the energy market. For the implementation of the charging systems, we use open source software [5] and deployed the systems as containerized applications on web services. The user interfaces are realized as desktop web applications, and for the end-user of the BEVs also via a mobile app. The systems of the energy provider are implemented as a microservice architecture. Each system runs indepedenently of the other systems with separate persistency and application layers, therefore we are following decentralized architecture principles, which allows more specific conversions into marketable solutions.

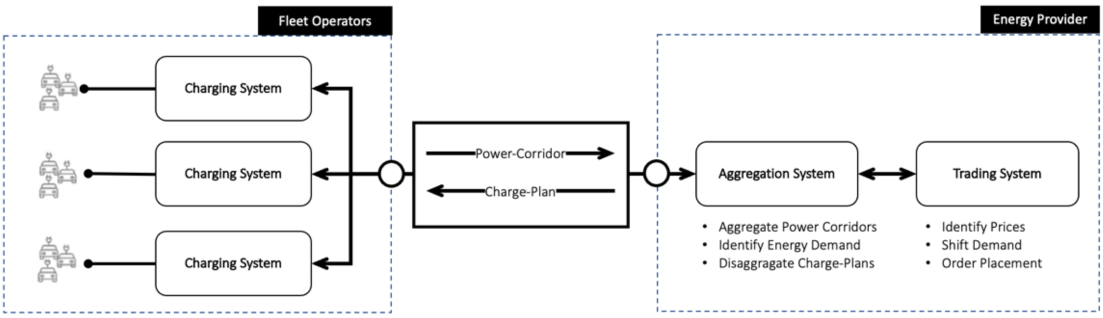

Figure 6: Architecture of the demonstrator.

Fleet operators have the task to charge the BEVs of the users in acceptable time while minimizing the cost of charging by considering CO_2 emissions, energy prices, and the local infrastructure situation. For the experimental setup, the fleet operators are obliged to communicate their flexible energy demand and the power-corridor for a given timeframe with the energy provider. In exchange, the fleet operator receives a charge-plan from the energy provider which depicts optimal consumption behavior. In the next step fleet operators will be incentivised to adapt the charge-plans on their fleets.

[1] https://www.tronity.io/

The energy provider has the task to aggregate the power corridors and identify the energy demand for the affected sections. On the energy provider level, the estimated power corridors from the connected fleet operators are aggregated. Here, aggregation involves summation of power maxima and minima, as well as of energy demands over periods of time. Furthermore, the aggregation system generates a consistent view of the flexibility originating from fleet operators, including "slicing" of energy demand segments appropriately, which eventually overlap in different source fleets, and feasibility checking. A technical interface offers pool flexibility potentials over rest to the trading system for corresponding procurement on electricity spot markets.

According to the flexible energy demand, the trading system finally identifies current price levels and shifts the demand within the flexible range to make the best procurement decision. The best order decision is determined by input parameters like the current energy price, the grid capacity and the situation of the charging systems which is "encoded" in the representation of flexibility received from the aggregation system. The result of procurement is a set of orders to be placed on the market and, in response a set of transactions (trades) that have been executed. All transactions on the market referring to the energy demand segments are ultimately composed into a pool schedule, i.e. the pool charge plan. For each time slot (typically 15 minutes), this result schedule contains the power value to be delivered in total for all fleet operator energy demands included in the original pool flexibility potential.

After obtaining the pool schedule from the trading system, the aggregation system disaggregates the pool charge-plans according to the individual fleet operator power corridors and energy demands. Herein the result is a charge plan for each fleet operator which will be published to the charging systems. In the next step the energy provider will also be able to receive real-time consumption data from the charging systems to react to unforeseen changes in consumption, either by shifting loads between fleet operators or place short term order decisions on the intraday energy spot market. This mechanism helps to minimize imbalance (i.e. the mismatch between actual energy consumption and the charge plan backed by trades on the market) which results in higher overall energy cost. Figure 7 has an overview of the aggregation, trading, and disaggregation process.

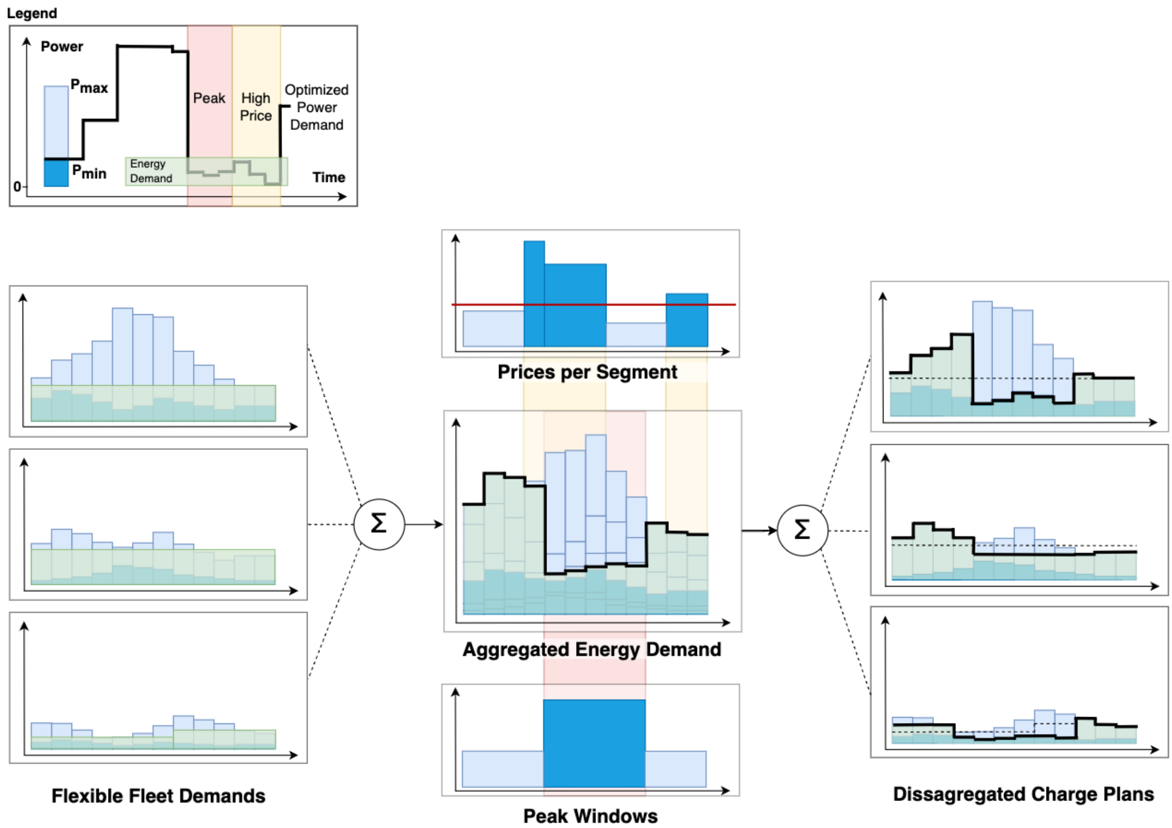

Figure 7: Energy aggregation process, the energy demand is aggregated to place purchasing orders at times with low prices and no peak loads, the disaggregation of energy considers the min and max power values communicated by the charging systems.

4 Evaluation

The assessment of the implemented system has been organized in three steps. The initial step focuses on testing the charging optimization for BEVs to align with local circumstances of the charging systems. The second step involves the collection of data from the charging systems, which will facilitate the forecast and the creation of the power corridor realistic for the BEV fleet consumption towards the placement of an aggregated energy order in the energy market. In the third step the breakdown of the centrally ordered energy quantity with realtime allocation processes for flexible demands is planned.

4.1 Preliminary Evaluation Results

Optimizing the energy demand of the charging systems is not trivial. The difference between the grid limit and the grid power in Figure 5 shows that BEVs do not simply charge up to the power of the assigned charge profile but each BEV has own power plateaus on which it charges, this steps which are vehicle model dependent, are not considered by the optimizer. This example behavior is also obeserved in the rest of the BEV fleet, out of that it is possible to identify different pattern depending on the battery size of the BEV and the commuting range of the car. This allows to separate smaller vehicles (less than 35kWh battery capacity) from BEV’s considered as new standard (50kWh up to 64 kWh) and long range (up to 120kWh). These BEV categories allow the further analysis of different consumption patterns. Further data analysis show the interdependencies with charge point models, car types and real time data to improve the optimization capabilities of the system. To identify the reasons for this different patterns a survey has been conducted.

Based on the test scenarios to forecast the flexible energy demand, customers have been surveyed how their behavior is affecting the charging processes. The clustering of the data showed that most BEV-drivers picked the car to fit for their driving scheme. The interview questions were the following:

- Where is your main location to charge your BEV?
- How often do you charge?
- How much is your charging behavior affected by energy prices?

Evaluating the results shows that smaller BEVs charge up to 80% at home, while standard BEVs charge only up to 60% and long range BEV only up to 40% at home. According to these results, the long range BEVs are the most relevant BEVs for aggregation purposes at charging sites. However, most long range BEV users are not interested in electrical cost optimization at all because they have no need to charge offsite from home. These drivers are often business users and triggered only by their individual charge demands which are paid by the company. They usually use high performance chargers during travel.

The drivers of smaller BEVs on the other hand are permanently looking for the next charging opportunity. This user group is really interested in the incentives a charging shift would offer them on a daily basis.

But the greatest potential is among the standard BEV users which can delay a charging sesssion to a next day. They have a larger battery, but still connect often to the grid. Their battery size allows to change dynamically their charging behaviour, if there is a sufficient incentive available. This promises a potential field for development to provide end user services and products offering optimized energy flexibility.

5 Discussion & Outlook

Overall the approach for operating multiple charging systems under an umbrella of a energy aggregator described in this paper is very promising as it proposes several new research avenues:

- Can the overall energy consumption become cheaper if an aggregator system can manage multiple demand sites in a central energy provisioning?
- How much business value can be created with energy flexibility from different BEV types?
- What are the potentials and dynamics between the aggregator and the energy markets, i.e. yo-yo effects between aggregators in the same accounting grid and its limitations?
- Can end-users also benefit by participating in the processes possible with energy flexibility, and how will an attractive product or service be designed to scale this functionality for public use?

Data availability has been identified as the limiting factor during the project to create substantial value from the data. The current optimization is only considering three charging systems which depend on the data transmissioned via OCPP, from 40,000 charging sessions from the last three years we could record 8,200 charging sessions which were optimized with SoC information from OBD devices or telematic services. The next step is to identify the predictors for charging behavior to improve the prediction accuracy for the power corridor and the flexible energy demand. Potential data sources could be booking systems with travel data, human resource systems with location and business car data, or facility management systems with data about the site infrastructure. The next challenge is to compare the data from the charging system forecasts with the actual energy consumption and the trading data, that can provide insights how much value can be created with flexible energy consumption and how effective incentive systems can be designed.

Acknowledgments

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Presenter Biography

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