Seamless Electromobility

Markus Eider*
Diana Sellner, Andreas Berl
Deggendorf Institute of Technology
[markus.eider, andreas.berl, diana.
sellner]@th-deg.de

Robert Basmadjian, Hermann
de Meer
University of Passau
[robert.basmadjian, demeer]
@uni-passau.de

Sonja Klingert, Thomas
Schulze
University of Mannheim
[klingert, schulze]@informatik.
uni-mannheim.de

Florian Kutzner, Celina
Kacperski
University of Mannheim
[kutzner, kacperski]@uni-mannheim.
de

Michal Stolba
Czech Technical University in Prague
stolba@agents.fel.cvut.cz

ABSTRACT

The existing electromobility (EM) is still in its fledgling stage and multiple challenges have to be overcome to make Electric Vehicles (EVs) as convenient as combustion engine vehicles. Users and Electric Vehicle Fleet Operators (EFOs) want their EVs to be charged and ready for use at all times. This straightforward goal, however, is counteracted from various sides:

The range of the EV depends on the status and depletion of the EV battery which is influenced by EV use and charging characteristics. Also, most convenient charging from the user's point of view, might unfortunately lead to problems in the power grid. As in the case of a power peak in the evening when EV users return from work and simultaneously plug in their EVs for charging. Last but not least, the mass of EV batteries are an untapped potential to store electricity from intermittent renewable energy sources.

In this paper, we propose a novel approach to tackle this multi-layered problem from different perspectives. Using on-board EV data and grid prediction models, we build up an information model as a foundation for a back end service containing EFO and Charging Station Provider (CSP) logic as well as a central Advanced Drivers Assistant System (ADAS). These components connect to both battery management and user interfaces suggesting various routing and driving behaviour alternatives customized and incentivized for the current user profile optimizing above mentioned goals.

CCS CONCEPTS

•Applied computing →Transportation; •Hardware →Smart grid; Energy distribution; •Social and professional topics →User characteristics; •Software and its engineering →Software architectures;

*Corresponding author: Markus Eider

Permission to make digital or hard copies of part or all of this work for personal or classroom use is granted without fee provided that copies are not made or distributed for profit or commercial advantage and that copies bear this notice and the full citation on the first page. Copyrights for third-party components of this work must be honored. For all other uses, contact the owner/author(s).

e-Energy '17, Shatin, Hong Kong

© 2017 Copyright held by the owner/author(s). 978-1-4503-5036-5/17/05...\$15.00
DOI: <http://dx.doi.org/10.1145/3077839.3078461>

KEYWORDS

Electric Vehicles, Battery Health, Smart Charging, Grid Prediction Models, ADAS, Range Modelling, Routing, User Guidance, Incentives

ACM Reference format:

Markus Eider, Diana Sellner, Andreas Berl, Robert Basmadjian, Hermann de Meer, Sonja Klingert, Thomas Schulze, Florian Kutzner, Celina Kacperski, and Michal Stolba. 2017. Seamless Electromobility. In *Proceedings of e-Energy '17, Shatin, Hong Kong, May 16-19, 2017*, 6 pages.
DOI: <http://dx.doi.org/10.1145/3077839.3078461>

1 INTRODUCTION

In 2011 the European Commission outlined its transport strategy for 2050 which focuses on low-emission mobility and aims at eliminating combustion-engine vehicles in cities by 2050 [3]. Considering the intuitive use case of people driving to work with their cars and charging them in the evening at home this would add a huge pressure on the power grid: A study estimating the impact of only 0.5 million EVs on the German power demand came to the conclusion that with this typical charging model, the German grid infrastructure would face a power demand increase of 16 % [31]! Keeping this pressure at bay, but at the same time increasing the attractiveness of EV mobility in order to spare nature excessive CO₂ emissions from combustion-engine vehicles - these are conflicting goals that the EU H2020 project Electrific aims at fulfilling. Dealing with these issues leads to challenges on different levels of the e-mobility eco-system:

- Battery management must be improved in order to both increase the driving range and reduce the charging impact on the grid
- Charging behaviour needs to be steered in order to organize the charging process in a grid-friendly and renewable-integrative way
- Driving behaviour and routing needs to be incentivized in order to further contribute to above mentioned issues
- Vehicle fleet management must be steered towards an optimized fleet charging and routing contributing to the goals of EV grid integration and optimized renewable energy utilization
- Charging Stations (CSs) need to be managed in concertation with all the other stakeholders

This creates a complex decision problem, which can be solved in a distributed computing process. Additionally the challenge of how to motivate drivers and fleet managers to follow these goals needs to be tackled. In order to pursue these goals this paper is structured as follows: In section 2, the methodological basis of the current approach is presented. Section 3 contains a detailed description of the current state of EM and envisions the challenges that have to be faced in the next years. Next, we present and explain the Electrific solution solve the decision problem in section 4. Finally, section 5 concludes the paper offering an outlook towards future work.

2 RELATED WORK

In the following, we give a broad overview of existing solutions to align both technical infrastructure with the users and the stakeholder's interests.

For one, an EV fleet operator is facing the problem to charge a fleet with respect to the booking schedule. Therefore, a charging scheduler needs to take into account this schedule but also the grid situation. The charging of a fleet anticipates the acquisition of data prior to schedule creation. This can be each single EV state [19] in form of the current State of Charge (SoC) and the needed energy for the upcoming trip [14]. The needed energy can be forecasted for the fleet [33] in form of a day-ahead plan [19].

There are different aims, a charging schedule can be optimized for. Petit and Periz [26] list the options to charge at night to reduce the risk of grid instability, or losses in Quality of Service [6], and to charge predominantly, if the ratio of renewable energy is high [26]. In this regard, Kong et al. [6] propose to primarily allocate energy from locally available renewable energies, and after that, use power from the grid [6]. To optimize for EV availability, EVs with lower SoC are charged with higher priority [19]. Furthermore, an optimal green charging is reached, if the EV is only charged to necessary capacity [7]. Other charging aims take the energy price into account [7, 19, 33]. Depending on these aims, the overall cost and power peaks in the grid can be reduced [7, 33].

The State of Health (SoH) is the capability to store energy. As the SoH decreases the gap of unusable energy increases over time [12, 22]. It can also be seen as a ratio between the capacity of a aged battery and a new battery [22] or as power fade [10]. The calendaric ageing as well as the capacity fade depend on battery temperature and SoC, because both high and low temperatures and high SoC values lead to higher mechanical stress for the battery components [7]. After loosing 20% SoH, a battery isn't considered suitable for EVs anymore [12]. The overall lifetime of an EV battery is considered 8+ years [12].

To predict the SoH in the future, a model needs to be developed. You et al. propose a model with SoH error less than 2,18 % with an equivalent circuit model by impedance spectrography [8]. For modeling the SoH, Kalman Filters, machine learning [8, 12] and feature extraction [8], can be used. To estimate the SoH of a battery, partial charging and discharging cycles [8] as well as the recovery voltage [12] after a trip need to be considered.

Some metrics that Electrific seeks to improve, such as optimizing charging, might infringe on users' reported needs [4]. For example, we can optimize the use of renewables in EV charging, but EV users might have to be persuaded to change their schedules, or use their

entire battery capacity before charging, which infringes on their need for flexibility or for a comfortable extra range plays a role. So the Electrific ADAS can suggest useful optimizations, but these can only be beneficial if users adhere to them.

Maximizing energy efficiency has been the topic of some discussion in recent psychological literature, often with the main goal of stabilizing and adapting electricity infrastructure [32]. Often, users are not considered as the main source of impact on these goals, even though their behavior largely determines the grid impact. It is the place of behavioral science to design incentives that allow users to use technologies such as the Electrific ADAS in the most efficient manner.

Psychological theories suggest variables that can predict which incentives are most effective for a given user [27]. For example, users with strong pro-environmental values or those highly engaged with novel technologies [25] should profit most from informative appeals and corrections to their lay models of battery functioning and energy economy. In contrast, impulsive and experientially driven users could react more strongly to social or comparative feedback [15], possibly conveyed in a gamified fashion [11]. Finally, financially motivated users should be sensitive to dynamic pricing and monetary rewards [5].

The Charging Capacity Allocation (CCA) problem is related to existing problems such as dynamic pricing of air tickets [24] or congestion pricing [20]. The last example target congestion in traffic, which in CCA displays as possible congestion at the charging slots. Game-theory and auction-based techniques [1] are also applicable in theory, but hardly achievable in the current or near-future state of interactions between CS and drivers. The CCA problem is also related to several well known models in operations research and decision theory. The benefit of looking at the problem by optics of sequential decision theory is hypothesized to bring strong theory and efficient existing solutions for the problem. The most promising direction is transforming the problem into a Markov Decision Process (MDP) [2].

The literature on EV routing and charging is very rich, but typically takes into account only a small subset of the whole problem [9]. Closely related is the tour gas station problem [18] which considers a number of locations to be visited while refuelling, but does not consider any temporal constraints. The Day Activity Planning (DAP) problem can be formulated as a classical planning or scheduling problem [13] if we consider a fixed number of discretized time-points for each day. Moreover, the temporal facet of the problem needs to be considered if we want to optimize for time or take concurrent actions (e.g. charging and shopping at the same time) into account. Interestingly, a planning problem closely related to DAP with EV charging is the Mars exploration rover planning problem, where resource-constrained movements between various locations of interest with temporal constraints are planned [17].

3 CURRENT AND FUTURE SCENARIO

By the end of 2016 about 1.3 million EVs were in use worldwide [30]. Compared to combustion engine vehicles with a sales volume of 75 million new cars in 2016 [28], EVs are just on the verge of becoming a part of the worldwide mobility picture. As the ownership of EVs, in spite of attractive subsidies, does currently not play a huge

role, the EV sharing business model is becoming more and more widespread. Furthermore, private and public transportation companies, like the Transports Metropolitans de Barcelona, have been enhancing their fleet with EVs [34]. In the next decade the share of EVs and the number of CSs is predicted to grow exponentially [29].

One major obstacle for (potential) EV users is the so called "range-anxiety" [4], which describes the notion of a constantly imminent depletion of the battery and the fear of being stuck on the road with an immobile vehicle. Given only a scarce distribution of CSs and extremely long charging times reinforces this fear. But considering the fact that e.g. 80 % of the trips in France are less than 40 miles [26], this apprehension is in most cases mainly psychological. The lack of information how charging and driving behavior impacts the battery range, hinders the user and fleet managers to change their behavior accordingly. Additionally, today EVs are being charged whenever possible in an uncoordinated way thus endangering (local) grid stability. CSs, especially privately owned ones, are usually connected to the low voltage grid. The impact of a single CS on the grid is negligible; in future, however, if charging processes remain uncoordinated, the impact on power quality will be high.

Additionally, in order to decrease the environmental impact of EM, also battery friendly charging and the increase of the share of renewable energy while charging must be considered. As the battery is a major cost driver of an EV, with 38 % of the overall EV price predicted to be battery-dominated until 2020 [29], battery health is an important factor. Also the interest in using locally produced renewable energy for charging an EV is high. As shown by a study performed by [21] 35 % of the participants regard this aspect as highly important. However, a lack of information regarding the current availability of the intermittent renewable energy sources hinders an optimal usage for charging an EV.

The proposed solution by the EU project Electrific will result in a smart combination of two interactive user devices: an app on the user's own smart phone integrated with the on-board ADAS. The logic and the incentive structure in the backend will bridge the communication gaps between EV users, fleet operators, CSs, grid operators and battery management system in a concentrated way.

The user does not wish to be directly confronted with the problem of range, neither with challenges of integrating renewables or supporting the power grid. Therefore, using the suggested solution,

he will only experience a support in daily mobility planning activities and will be incited to change his plans earning some green point or a financial reward if he adapts his behaviour slightly, respecting his personal constraints (see figure 1).

The use case could lead to the following situation: as the user plans are being known in beforehand, the EV is charged only partially overnight. And instead of going to the supermarket first and the shopping centre second, where he had intended to do a fast charge, the system suggest him to go to the shopping centre first. Then to the supermarket where the sun is predicted to shine on the local solar cells so that he can charge environmentally friendly during shopping. This leaves ample time to pick up the kids at school punctually. The backend logic has computed that the grid thus is less stressed and the battery charges more battery-friendly. In order to make the user adhere to this plan, a clever combination of financial incentives and psychological enticement, customized to this very user and usage profile will tempt him accordingly.

4 OUR APPROACH FOR SEAMLESS VEHICLE AVAILABILITY

The main idea of the Electrific solution is to view the whole ecosystem as a multi-agent systems, where the participating actors (or agents) have conflicting goals. For example, the EV user wants to save time, money and possibly act eco-friendly, whereas the CS provider (CSP) wants to increase its profit. Obviously the two aims may be in contradiction. Moreover the CSP interacts with the grid and the EV user may interact with an EV rental company. Each of the agents solves its internal optimization problems which also more or less depend on interactions with other agents. The particular problems and aspects we are focusing on are described in more details in the following sections.

4.1 Charging Scheduling and Battery Health Monitoring

In this section, our perspective on fleet assistance services for the EFO is explained. These are used to monitor the fleet health state and to automatically optimize and follow a charging schedule.

For an automatically scheduled charging plan, which considers each single EV, various input parameters are needed. Firstly, the SoC and the fleet booking schedule need to be known. This shall enable the calculation of the needed energy for the upcoming trips of the EVs. By this way, the EVs needed earliest can be prioritized for charging. Secondly, the SoH classification of an EV battery is crucial for the decision on how to charge the EV while minimizing battery ageing. Our third aim is the stabilization of the grid. Since we intend to optimize charging schedules for night time application, a forecast of grid properties with a range covering the interims of EVs until their individual booking starts is required. Section 4.2 describes this prediction in more detail. This approach saves energy costs [26] on one hand. Considering parcel services on the other hand, night time charging could be highly convenient, because operation times are usually during the day.

These input parameters can be used to scale the schedule from one EV to the whole fleet, while increasing the longevity and availability of the EVs. Grid stability and the ratio of renewables should

Figure 1: A trip with and without Electrific

also be considered, here. Firstly, EVs shall be charged to an exact SoC which is sufficient to guarantee the driving range for a planned trip. If there is no trip planned for the next day, the EV should be charged fully. The second goal is the minimization of battery degradation. Therefore, different charging types and their impact on EV battery health shall be analysed. Also, the charging scheduler should suggest the EFO to reallocate EVs based on their usage to different home locations, e.g. swap rarely and frequently used EVs, to homogenize fleet degradation. To reach our third goal of environmentally friendliness and cost saving, EVs should be charged predominantly in time slots, when the energy price is low and the ratio of renewables in the energy is high. Since this is not always possible, the stability of the grid shall be prioritized.

The classification of a single EV's battery health also requires historical and momentarily data of both EV and its battery. We separate the data in influences and health criteria, leaving input and output parameters for the battery model. The influences can be further divided in two categories. Firstly, the charging model describes the case, when an EV is being charged. In this case, we request data from a CS, e.g. type of technology and power demand at a CS. Secondly, a discharge model is used when the EV is driven. Here, parameters like the discrete SoC curve of a trip could be used to determine the battery state. Likewise, health criteria can be used to determine the battery condition, roughly. These can be, amongst others, the SoH from the Battery Management System (BMS). To determine the correlations between data and results, we need to use practical trials to get performance data of the EVs. This data is analyzed and compared to the health criteria. Based on this evaluation, we aim to develop a more precise classification of battery health which is more universally applicable, than current commercial approaches.

4.2 Power Prediction and Grid-Friendly Charging Stations

In this section, we describe the ecosystem consisting of Distribution System Operator (DSO) on one hand, and CSP on the other. In order to enable such an ecosystem, there is a high need for bidirectional communication for the sake of exchanging relevant information using the Open Smart Charging Protocol (OSCP). Each party of the ecosystem has its own objectives which can sometimes be competing with each other. From the DSO perspective, the following two objectives are considered:

- Maximize the intake of renewable energy sources as much as possible
- Stabilize the grid and its power quality

Regarding the first objective, due to the high intermittency of renewable energy sources, power generation prediction models are necessary. The second objective can be achieved by quantifying the quality of the provided power. Such a power quality quantification is a complex process and in this paper we take the voltage fluctuations as the main Key Performance Indicator (KPI) due to its ease of measuring. From the perspective of CSP, its main objective is to maximize the net profit through the use of local renewable energy sources (e.g. solar panel directly installed at the CS). It is worthwhile to note that in this paper we consider controlling methods applied only to low voltage grids.

In order to take the most convenient decisions, CSP considers the combination of forecasted and real-time information. The former is related to the forecasts concerning the renewable energy generation (the so-called power planner) as well as the voltage fluctuations (the so-called voltage planner) sent by DSO and the latter is relevant to power quality indicator gathered on the spot through smart meters (local to CS or sent by DSO). The gathered forecasted information of power and voltage planners serve to generate the corresponding charging capacity predictions (see Table 1). Those predictions are then later used in order to create the corresponding price schemes which will be sent to ADAS for the multi-objective optimization process. Note that the details of such pricing schemes are out of the scope of this paper. ADAS upon the request of the EV driver, sends to CSP the reservation request. Once the charging process of an EV starts, the smart charger checks frequently the real-time values reported by the power quality indicator. In case of high voltage fluctuations, the smart charger switches to the next convenient charging rate for the purpose of stabilizing the grid and its power quality. Note that, in worse case scenarios (e.g. potential blackouts of the grid), this could sometimes lead to completely stopping all the ongoing charging processes.

Table 1: Charging capacity availability

Time Period	%RES	Max Cap	Charging Mode	Power Quality
11:30 – 13:30	59	30 kW	CHAdEMO	Excellent
15:30 – 17:30	45	28 kW	CHAdEMO	Medium
17:30 – 20:30	38	30 kW	CHAdEMO	Bad

4.3 User Guiding and Incentives

We aim to gain a better understanding of how EV users can best be guided towards behavior patterns that are sustainable for the user and the grid. These behavior patterns include grid-optimized and battery-friendly routing and charging, as well as energy and range beneficial driving styles. Adherence to the optimizations provided by the Electrific ADAS will thus increase cost-efficiency for drivers, fleet and grid operators. While psychology and behavioral economics offer a plethora of theoretical predictions on behavior change, mostly developed in laboratory studies, the current project offers unprecedented opportunities for empirical real-life tests in the context of EVs.

Within Electrific, we aim for a two-fold analysis. On one hand, we collect user-specific information using surveys. These will allow us to develop detailed usage profiles, as well as psychological user profiles. Cluster analyses on usage will probably reveal usage profiles to be characterized as a function of ownership-status (e.g. owned, car-sharing, rental, etc.), frequency of use, type of use (e.g. leisure, commercial, etc.) and the extent of other means of transportation used (e.g. public transport, bike, etc.). The online survey also includes psychological variables; we will assess, among others, environmental attitudes, need for speedy and exciting driving, confidence in using novel technologies and the types of motivators and barriers regarding electro-mobility including idealistic and practical aspects on both sides. User profiling based on these variables will be carried out on data of EV users as well as users of combustion

engine cars. This will allow for a systematic differentiation and will suggest marketing strategies for non-EV users. User profiles created in such a manner should help us qualify which incentive will be most effective for which user.

In the second step of the project, we will build on the usage and user profiles to tailor interventions that increase sustainable behavior patterns. We will conduct a series of experimental field trials (randomized controlled trials) involving control groups and interventions based on social norming [16], default setting [23] and gamification [11]. The effectiveness of these interventions will be analyzed as a function of usage and user profiles. To exemplify, we outline two initial RCTs.

(1) Social norms, i.e., informing someone that many others have performed a certain behavior, typically results in imitation. In one trial, we will use information about how many car-sharing users have activated the eco-drive mode to instigate energy and battery-health beneficial driving behavior. Users will be randomly allocated to cars that inform about the frequency of the eco-button being pressed (social norm condition) or to one of two control conditions: information about the eco-mode, or no information at all. We predict that low-frequency users with short drives, and environmentally motivated ones, will be the most susceptible to this information.

(2) Many metrics we are using do not bear a linear relationship with the quantities of interest. For example, measuring fuel-economy in miles per gallon (mpg), as typical in Anglo-Saxon countries, results in fuel savings being larger when going from a wasteful (e.g. 15 mpg) to an average car (e.g. 20 mpg) than going from an average (e.g. 20 mpg) to an efficient car (e.g. 25 mpg). Yet, users assume linear savings. The same is true for time savings when measuring "time-economy" in kilometers per hour (km/h) or miles per hour (mi/h). Speeding up from 80 to 100 km/h will save 1.5 minutes on 10 km, while speeding up from 100 to 120 km/h will only save 0.5 minutes. Yet again, users assume linear time savings. Because energy use also increases non-linearly with speed, approximately quadratic, reduction of speeding is essential for energy economy and range. A trial will test whether presenting time per kilometer on a tachometer next to the typical speedometer will reduce speeding (as compared to no information). This intervention should be more effective for those drivers with strong pro-environmental attitudes and those high in technological self-efficacy.

Further trials will deal with the use and adherence to ADAS suggestions. Incentives will include different versions of "green point systems", employed in a gamified manner, instigating social competition or as a loyalty program with monetary incentives. Trials will also involve the effectiveness of default routing options, set to either the greenest or the fastest routes, with users being able to change their decisions at all times.

4.4 Charging Capacity Allocation and Day Activity Planning

In order to provide open platform for seamless EM, the involved stakeholders have to be incentivized to provide their services. Such involvement can be hardly forced, therefore we propose to use open market-based principles and provide algorithms acting on

behalf of the stakeholders. An straightforward model is a multi-agent system with self-interested agents. In such model a charging provider wants to utilize the charging slots it controls as efficient as possible to maximize its profit, whereas, the EV users want to minimize their cost of charging and waiting times.

The main interactions between the CSO and EV user agents in our model are the request for prices sent from the EV user agent to the CSO and a reply containing prices for charging slots available in the future. The request contains information such as the considered time-window when the charging can happen, the required energy and the limits on the charging speed (e.g. if the user wants to save battery health and thus does not want to use fast charging). The reply then provides prices for available charging slots at particular times throughout the time-window.

Charging Capacity Allocation. The Charging Capacity Allocation (CCA) problem is a problem of how the charging provider should price the particular charging slots at a particular location and in particular time, provided that it knows the prediction for energy costs, assumes rational customers who can select a different charging provider if its price is lower, and want to maximize the overall profit. The model we propose builds on a finite and homogeneous set of discretized time intervals, for which the price has to be deduced. The charging provider receives booking requests in time from the users wanting to charge their EVs at a provider's charging slot at a particular location, in a particular time interval and with a minimal and maximal charging rate. From the perspective of the charging provider the incoming bookings are a random phenomena described by conditional probability on the currently provided prices of charging. For the model as proposed, a theoretical lower-bound can be found by maximization of the expected sum of profits for the charging slots. Such direct approach is, however, with a high chance practically intractable, therefore we will aim at tools applicable for the problem but with known tractable variants. MDP solvers can provide both off-line (as the direct approach) and on-line solving of the CCA problem iteratively, where the decision points in the MDP would correspond to the incoming bookings from the EV users. Such approach should provide a tractable solution of CCA with a prospect to extend the model towards realistic predictions, exogenous phenomenons and uncertainty.

Day Activity Planning with EV Charging. We formulate the Day Activity Planning (DAP) problem including the EV rental and EV charging as a temporal planning problem. Moreover, an important part of the problem is the routing itself, which needs to consider the charging and discharging model of the used EV and which also needs to be scalable enough to work for millions of nodes and edges in the real-world road network.

The input of the DAP problem is the road network, a description of personalized activities for the day (or a time-window) and a description of the available transport options. The road network also includes locations of CSs and locations of (personalized) points of interest, such as shops, work-place, home, etc. The points of interest can be arranged in a hierarchy from particular map locations to abstract notions (e.g. the supermarket on a particular address is a local branch of some brand which is a general store). Each activity is described by the point of interest type where it can be performed (e.g. a grocery store), a time-window when it can be performed

(e.g. from 4PM to 6PM) and the estimated duration (e.g. 1 hour). The transport options are obtained from the Electrific backend and may include an EV owned by the user or long-term hired, typically located at home and EVs offered by rental companies, such as EV cars and scooters, including information on EV type, SoC, etc.

As a result of the planning process, the user obtains the resulting plan which satisfies both the spatial and temporal constraints of the user's activities and the energy constraints of the used EV(s) and is optimizes the cost to the user, the shortest time, friendliness to the battery or use of renewable energy. The user receives the plan in the form of a recommended route, together with the scheduled activities and their locations and the charging slots booked for a particular time.

5 CONCLUSION

In this paper, the future of EM with the focus on EV availability and adaption with the EM infrastructure, is discussed.

We describe stakeholder's interests in EM, firstly. High vehicle availability and driving range are demanded by the users. EFOs want the fleet health to be extended, contradicting charging which is aimed on availability. Also, peak energy demand in combination with increasing EV numbers will impact grid stability, which is a challenge for CSPs and DSOs. With the stakeholder's goals not being reconcilable completely, a decision problem is identified. Based on this, we propose our methodology to optimize a solution with various aims. Here, users are guided by incentives for ecological and forward-looking driving. Unbooked EVs at the EFO location are charged automatically in a battery-friendly way while considering energy price and the ratio of renewables. These grid parameters are generated by prediction models and CSs are coupled to our proposed system. This way, grid stability is directly controlled.

Furthermore, we commence scientific work to develop the methodology and increase its accuracy. We strive to increase the performance of the ELECTRIFIC solution in such a way, that EV attractiveness will gain the same or a higher level than the comfort of combustion engine vehicles.

ACKNOWLEDGMENTS

This research was funded by the European Union Horizon 2020 research and innovation programme under the grant agreement N° 713864.

REFERENCES

- [1] P. Krysta et al. 2013. Mechanisms for Multi-unit Combinatorial Auctions with a Few Distinct Goods. In *Proceedings of the 2013 International Conference on Autonomous Agents and Multi-agent Systems (AAMAS '13)*. International Foundation for Autonomous Agents and Multiagent Systems, 691–698.
- [2] R. Bellman. 1957. *A Markovian decision process*. Technical Report. DTIC Document.
- [3] European Commission. 2011. Press release - Transport 2050: Commission outlines ambitious plan to increase mobility and reduce emissions. (Mar 2011).
- [4] O. Egbue and S. Long. 2012. Barriers to widespread adoption of electric vehicles: An analysis of consumer attitudes and perceptions. *Energy Policy* 48 (Sep 2012), 717–729.
- [5] A. Faruqi et al. 2009. Unlocking the €53 billion savings from smart meters in the EU: How increasing the adoption of dynamic tariffs could make or break the EU's smart grid investment. *Energy Policy* 38, 10 (Dec 2009), 6222–6231.
- [6] F. Kong et al. 2016. Smart Rate Control and Demand Balancing for Electric Vehicle Charging. In *2016 ACM/IEEE 7th International Conference on Cyber-Physical Systems (ICCCPS)*. 1–10.
- [7] F. Rücker et al. 2016. Development and Evaluation of a Battery Lifetime Extending Charging Algorithm for an Electric Vehicle Fleet. *Energy Procedia* 99 (Mar 2016), 285–291. 10th International Renewable Energy Storage Conference, (IRES).
- [8] G.-W. You et al. 2016. Real-time state-of-health estimation for electric vehicle batteries: A data-driven approach. *Applied Energy* 176 (2016), 92–103.
- [9] H.G. Chale-Gongora et al. 2014. Planning an itinerary for an electric vehicle. In *Energy Conference (ENERGYCON), 2014 IEEE International*. IEEE, 1385–1391.
- [10] J.R. Belt et al. 2003. A capacity and power fade study of Li-ion cells during life cycle testing. *Journal of Power Sources* 123, 2 (2003), 241–246.
- [11] J. Hamari et al. 2014. Does Gamification Work? – A Literature Review of Empirical Studies on Gamification. In *2014 47th Hawaii International Conference on System Sciences*. IEEE, 3025–3034.
- [12] L. Canals Casals et al. 2016. PHEV Battery Aging Study Using Voltage Recovery and Internal Resistance From Onboard Data. *IEEE Transactions on Vehicular Technology* 65, 6 (Jun 2016), 4209–4216.
- [13] M. Ghallab et al. 2004. *Automated Planning: theory and practice*. Elsevier, Burlington.
- [14] M. Mureddu et al. 2014. An agent based approach for the development of EV fleet Charging Strategies in Smart Cities. In *2014 IEEE International Electric Vehicle Conference (IEVC)*. IEEE, 1–8.
- [15] N.J. Goldstein et al. 2008. A Room with a Viewpoint: Using Social Norms to Motivate Environmental Conservation in Hotels. *Journal of Consumer Research* 35, 3 (Oct 2008), 472–482.
- [16] R.B. Cialdini et al. 1991. A Focus Theory of Normative Conduct: A Theoretical Refinement and Reevaluation of the Role of Norms in Human Behavior. In *Advances in Experimental Social Psychology*, M.P. Zanna (Ed.). Vol. 24. Academic Press, 201–234.
- [17] S. Chien et al. 2000. Aspen—automated planning and scheduling for space mission operations. In *The 12th International Conference on Space Operations*. 1–10.
- [18] S. Khuller et al. 2011. To Fill or Not to Fill: The Gas Station Problem. *ACM Trans. Algorithms* 7, 3, Article 36 (Jul 2011), 16 pages.
- [19] S. Vandaal et al. 2015. Reinforcement Learning of Heuristic EV Fleet Charging in a Day-Ahead Electricity Market. *IEEE Transactions on Smart Grid* 6, 4 (Jul 2015), 1795–1805.
- [20] S. Zou et al. 2016. An Efficient Game for Coordinating Electric Vehicle Charging. *IEEE Trans. Automat. Control* PP, 99 (2016), 1–1.
- [21] Institut für Verkehrsforschung, In Statista - The Statistics Portal. 2017. Relevanz verschiedener Motive bei der Anschaffung eines Elektroautos in Deutschland im Jahr 2014. (2017).
- [22] M. Gholizadeh and F. R. Salmasi. 2014. Estimation of State of Charge, Unknown Nonlinearities, and State of Health of a Lithium-Ion Battery Based on a Comprehensive Unobservable Model. *IEEE Transactions on Industrial Electronics* 61, 3 (Mar 2014), 1335–1344.
- [23] E.J. Johnson and D. Goldstein. 2003. Do Defaults Save Lives? *Science* 302, 5649 (2003), 1338–1339.
- [24] R.P. McAfee and V. Te Velde. 2006. Dynamic pricing in the airline industry. *forthcoming in Handbook on Economics and Information Systems*, Ed: TJ Hendershott, Elsevier (2006).
- [25] J.D. Oliver and D.E. Rosen. 2014. Applying the Environmental Propensity Framework: A Segmented Approach to Hybrid Electric Vehicle Marketing Strategies. *The Journal of Marketing Theory and Practice* 18, 4 (Dec 2014), 377–393.
- [26] M. Petit and Y. Perez. 2013. Coordination of EV fleet charging with distributed generation to reduce constraints on distribution networks. In *2013 World Electric Vehicle Symposium and Exhibition (EVS27)*. 1–9.
- [27] R.E. Petty and D.T. Wegener. 1998. Matching Versus Mismatching Attitude Functions: Implications for Scrutiny of Persuasive Messages. *Personality and Social Psychology Bulletin* 24, 3 (Mar 1998), 227–240.
- [28] Forbes, In Statista - The Statistics Portal. 2017. Global car sales by manufacturer in 2016. (2017).
- [29] Statista - The Statistics Portal. 2017. Statista Dossier about the global market for electric vehicles. (2017).
- [30] ZSW, In Statista - The Statistics Portal. 2017. Worldwide number of electric vehicles in use from 2012 to 2016. (2017).
- [31] W-P. Schill and C. Gerbaulet. 2015. Power system impacts of electric vehicles in Germany: Charging with coal or renewables? *Applied Energy* 156 (Oct 2015), 185–196.
- [32] N.D. Sintov and P.W. Schultz. 2015. Unlocking the potential of smart grid technologies with behavioral science. *Frontiers in Psychology* 6 (Apr 2015), 410.
- [33] O. Sundström and C. Binding. 2010. Planning electric-drive vehicle charging under constrained grid conditions. In *2010 International Conference on Power System Technology*. IEEE, 1–6.
- [34] Ekoenergetyka Smart Energy Systems. 2017. News from Ekoenergetyka. (2017).