# Energy-Management-as-a-Service: Mobility Aware Energy Management for a Shared Electric Vehicle Fleet

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Keywords: Energy Management System, Electric Vehicle, Distributed Energy Resources, Cloud-based, Information and Communication Technology, Optimal Charging, Direct Load Control.

Abstract: The combination of sustainable energy generation and transportation is one of the biggest challenges of the 21st century. In this work, an energy management system is presented which provides energy-management-as-a-service for electric vehicle fleet operators. Energy production and price forecasts are integrated with near real-time telematics data from a shared electric vehicle fleet, to optimize charging profiles for multiple charging sites of fleet operators. For this purpose, system architecture and a proper optimization method enabling different charging strategies are introduced. The presented system is finally evaluated by real world model trails and an optimization benchmark.

## 1 INTRODUCTION

One of the biggest challenges of the 21st century is the transition to sustainable transportation and energy generation (Chu and Majumdar, 2012). The need for ensuring sustainability is not only driven by rising fuel cost or the increase of $CO_2$ emissions, but also due to economic and political issues. In the field of transportation, battery electric vehicles (BEV) and plug-in hybrids (PHEV) help to reduce $CO_2$ emissions as well as fossil fuel dependency. Unfortunately, using these vehicle types incurs high investment costs, due to the cost of vehicles themselves and the cost of charging infrastructure. Nevertheless, these cost issues can be mitigated, using electric vehicles (EV) in corporate car pools. The study presented in (Plötz et al. 2014) calculates that the total cost of ownership (TCO) of EVs is lower compared to vehicles with internal combustion engines (ICE) when used in corporate vehicle fleets due to uniform driving profiles. Thus, corporate car fleets are a field of high potential for electric vehicle usage, especially since the study shows that 60 percent of today's newly registered cars are equipped as commercial cars in Germany. Furthermore, the German Federal Government (German Federal Government 2009) projected a market ramp-up of 1 million EVs by the year 2020. The project Shared E-Fleet (Ostermann et al. 2014) aims to leverage this potential by providing a software solution to enable small and medium sized enterprises which are not able to operate a sufficient amount of EVs economically on their own. The solution helps sharing vehicles between companies and users, realizing cross-company electric car pools.

Compared to conventional cars, the usage of EVs in a corporate shared vehicle fleet imposes unique challenges. Besides the limited range of EVs and indispensable charging times, concurrent charging of EVs might result in power peaks at a common charging site that might violate local grid constrains. Especially the operation of large fleets will not only affect fleet operators but also energy grid operators. These must provide the grid with a suitable amount of energy during peak times (Clement-Nyns 2010, Lopes et al. 2010, Deilami et al. 2011). The grid operators fear that uncontrolled integration of a large amount of EVs into the distribution grid might have a huge impact on the grid stability (Lopes et al. 2010). One solution is the integration of EV fleets as part of the smart grid. In this way, grid operators can prevent cost intensive grid expansion given the fact, that information and communication technologies (ICT) are harnessed to realize coordinated charging strategies. On the other hand, fleet operators can utilize coordinated charging to prevent demand peaks caused by concurrent charging of their vehicle fleet and thus enable scheduled charging in order to



Ostermann, J. and Koetter, F.
Energy-Management-as-a-Service: Mobility aware energy management for a shared electric vehicle fleet.
In *Proceedings of the 5th International Conference on Smart Cities and Green ICT Systems (SMARTGREENS 2016)*, pages 340-350
ISBN: 978-989-758-184-7

preferably consume locally generated renewable energy as it is produced.

In order to leverage these capabilities of EV fleets, an energy management system (EMS) is required which is able to easily integrate with various system services and business processes to provide dedicated control of the operation. Furthermore, it enables coordinated grid to vehicle (G2V) charging of EV fleets at multiple locations under consideration of local and decentral energy production. In the process, forecast services shall be used to take into account weather-dependent renewable energy production.

In this work, we present the results of our research in a mobility aware intelligent energy management aggregator, serving as an EV virtual power plant (VPP) as part of the Shared E-Fleet architecture. It enables a direct load control of intelligent charging stations. Thus, a centralized control architecture is introduced, interacting with multiple ICT components to apply optimized charging schedules, based on real time needs of a shared EV fleet.

This work is structured as follows: Section 2 gives an overview of relevant related work. Section 3 introduces the use case of the project Shared E-Fleet from an energy related viewpoint. Section 4 describes the architecture of the aggregator. In Section 5 the applied energy optimization algorithm is outlined. The prototype and evaluation are given in Section 5. Finally, Section 6 concludes this work and gives an outlook on future work.

## 2 RELATED WORK

Considerable research has been contributed already, investigating the integration of all kinds of EVs into a future smart grid. Since research in this area started already when adaption of PHEV began, not all work does solely concentrate on BEVs. Nevertheless, both types of vehicles do behave the same regarding the goal to develop coordination of charging and smart grid integration. In (Jansen et al. 2010), the authors present a modular VPP centralized architecture and necessary communication protocols to realize coordinated charging for a fleet of EVs as part of the EDISON project. Similar approaches concerning VPP for EV fleets with integration of distributed energy resources (DER) were already explicitly investigated by (Raab et al. 2011, Vandoorn et al. 2011). In literature, two different approaches of integration of DER are discussed. Besides VPP which aggregate DER units to provide controllability and enable market participation, micro grids (MG) aggregate local DER to provide a controllable entity that can operate in grid-connected and islanded mode (Vandoorn et al. 2011). In both concepts, an EV fleet acts as controllable battery storage system. Beside energy storage systems a MG or VPP can also include charging stations or a PV plant. Although the MG and the VPP concepts are similar, they can be differentiated by seeing a VPP aggregator as virtual, software-based aggregation and the MG as physical aggregation of DER units. In this work, we introduce an approach, not only focusing on a central VPP acting as aggregator but a multi-station aggregator, being able to provide second level control and operate multiple MGs independently. Thus, it enables the aggregator to consider preferences and local load management constraints defined by the respective MG operator.

The later proposed aggregator is able to perform smart charging. With smart charging, charging stations are basically provided with predefined charging profiles. These profiles have to be followed by the battery management systems (BMS) of the vehicle. Smart charging has the advantage to enable charging stations and subsequently each connected EV to defer charging processes to a later point in time or directly control the drawn current according to a given profile. Smart charging for EV fleets is already addressed in previous research. For example, in the work of Hu et al. (Hu et al. 2014), optimization and control methods are summarized to present an overview of this field regarding smart charging as part of EV aggregators. The authors in (Valogianni et al. 2014) are presenting a management system leveraging the battery storage capabilities provided by EVs. An extensive review of smart charging approaches and architectures is presented in (García-Villalobos et al. 2014).

Especially the sprawl of distributed energy generation, energy storage systems, privately owned photovoltaic (PV) power plants, wind power generation, or combined heat and power-plants (CHP) presents a challenge for future charging aggregator systems, making support of smart charging necessary. The flexibility of EVs as controllable loads to mitigate uncoordinated charging impacts was investigated in (Han et al. 2010, Saker et al. 2011, Sundström and Binding 2012, Alonso et al. 2014, Valogianni et al. 2014). Extensive reviews regarding charge scheduling for EVs is given by (García-Villalobos et al. 2014, Mukherjee and Gupta, 2014).

Nonetheless, previous work considered only optimization methods isolated from productive systems and not integrated into working prototypes. VPP aggregators realizing smart charging as part of a smart grid have been presented (Chynoweth et al. 2014, Lutzenberger et al. 2014, Zuccaro et al. 2014). Additionally, various researchers developed multi agent systems to accomplish a VPP aggregator (Lutzenberger et al. 2014). Although the approach in (Mültin et al. 2012) is similar to our approach, we provide a hierarchical controlled VPP, monitoring and controlling multiple sites as a cloud-based solution. As proposed in (Hu et al. 2013, Mukherjee and Gupta 2014), we orchestrate a distributed service oriented architecture (SOA) as a cloud-based solution, enabling the aggregator to react in near real-time to the fleet operation. Hence, we develop a solution for fleet operators, with the goal to enable their fleet to participate in the smart grid, without being dependent on solutions provided by a utility company, as well as being flexible to scale.

# 3 SHARED E-FLEET SCENARIO

In the research project Shared E-Fleet (SEF) a cloud-based solution was investigated which enables a car fleet operator to manage and provide a fleet of BEV across several companies at one or multiple sites. Different works (see (Barth et al. 2000, Delucchi and Lipman, 2001, Lee et al. 2005)) suggested that increasing the utilization of EV fleets for example by increasing trips per day, decreases the TCOs and make them more economic than combustion engine vehicles regarding short range trips. Hence, the SEF IT solution provides a system including mandatory functionalities for car fleet management like booking, billing and operation, to be able to realize a corporate car sharing platform. Compared to other already available commercial solutions, the SEF solution was intended as an extensible, service-based cloud-platform to integrate various fleet management services in a highly configurable matter, making the operator independent of vendor specific solutions (Ostermann et al. 2014).

Unlike state of the art solutions, in the SEF use case, instead of booking a car, the user books a mobility demand by defining the start and end point and time of his business trip. Since SEF uses a station based car sharing approach, the start and endpoint of each mobility demand is always at a dedicated station of the SEF system. Certainly, the start and end station do not have to be the same. Until one hour before the respective beginning of a trip, a booking is not explicitly bound to one vehicle. Only after reaching this time, it is fixed to a dedicated vehicle. A one hour time frame was chosen to assure the user a safe operation of the system by this feedback and leave a margin in case of failure. In this way, the disposition optimization management service reschedules journeys in real time and reacts to unforeseen issues like delayed vehicle returns or unexpected state of charge (SOC) at the time of return (Koetter 2015). The latter one is especially crucial in EV fleets, since a properly predicted SOC influences all succeeding, already booked journeys on the same vehicle. Thus, already booked trips may be canceled in case of unforeseen issues. During the booking process, the disposition optimization assesses the current schedule whether the user request can be fulfilled even considering a suitable buffer in time and SOC, but large deviations of the expected SOC or return time can only be intercepted by standby vehicles.

Thus, the platform is constantly aware of the vehicle state. During each trip, the vehicles are monitored, predicting their estimated return time and their SOC based on real-time data from an on-board unit (OBU). Future states of the vehicles at the end of a journey can be estimated and used for future optimization procedures. On return of a vehicle, its user has to reconnect the vehicle to the charging station, enabling them to recharge for the upcoming trip.

As part of the SEF ecosystem, a service is required for managing the charging processes and energy demand of the vehicles according to grid constrains and operator specification as part of a smart grid. Considering that, an energy management system controls the charging of the EVs at the SEF charging sites. To perform these tasks, the following requirements have to be fulfilled:

**R1.** All EVs of the fleet must always be able to satisfy the needs of the mobility demand of the user. Hence, the EMS is responsible for sufficiently charged vehicles according to the journey schedules of the disposition management. The schedules for the vehicles must contain a predefined start and end time as well as a consumption forecast for each journey.

**R2.** Vehicle disposition schedules may change over time. Due to unforeseen influences, vehicles may return with different SOC or return late at the station. The EMS has to update the charging schedules continuously according to the current state of the system.

**R3.** In order to sufficiently fulfill R1 and R2, an algorithm is required which is capable to calculate an optimal charging schedule regarding the constrains of the system. Thus, optimal charging schedules have to be computed based on different charging strategies which are ought to be selected by the operator of the respective fleet ensuring R1 and R2.

**R4.** In order to perform tasks as part of a smart grid, the EMS is supposed to be able to monitor and control distributed and local energy resources. A model is required, describing the involved components and their properties to provide optimization algorithms with system constraint boundaries.

**R5.** Especially renewable energy resources are dependent on weather conditions. Thus, weather conditions have to be considered during charge scheduling. A forecasting system has to be integrated which provides information about the prospected energy production of individual components.

**R6.** As stated in R1, the state of the complete EMS is time dependent. The EMS has to be provided with information about the state of all relevant system components. The EMS has to store these states in order to enable the user to keep track of them at a later point in time.

**R7.** The EMS must integrate intelligent charging stations which are capable of directly controlling the output current. This way, pre-calculated charging profiles can be applied to the EV.

**R8.** Furthermore, various fleet operators with multiple fleet charging sites must be able to use and integrate their master data management with the EMS.

**R9.** The EMS must keep track of the current energy production and EV charging at the respective charging sites and always ensure safe operation of the energy system by staying in system boundaries.

**R10.** The system must also be able to fulfil non-functional requirements. Thus, it must be able to scale in order to provide services to multiple users. Robustness is required to provide services even in case of failure. Additionally, the EMS must perform well, even with a large amount of managed components.

# 4 AGGREGATOR SYSTEM ARCHITECTURE

In the following, we present the architecture of the EMS, showing how it is able to provide energy-management-as-a-service. The system architecture of the complete SEF ecosystem for a shared EV fleet is described in (Ostermann et al. 2014). The EMS is part of this ecosystem. Its system architecture is depicted in Figure 1. The EMS is acting as central node, integrating all mandatory components to fulfil all previously stated requirements. All components are integrated by connecting to their web services.
Through the integration of master data management (MDM) services, the EMS can obtain properties of all physical system components. Thus, by defining a mutual data exchange interface, various MDM systems can provide information about the deployed EVs, the energy production resources, the charging stations and about charging sites of the individual fleet operator.

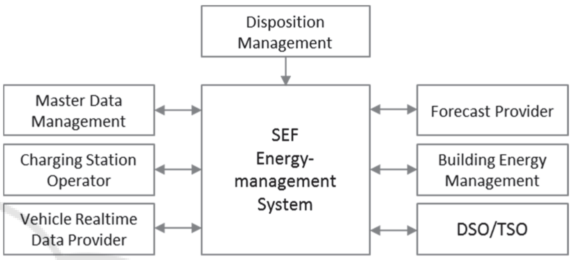


Figure 1: EMS system architecture.

An interface to a charging station operator (CSO) provides the EMS with means to monitor and control charging stations. CSO are business entities, owning, managing, maintaining, and operating an aggregation of charging stations. Note that EV fleet operators can also be CSOs themselves. In order to provide the EMS with real-time state data of the vehicles, a external database is interconnected to the EMS which stores telematics from vehicles. Telematic real-time data of the vehicles might be provided by OEMs in near future. However, today this data is provided by third-party developers using proprietary hardware which is amalgamated in separate provider specific databases.

A forecast provider service supplies the EMS with up-to-date and day-ahead energy production forecasts. Similarly, the energy grid operator, e.g. the transmission system operator (TSO) or distribution system operator (DSO), is connected with the EMS. Thus, the operator can either request the EMS to perform ancillary services on the grid or send price signals or dynamic day-ahead price curves. By integrating a building energy management system, information about locally generated energy (e.g. by a photovoltaic power plant) and the energy consumption of the building can be obtained.

The software architecture is depicted in Figure 2. The EMS is constructed as a multi-tenant platform.

In this way, collaboration between different customers (EV fleet operators) can be implemented instantaneously without the need to programmatically extend the platform or integrate multiple instances. Additionally, updates and maintenance of the platform is more flexible while ensuring contracted service-level agreements and quality of service without the need for extensive IT infrastructure at the customer site (Buyya et al. 2009).

Consequently, managing the tenants of the platform is a crucial part. A tenant manager is responsible for managing all data belonging to its respective customer avoiding and handling cross-access to other customer's data. All collected data of all tenants is stored in one shared database. Therefore, each fleet operator can configure the setting of its own controllable charging sites.

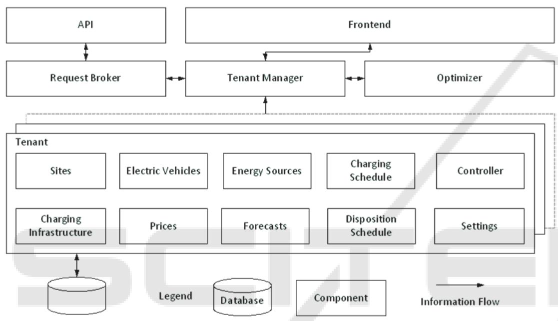


Figure 2: Software architecture of the EMS.

A frontend visualizes the system state for each customer and provides the means to control all integrated components. A screenshot of the actual frontend of the EMS prototype is depicted in figure 3 showing the real-time load at a charging site, the current energy production and an overview of the vehicle states.

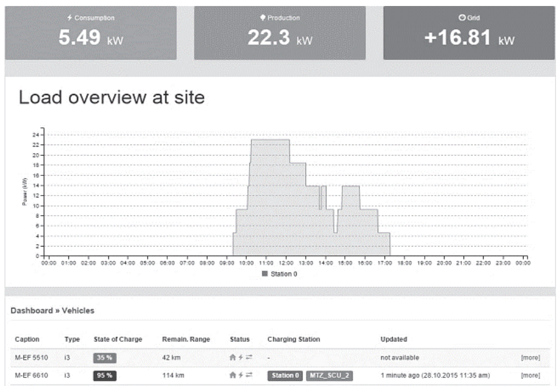


Figure 3: Frontend visualization showing the load and production parameters and the state of the cars for the customer.

As depicted in Figure 2, each tenant possesses a set of the master data of all components in their system. Furthermore, each tenant possesses a controller which has timed tasks that run multiple times a minute to read out the value of the pre-calculated charging profiles from the charging schedule and set the power-output set-point to the charging station while minimizing the error between production and consumption.

Here, the association between charging station and physically connected vehicle is important. The identification of the car which is connected to the charging station can be done in several ways. Each user is assigned a user-specific token. A token is an identification number which uniquely identifies each user in the system. In this way, the EV can be identified by looking up the vehicle which was used by the user who checked in to the charging station. During this procedure, the token can either be transmitted via a smartphone application or be read from a RFID-card in the charging station. Unfortunately, current EVs do not transmit any unique identification to the charging station. Hence, in the SEF project, we used a user identification which is transmitted to the charging station for authentication with the system via a smartphone application.

During charging, the controller continuously measures the power drawn from the connected EV and compares it to the pre-calculated profile. Any occurring deviation is reduced according to the individually selected strategy. This ensures that grid limitations and optimization goals are met.

During each charging session of the EV the smart meter values of the charging stations are sampled in a 15 minute interval. Using this data, the consumption module computes time dependent energy costs of each session. This enables the fleet operators to use dynamical energy plans of their DSO.

A charging schedule holds the charging profile for each EV in the system. It is calculated based on the EV disposition schedule. As soon as the disposition schedule is updated by any entity, the charging schedule is updated subsequently. For planning the charging schedule, it is assumed that a vehicle is connected to the charging station as soon as it returns from its trip. Connecting the vehicle is mandatory for each user. In case of a missing, but expected connection, the user is notified. As a consequence, the time between the end of a proceeding and the start of an upcoming trip is considered available for charging. Only if a user explicitly wishes to charge in the meantime, during

an ongoing booking, this request is taken into account in the charging optimization. The charging optimization is performed by the optimizer. Based on the selected charging strategy, the optimizer schedules and performs an optimization calculation which is described in detail in the next section.
Through this architecture a multi-tenant, flexible and scalable EMS aggregator is realized connecting multiple sites respectively integrating multiple self-sufficient micro grid into one control unit.

# 5 CHARGING PROFILE OPTIMIZATION

The central component of the EMS is the optimization module. Controlling the charging processes of a fleet of EVs requires the system to continuously update the charging schedule based on the current system state. Two distinctive events trigger the optimization of the charging plan. Since the EMS does not plan the disposition of the fleet, it has to react to changes of the disposition schedule. Hence, an event is sent by the disposition optimizer, notifying the EMS about the updated or changed disposition schedule. Even without disposition changes, the charging schedule is periodically updated in constant intervals by the EMS. Thus, it is always able to react to the actual state of the system. In this way, deviations of the expected SOC can be taken into account. A task manager triggers an optimization every 15 minutes if the schedule has not changed in the preceding 5 minutes. On this way, the optimization process has enough time to perform a complete iteration before the next start is triggered.

Especially for larger fleets, a fast optimization process is mandatory, since the amount of vehicles in the fleet have an impact on the computation time. This can be reached for example by reducing the complexity of the optimization problem to speed up computation time. Different authors already found out that linearization of the charging processes respectively the battery behavior of EVs is sufficient for coordinated smart charging. Nonlinear approximation of the charging behavior does not justify the increase in computation time (Sundstr. 2010; Hu et al., 2013). Because of that, we followed the recommendation and chose linear programs (LP) (Rardin, 1997) to perform optimized charging profiles for EV charging. Thus, we picked a LP to describe the constrains of the system at hand and solve the objective function considering a specifically selected charging strategy. For the algorithm we discretized the time into timeslot intervals of 15 minutes. Hence, a day of 24 hours has 96 individual timeslots. We designed the objective function of our LP in order to minimize cost.

Based on the selected strategy the cost vector can either be a time dependent energy price or the amount of $CO_2$ emission produced by a certain energy source when used for charging. Thus, an economic or ecologic charging strategy can be realized by adjusting the cost vector appropriately. This way, the optimizer is capable of calculating the optimal amount of power used at a designated timeslot under consideration of the time dependent cost of a specific energy source. Therefore, the objective function of our LP looks as follows:

$$\min \sum_{v=1;\, g=1;\, t=1}^{v=n_v; g=n_g; t=n_t} c_{v,g,t} \tag{1}$$

Here, $v$ describes the index for the vehicle and $n_v$ is the maximum number of vehicles available to optimize. Furthermore, $g$ describes the index of the energy source and $n_g$ the maximal number of energy sources available to use. Each timeslot is denoted by the index $t$, whith $n_t$ being the number of total timeslots and by that the total timespan to be optimized. Following, the parameter $c_{v,g,t}$ is defined as

$$c_{v,g,t} = c_{g,t} * p_{v,g,t} * 0.25, \tag{2}$$

where parameter $c_{v,g,t} \in \mathbb{R}$ from equation 2 being the cost of the energy charged into a EV *v*, using energy source $g$ at timeslot *t*. The parameter to be optimized by the solver will be the output power $p_{v,g,t} \in \mathbb{R}$. With the objective function given, the following constrains are limiting the solution space. First, the sum of the allocated power for charging all vehicles using an energy source at timeslot t being denoted as $p_{g,t}$ must be lower or equal to the forecasted amount of power for this respective timeslot $p_{f_{g,t}} \in \mathbb{R}$ :

$$p_{g,t} = \sum_{v=1,\dots,n_v} p_{v,g,t} \tag{3}$$

$$\sum p_{g,t} \le p_{f_{g,t}} \tag{4}$$

Vehicles can only be charged while connected to a charging station. Thus, by using a vector modelling the connection of the EV to the charging stations, the charged energy up to the trip $k$ subsequent to a charging session, can be defined to:

$$E_{v,T} = E_{v,0} + \sum_{t=1\ldots T} p_{v,t} * d_{v,t,k} - \sum_{k=1\ldots n_k} E_{k-1}, \tag{5}$$

$$E_{v,T} \geq E_k \tag{6}$$

$$E_{v,T} \leq E_{max,v} \tag{7}$$

where $E_{v,T}$ is the total amount of energy charged for EV $v$, $E_{max,v}$ the maximum amount energy which can be charged into the battery of EV $v$. Further, $d_{v,t,k}$ describes the parameter, denoting each timeslot $t$ in which the EV $v$ is connected to a charging station up to the beginning of trip $k$. The parameter $d_{v,t}$ describes the state of the connection with $d_{v,t} = 1$ as connected and $d_{v,t} = 0$ as not connected to the charging station. Equation 5 ensures that the sum of the energy charged up to the start of trip $k$ plus the initial SOC of the EV $E_{v,0}$ has to be at least the size of $E_k$, the amount of energy required for trip k. Equation 7 ensures on the other side, that the charged amount of energy does not exceed the battery capacity of the respective EV. In addition, assume $p_{v,t}$ being the sum of the energy charged at timeslot t:

$$p_{v,t} = \sum_{g=1,\ldots,n_g} p_{g,v,t} \tag{8}$$

At any time, the amount of energy $p_{v,t}$ drawn from the charging station should neither exceed its maximal power output capabilities nor the maximal input power of the respective EV $v$, letting the maximal power output be set to $p_{max,v,t}$.

$$p_{v,t} \leq p_{max,v,t} \tag{9}$$

Additionally, charging has always to be limited to the times the EV is physically connected to the charging station. From this follows:

$$p_{v,t} = p_{v,t} * d_{v,t} \tag{10}$$

If the vehicle is not connected the parameter $p_{v,t}$ at this timeslot has to be zero.

If these constrains can be satisfied, the optimizer calculates the best fitting charging profile for the vehicles. Note, that the problem space of the described LP scales linearly with the amount of regarded EV, energy sources and days. Computation time scales linearly with the size of the problem space. Both can be reduced by either simplifying the constrains to only focus on one single energy source making the sum of all forecasts the maximum available power or by reducing the amount of regarded timeslots by decreasing computation range or increasing slot duration.

In the Shared E-Fleet project, we focused on two strategies for charging plan generation. We differentiated between economic and ecologic charging. Based on price forecasts only time intervals will be considered for charging which are ultimately required for charging the car to a specific SOC necessary to perform a journey or which offer considerably lower prices in comparison to another time of day. With an ecologic strategy the algorithm is supposed to charge the EVs mainly at times of the day when renewable energy is generated. Subsequently of the computation, the set points for the maximum allowed output power is transformed in a charging profile and stored as a charging schedule. Based on the chosen strategy, different charge profile schedules may emerge from the calculations. After having stored the charging profile for each vehicle, it is possible to calculate an estimation for the SOC of each EV at a specific point in time based on current system state. Thus, it can be validated if the computed charging profiles are able to perform all booked trips sufficiently.

# 6 PROTOTYPE AND EVALUATION

Based on the proposed system architecture, we developed a multi-tenant web application using Java as a framework system. Hence, it was possible to evaluate the previously introduced architecture and algorithms as part of two model trials at two charging site locations. As parts of this system we integrated intelligent AC Level 2 charging stations at each location with a capable maximum power output of 22kW with our EMS. However, the here applied EVs, four BMW i3, which were selected due to overall project requirements, were only capable to draw a maximum power of 4.6 kW. The vehicles were equipped with specifically developed telematics units, sending data to a real-time data pool. This way, data is read out from the vehicles' CAN-Bus. The collected data included among others the SOC, position, and estimated range. Data was continuously sent to the data pool in five minute intervals via a GSM module. The charging stations were connected through a proprietary manufacturer specific interface. This enabled the EMS to set the maximum power output, as the acquired charging stations were only supporting Open Charging Point Protocol (OCPP) version 1.5 (Open Charge Alliance 2015). At the time of purchase, OCPP version 2.0 which supports power output set-point specification had neither been finalized nor been implemented in the hardware by any manufacturer.

Additionally, we monitored a PV power plant at one of the locations continuously as a reference for locally generated energy. Although it was not physically connected to the charging stations due to regulatory issues, the obtained data served as real time data to model the behavior of a real PV plant. In addition to the real time data of the PV plant, we connected a production forecast system called PVCast (Klein 2013). PVCast is a commercial service, which predicts the generated power of a given PV power plant, based on previously measured data and increases its accuracy by new measurements. Master data of charging stations, vehicles and charging sites is provided by services of the SEF system. As part of the SEF system, a dynamic disposition management reschedules the vehicles according to the vehicle SOC states. In the prototype, the disposition management is connected with the EMS and triggers it as soon as the schedule is changed. With every trigger, it transmits the complete disposition of the vehicles including the start and end time of each trip, the distance and the expected consumption.

With all services connected to the EMS, new charging schedules are created as soon as the disposition schedule changes. Unforeseen changes in the states of the vehicles are mitigated by periodically conducted optimizations taking into account the holistic system state. Through that, requirements R1 and R2 are fulfilled. Applying the previously presented LP different charging strategies are possible, fulfilling the requirement R3. Furthermore, the integration of a building energy management provides the EMS with data about the connected electric power system components. Therefore, R4 is fulfilled. Requirement R5 is fulfilled by introducing a forecast system providing the EMS with day-ahead energy production information. Through the integration of a database, storing the states of all integrated components and a frontend, history data is always accessible fulfilling R6. In the prototype, intelligent charging stations were integrated and direct load control was possible. By this, requirement R7 is fulfilled. The requirement R8 is fulfilled by using a tenant manager in the software architecture to support different MDM clients. Furthermore, the tenant manager enables the EMS to be dynamically scalable fulfilling R10. However, the model trails could not be used to fully evaluate all requirements. Due to real time operation and its prototypic state, the system was not running without interruption. Additional to that, not all EVs were available at the same time because of maintenance reasons. Because of that, a synthetic scenario was created, using a fleet of 30 EVs This scenario is similar to the situation at our institute campus, if all vehicles with ICE were replaced with BEV. Furthermore each of the EVs has its own charging station. In this way, the vehicle will always have the ability to charge . It is assumed that the EV as well the charging stations are homogenous. For the sake of the project context, the charging characteristic of a BMW i3 was used to model the charging behavior. That means that each vehicle has a battery capacity of 18.8 kWh which is useable for storing energy. The average power consumption of the vehicles is assumed to be 12.3 kW per 100 km distance. Making each car able to reach a total range of approx. 147 km. Each vehicle can charge a maximum power of up to 4.6 kW. That would require the transformer to handle a maximum concurrent peak power demand of 138 kW. To simulate coordinated charging, the maximum usable power is limited to 100 kW. Any additionally required power can be provided by a physically connected PV power plant at the charging site where the charging stations are setup. For the evaluation, the grid as well as the PV power plant serve as energy source, supplying the charging station and by this the connected EVs, to always provide energy when needed. To present the results of the optimization algorithm appropriately, three different disposition schedules are applied to the fleet. Each profile is applied to a third of the fleet. If EVs were charged concurrently in this condition, they would exceed the given local maximum power. The consumption of each trip is assumed to be linear according to the EV's average consumption per distance. The three profiles are listed in Table 1.

In this evaluation, optimizations regarding an ecologic and an economic strategy are conducted. Each result is compared with dumb charging. Dumb charging means that the vehicles are charged directly after plugging in the cable of the vehicles into the charging station. The charging session is then performed as long as the EV is connected and not

Table 1: Applied disposition schedule profile types.

| Profile Number | Start Time | End Time | Distance [km] | Consumption [kW] |
|---|---|---|---|---|
| 1 | 05:30:00 | 14:10:00 | 65 | 8,00 |
| | 17:30:00 | 18:30:00 | 85 | 10,46 |
| | 21:00:00 | 23:30:00 | 45 | 5,54 |
| 2 | 07:30:00 | 11:30:00 | 75 | 9,23 |
| | 14:45:00 | 16:00:00 | 30 | 3,69 |
| | 18:00:00 | 22:30:00 | 100 | 12,30 |
| 3 | 05:30:00 | 09:30:00 | 55 | 6,77 |
| | 15:00:00 | 18:30:00 | 30 | 3,69 |

fully charged. If not directly controlled by the charging station itself, concurrent charging of the vehicles would lead to stress on the transformer at the site which might even lead to an overload or fatal hardware failure. An production forecast is created using a forecast given by PVCast with an adjusted peak power of 40 kW. Additionally, an off-peak tariff is assumed. In the peak time, between 6 am and 8 pm, the energy costs 11 cent/kWh, whereas in the off-peak time at the rest of the day, energy costs 7 cent/kWh. The cost of using solar energy is set to be 9 cent/kWh for the whole regarded time period and hence being cheaper than the energy from the grid in the peak time period. Each optimization is performed considering a time span of 24 hours, resulting in a total time span of 96 timeslots. Each vehicle is supposed to be completely empty at the start of the day. As a solver, the solver of the free Apache Commons Library (The Apache Software Foundation 2016) was used. The result of the economic strategy is depicted in Figure 4.

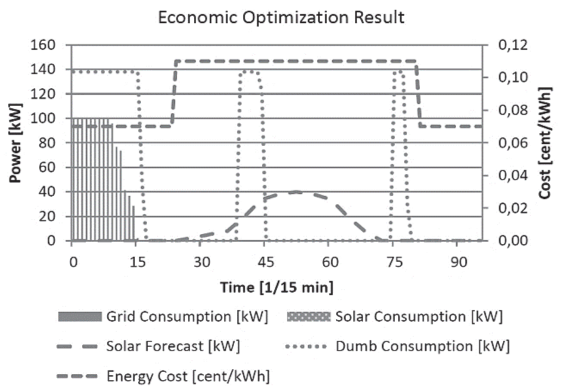


Figure 4: Comparison of optimization results of economic charging strategy and dumb charging.

Figure 4 compares dumb charging with economic charging. In the applied scenario, the concurrent charging is limited by the local load constrain to the maximum power limitation of 100 kW. Only as much energy is charged as is required to conduct the trips. All charging operation is only performed during the morning hours of the day, due to the low energy costs. With dumb charging, the fleet would be charged two additional times during the day. With a smart charging strategy, this is not necessary. Since in case of the economic and the ecologic strategy, only the trip demand is charged, 64% of the energy can be saved compared to dumb charging and thus being more energy efficient. Regarding the energy cost, in the economic scenario, 30% of the energy cost could be saved. In Figure 5, the results of optimization with the ecologic optimization strategy are depicted.

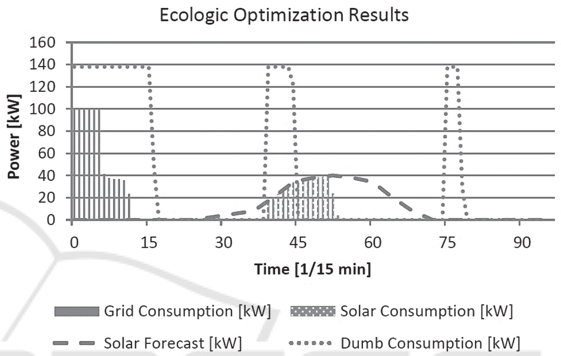


Figure 5: Comparison of optimization results of ecologic charging strategy and dumb charging.

In Figure 5, it can be observed, that charging in the morning is deferred and continued in the afternoon, when solar energy is available. Thus, $CO_2$ emission is mitigated by using renewable energy instead of energy from the grid. With the ecologic strategy, it's possible to save even 76% of $CO_2$ emission by not immediately start charging the EVs and by deferring the charging sessions into times of renewable energy production. This synthetic evaluation shows, that local grid constrains are not exceeded, and thus requirement R9 is always fulfilled. Furthermore, requirement R5 is satisfied by taking into account the production forecast of the PV power plant with the ecologic evaluation.

By fulfilling all requirements, a fully functional framework is created, serving as EMS and being able to perform smart charging as part of an intelligent energy management service.

# 7 CONCLUSION AND OUTLOOK

In this work, we introduced the architecture of a cloud-based EMS, serving as a scalable and flexible system to monitor and control the charging of a fleet of EVs. It enables fleet operators to integrate their energy components and a fleet of EV into an EMS, providing them with the means to systematically improve the usage of these components. For this, we included an optimizer to calculate charging profiles for an EV fleet, in order to exploit energy production forecasts and dynamic price tariffs. The evaluation showed that optimization of the charging profile delivered charging profiles which sufficiently served the mobility demands of the user, kept the boundaries of the energy system and minimize costs. By this, the here presented aggregator can accomplish primary objectives of energy management systems like increasing energy efficiency, reduction of the energy used for charging and maximization of profits by minimization of costs. (Barney et al. 2008)

In the future, we plan to extent this approach to completely control different micro grids in islanded mode operation resulting in a smart micro grid. By providing this framework for a cloud-based and flexible EMS, we plan to integrate more energy components, further investigating cloud-based hierarchical control. Thus, enabling the combination of free floating EV fleets with multiple micro grid controls to provide ancillary services and to maximize profits and simultaneously stabilizing the grid. As a consequence, we will conduct further research to decrease runtime of optimization processes in order to tackle a growing amount of optimization parameters. Especially interesting is the coordination of EMS optimization and disposition planning considering different charging sites and energy-aware routing of vehicles.

## ACKNOWLEDGEMENTS

This research has been supported by the IKT II program in the Shared E-Fleet project. They are funded by the German Federal Ministry of Economics and Technology under the grant number 01ME12105. The responsibility for this publication lies with the authors.

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