

SIMULATION-BASED EVALUATION OF BATTERY SWITCHING STATIONS FOR ELECTRIC VEHICLES

Research in Progress

Dauer, David, FZI Forschungszentrum Informatik,
Haid-und-Neu-Str. 10-14, 76131 Karlsruhe, Germany, dauer@fzi.de

Flath, Christoph M., Julius-Maximilians-Universität Würzburg,
Josef-Stangl-Platz 2, 97070 Würzburg, Germany, christoph.flath@uni-wuerzburg.de

Abstract

To meet future mobility challenges, major original equipment manufacturers (OEM) are pushing forward various technical solutions. The electric drive is considered to be a particularly promising approach. Yet, the required battery technology brings new limitations: Besides long charging times and high costs, very limited range is seen as a major disadvantage. While most OEMs focus on charging the battery in the car, some pursue an approach that combines charging with battery swapping. This allows the driver to automatically get an empty battery replaced with a charged one in a switch station. Both the extensive infrastructure as well as the necessity of buying additional batteries result in additional cost for customers and switch station companies. With the help of a simulation model, this paper explores requirements for battery inventory as well as switching station utilization. We find that for a higher number of customers, the pooling effect of stochastic variables will greatly reduce the number of spare batteries per customer. Switching stations therefore provide a well-suited business case for station operators which enables efficient re-use of batteries and contributes to a greener mobility system. Additionally, customers could be incentivized to purchase cars with changeable batteries.

Keywords: Smart Grid, Electric Vehicles, Battery Swapping, Agent-based Simulation

1 Introduction

In today's society, individual mobility is a central part of people's basic needs, whether for commuting to work or to pursue leisure activities. Against the background of growing environmental pollution and the shortage of fossil fuels, sustainable solutions are increasingly required. In meeting these challenges, automotive companies are working on different solutions. In the long term, the electrical drive is a central solution concept. However, the associated battery technology implicates new challenges: Besides limited energy density, possibly shorter lifespan and long charging times, range limitations are a key disadvantage of this technology. Currently, electric vehicle (EV) driving range is limited to distances of approximately 120 km (24 kWh) for the Nissan Leaf and up to 330-430 km (60/85 kWh) for the Tesla Model S, respectively. While most OEMs focus on EV-internal charging solutions, companies such as Tesla or Mitsubishi pursue an additional combined approach of charging and battery swapping. This battery swap offers the driver the possibility to automatically exchange the battery in switch stations to instantaneously increase vehicle range.

The following paper provides an economic analysis of a battery swapping approach on the basis of an agent-based simulation model. The goal is to determine the number of required spare batteries in a commuter scenario based on empirical mobility data as well as to determine switch station utilization. We

consider three different types of EVs, one Nissan Leaf and two Tesla Model S, which are distinguished by their battery capacity as mentioned above. In the next section, we discuss EV charging scenarios and the battery swapping approach. Section 3 presents the assumptions for the simulation model and the simulation structure. We evaluate the required number of spare batteries and the infrastructure utilization level for different scenarios in Section 4. Section 5 summarizes the results and provides an outlook on possible extensions and open research questions.

2 Related Work

Various IS business models have been discussed for the purpose of marketing electric vehicles (Wagner, Brandt, and Neumann, 2013). Many manufacturers focus on the joint sale of battery and vehicle whereas others sell the vehicle without a battery, allowing the battery to be leased for a monthly fee that is either based on distance traveled or on length of the leasing period. In case of leasing a battery, it remains property of the seller, allowing new business models such as improving charging time by swapping batteries in a battery switching station. This process usually takes only a few minutes and is therefore similar to refueling conventional vehicles (Agassi, 2009). This offers substantial benefits and solves some major problems of EVs: First, the so-called range anxiety (Pearre et al., 2011) is greatly reduced. Range-anxiety refers to the fear of EVs breaking down with an empty battery away from the next charging station (Eberle and Helmolt, 2010). Secondly, EV batteries can be charged in a more ecological and system-conform manner within the charging station due to a smoother charging schedule (Birnbaum and Linssen, 2009; Wang and Yang, 2011). Furthermore, exchangeable batteries increase the reliability of EVs and avoid the risk of decreasing battery performance or even defects. This reduced risk of losing resale value is not to be underestimated from a customer perspective as EV batteries typically account for about one third of the total vehicle value (Agassi, 2009). So far, only few authors have analyzed the concept of battery switching in detail. Raviv (2012) focuses on optimal scheduling of charging in a switch station based on quality of service and cost. Yudai and Osamu (2009) use queuing theory to model the safety stock problem in battery switch stations. Worley and Klabjan (2011) use dynamic electricity rates to determine optimal charging schedules and to make battery purchase decisions accordingly. More recently, Mak, Rong, and Shen (2013) and Raviv (2012) develop optimization models to study the optimal scheduling of and infrastructure deployment for battery switch stations. Using repairable item inventory theory, Avci, Girotra, and Netessine (2014) assess EV adoption in and environmental impacts of battery switch stations.

Clearly, the system operator bears some of the battery defect risks and is expected to cope with this risk. The battery switching approach also results in additional cost and effort in construction and operation. Battery switch stations must always provide spare batteries in order to serve the swap requests. Given the high cost of batteries, the number of replacement batteries are a critical cost factor for the realization of such business models. For an EV with an expected range of 120 km, a battery capacity of 24 kWh is necessary. With a market price of 500 EUR/kWh, a typical battery system costs approximately 12,000 EUR. Furthermore, vehicle architectures need to be adopted for the use of standardized exchangeable batteries. In particular, batteries for EVs are involved in the temperature management, which means additional design complexity. Finally, switch stations require significant infrastructure investments that must ultimately be borne by the users. Investors aim to establish a widespread switching and charging infrastructure to greatly increase the range of EVs. However, due to limited data, only a limited assessment of the system costs is possible. The following sections examine specifically the need for replacement batteries and the resulting consequences for the station operator model.

Electric vehicles and related business models have received increasing attention in the fields of IS and energy informatics (Goebel et al., 2014; Watson, Boudreau, and Chen, 2010). Brandt, Wagner, and Neumann (2012) provide a research agenda to analyze IS-supported business models and highlight the importance of intermediaries such as aggregators to provide ancillary energy services. Furthermore,

Brandt, Feuerriegel, and Neumann (2013) investigate benefits of the specific case of Vehicle-to-Grid (V2G) technology for households. In both cases, also battery switching station operators could benefit from providing V2G services. More recently, Valogianni, Ketter, and Collins (2014) investigate the benefits of EVs in case of smart homes using intelligent agents for decision support.

3 Battery Swapping Simulation

We use a Python-based agent-based simulation approach to analyze the required number of batteries in a switching station. We focus on the relationship between the number of customers and the required number of spare batteries in case of a single battery switch station. Each time a customer visits this station, the empty battery is added to the charging pool of the switch station. The number of batteries in the charging pool indicates the minimum number of batteries that is needed to meet customer demand.

3.1 Model Variables

The basic structure of the simulation is a 5-day work week, which is divided into 480 time-slots of 15 minutes. We use mobility profiles from the German Mobility Panel (Zumkeller et al., 2010) to represent the driving behavior of commuters, which are a natural fit as EV customers. Focusing on commuter driving profiles that match the range of electric vehicles, we can use approximately 900 profiles. The mobility profiles provide weekly trip information in terms of kilometers driven at a 15-minute basis. Furthermore, we assume a random threshold between 0% and 50% of the minimum battery capacity for each customer. Reaching this threshold triggers a visit at the battery switching station for the customer. The random initialization of the threshold reflects the heterogeneity of customer preferences regarding the minimum EV range. Regarding customer behavior, we also assume that customers can only use the swap option and cannot recharge at home or at work. The focus on a single station is a worst case view on the required station power level but this is because utilization is highest since it is a best case for pooling effects.

Both the focus on a single station and the disregard of individual in-vehicle charging activity represent a conservative worst case scenario with regard to the use of the changing station. However, our analysis represents a best case scenario when considering pooling effects as we do not incorporate factors such as unequal redistribution within multiple charging stations or usage patterns in this case.

The battery in the simulation follows a linear charging and discharging behavior. Note that this is a simplified assumption, given that batteries usually exhibit non-linear charging behavior. In Section 4.2 we also consider a non-linear charging process. Furthermore, we assume battery capacities of 24, 60 and 85 kWh, equal to a range of 120-430 km. These capacities correspond to currently available EVs, namely the Nissan Leaf and the Tesla Model S. Naturally, battery capacities are vehicle specific and may vary considerably for other vehicles. Charging powers are varied between 3.6, 11 and 22 kW as specified by the IEC 62196 standard. With a slow charging rate of 3.6 kW, total recharging time for a battery is about 400 minutes. We assume consumption to be linear in driving distance (Hofmann, 2010). The initial battery is charged randomly between 50% and 100% of its capacity, again reflecting customer heterogeneity. In addition, the switching station is directly located en route, saving customers from covering any additional distances. Also, the time required for battery swapping is neglected. As such, we implicitly make the simplification that battery swapping procedures have no influence on driving profiles. Batteries are always swapped at the beginning of a time-slot when the remaining range of the EV is below the customer-specific threshold. Table 1 summarizes all model assumptions and simulation parameters.

3.2 Simulation Structure

The following listing describes the simulation structure for a single run $r_i \in [0, R)$.

Table 1: Model and Simulation Parameters

Parameter	Value	Description
R	50	Number of runs
T	480	Number of time-slots
C	{50, 100, ..., 450, 500}	Number of customers
Ψ	{24, 60, 85} kWh	Battery capacity
φ	{3.6, 11, 22} kW	Charging power
η	0.25 kWh/km	Power consumption

Algorithm 1 Simulation Structure

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1: procedure SIMULATIONRUN( $\Psi, \varphi$ )
2:   for all  $c \in C$  do
3:     create  $c$  customers with  $\sigma \leftarrow$  random driving profile, battery capacity  $\psi_0 \leftarrow \text{Rand}[0.5 \cdot \Psi, \Psi)$ 
       and swapping threshold  $\tau \leftarrow \text{Rand}[0.0, 0.5 \cdot \Psi)$ 
4:     for  $t \leftarrow 0, T$  do
5:       charge batteries in charging pool and move full batteries to full pool
6:       for all customers do
7:          $\omega \leftarrow \text{getConsumption}(\sigma(t), \eta)$ 
8:         if  $\psi_{t-1} - \omega > \tau$  then
9:            $\psi_t \leftarrow \psi_{t-1} - \omega$ 
10:        else
11:          battery  $\leftarrow$  fullest battery from pool which is at least half full
12:          if battery then
13:            swap batteries
14:          else
15:            buy new battery
16:          end if
17:           $\psi_t \leftarrow \Psi$ 
18:        end if
19:      end for
20:    end for
21:  end for
22: end procedure

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4 Evaluation

In the following the simulation results of the battery switch approach are presented. We analyze the underlying effects and try to characterize system costs and requirements. This allows us to derive recommendations for system design and operating strategies for a battery swap system operator.

4.1 Base Scenario

Due to high costs, batteries represent a major investment for battery switch systems. Therefore, the number of additional batteries kept in the change station should be chosen as small as possible to achieve the required service level. Given a single switch station, the number of batteries required for serving n customers is to be expected somewhere between $n + 1$ and $2n$: In the most optimistic case only one extra battery is provided for the whole population while in the most pessimistic case one extra battery is needed

for each customer in the system. One central lever in reducing the number of extra batteries is the pooling effect. The pooling effect has been studied for instance in order to optimize logistics systems and reduce costs by decreasing inventories through reduced safety stocks (Eynan and Fouque, 2003). Within battery switch systems this effect can also emerge due to non-homogenous driving behavior. Therefore, the demand for battery replacements is somewhat spread across the day. This creates an economic potential for the central charging pool. A switch station's battery pool is jointly used by all of its customers. It can thus be much smaller compared to an individual battery change scenario. The resulting number depends on the number of customers, customer behavior as well as the technical specifications such as battery size or charging speed.

Figure 1a shows the number of spare batteries in the system for varying population sizes (50 simulation runs each). The slope of the trend line is below one and provides an indication for system savings over the pessimistic one spare battery per customer case. This reduction effect is due to decreased forecast uncertainty (pooling of random variables) and driving profile complementarity (some drivers will return the battery just in time for another customer to retrieve it).

In addition to the total number of batteries the number of extra batteries per customer is of particular interest (Figure 1b). While for fifty customers between 1.2 and 1.25 batteries (main boxplot mass) are required per customer, this number reduces to 1.17 to 1.2 for 100 customers. This decreasing trend continues and converges to approximately 1.15-1.17 batteries per customer. Therefore, a significant pooling effect can be realized and battery switch systems require a much smaller number of spare batteries than suggested by the worst case scenario of one extra battery per customer.

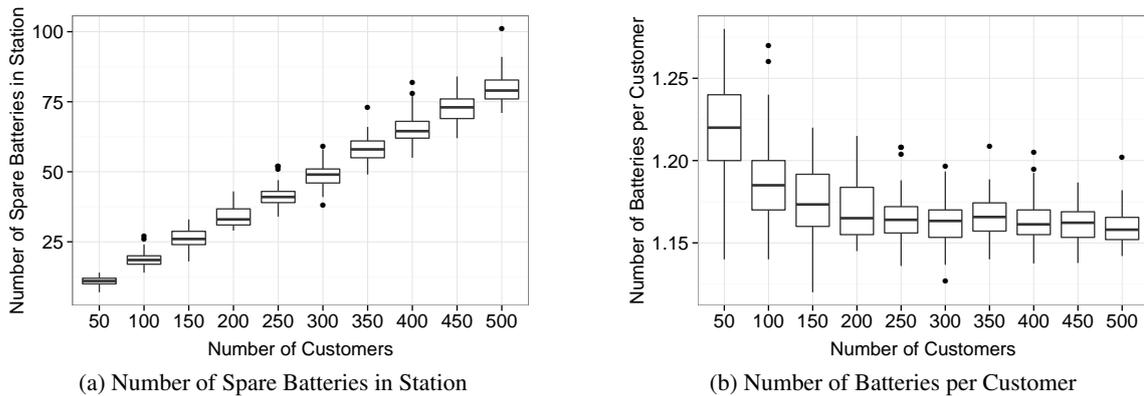


Figure 1: Base Scenario Evaluation

Note that the simplified scenario of a single switching station with a unique battery type inflates the pooling potentials as all batteries are located in the same location and can be used for any customer. However, the present analysis can also be applied to analyze a more fragmented scenario with multiple stations and battery types. In an optimistic balanced case every battery inventory and usage will be evenly distributed across types and locations. The results from Figure 1b can then be interpreted as follows: a customer population of 300 split across three stations will resemble three customer pools of size 100 with corresponding battery requirements. This analysis allows operators to better assess the trade-off between the customer/ vehicle benefits of fragmentation (more stations, customized batteries) versus the operational benefits of centralization.

4.2 Sensitivity Analysis

To validate the robustness of our findings from the baseline scenario, we complement the analysis with parameter variations and an alternative charging model.

Parameter Variations We consider eight additional parameter sets. For each scenario we vary the charging speed and or battery size. Figure 2 shows the results of the different scenarios. Clearly, battery requirements are decreasing in both parameters as either the battery turn-around is handled faster due to higher charging speed or batteries are switched less often due to larger size. Still, the pooling potentials are retained in the presence of larger batteries as well as faster charging capabilities. To be precise, the saturation level of customer pooling potentials is very similar for all treatments and typically between 100 and 150 customers. Such an analysis can also be analyzed to guide operators to identify appropriate technical specifications for their switching system. For example, if incremental battery size is less costly compared to additional battery requirements it may pay off to choose a larger battery capacity option.

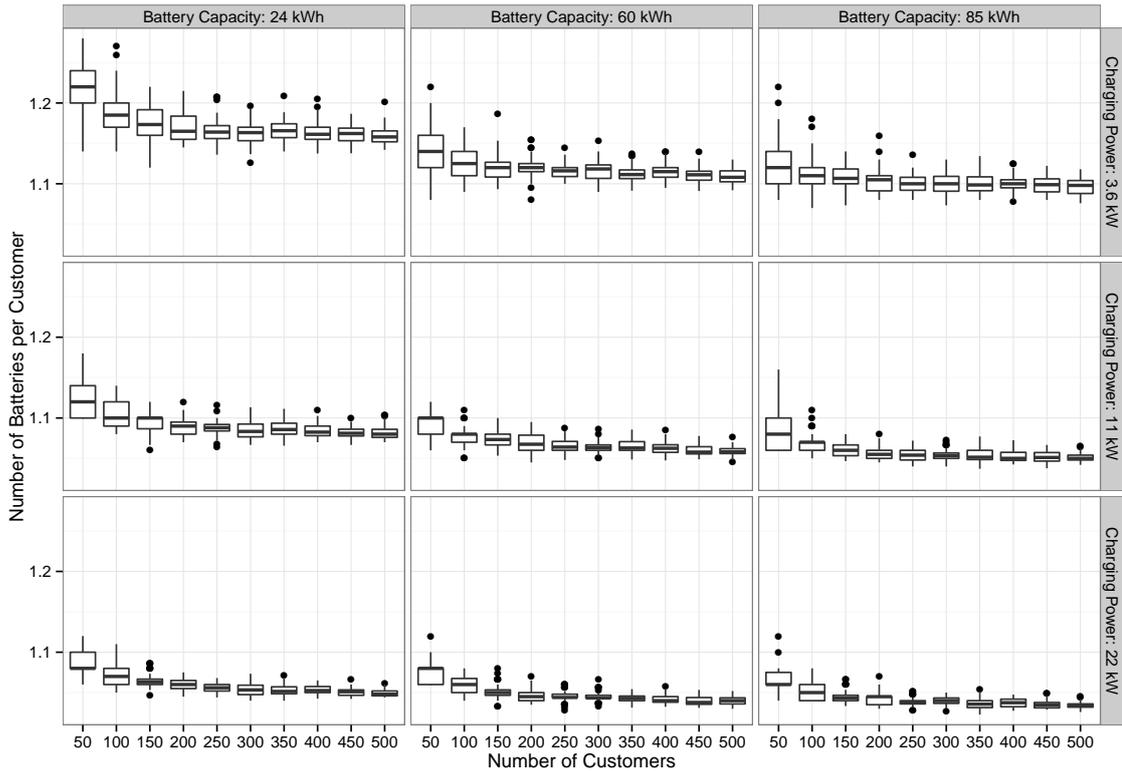


Figure 2: Sensitivity of Battery Requirements to Battery Capacity and Charging Power

Non-linear Charging Behavior As noted before, the linear charging assumptions is a simplification of real-world charging processes. We also applied a non-linear charging process to explore the effects of this simplification. We find the differences to be minimal (see Table 2). This warrants the application of the linear model which facilitates better integration into optimization and scheduling approaches.

Table 2: Sensitivity Analysis for Different Charging Behavior for 250 Customers

Parameter	Linear Charging			Non-Linear Charging		
	24 kWh	60 kWh	85 kWh	24 kWh	60 kWh	85 kWh
Battery Capacity						
Avg. Number of Spare Batteries	26	20	17	26	19	16
Avg. Number of Batteries/Customer	1.10	1.08	1.06	1.10	1.07	1.06
Avg. Station Utilization	0.44	0.47	0.46	0.44	0.47	0.47

4.3 Inventory Dynamics and Capacity Utilization

In addition to the required number of spare batteries, the infrastructure utilization level is of great importance for profitable operation of a battery swap station. We define the capacity utilization of the charging station as the ratio of the average number batteries in the charging pool and the maximum number of batteries in the charging pool. Infrastructure utilization is by no means constant over time: In peak times (morning and evening) the charging pool will be very full, while at night only few batteries are in the charging pool. Figure 3 illustrates the dynamics of the charging pool inventory over five working days. This utilization pattern is clearly driven by the commuter mobility behavior. Looking at the usage behavior for a varying number of customers, this shows, especially for large numbers of users that use the strongly driven by the mobility patterns.

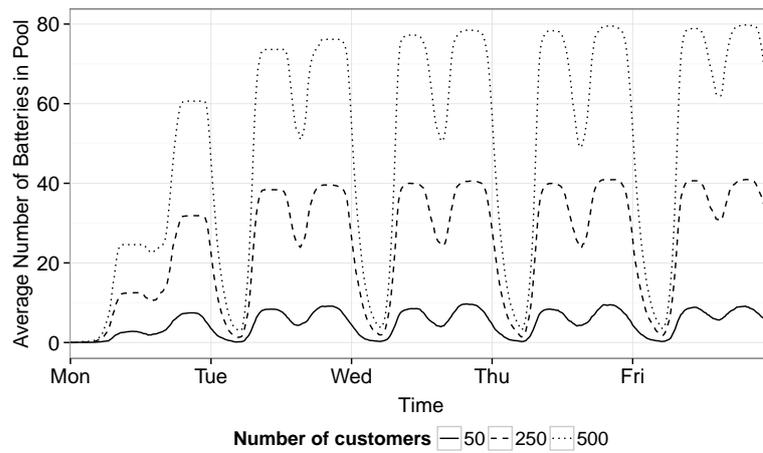


Figure 3: Average Battery Pool Size over Time

Just like the number of batteries required, station utilization benefits from a greater number of customers: For 500 users a utilization level of over 60% is achieved (see Figure 4). The greatest efficiency gains arise in the area between 50 and 100 customers. This means a charging station will need to attain a critical mass of 100 customers to operate in a sufficiently efficient manner. Based on the usage analysis, operators can identify strategies and measures to optimize their system efficiency. Especially policies that induce battery-changes during off-peak times are of special importance.

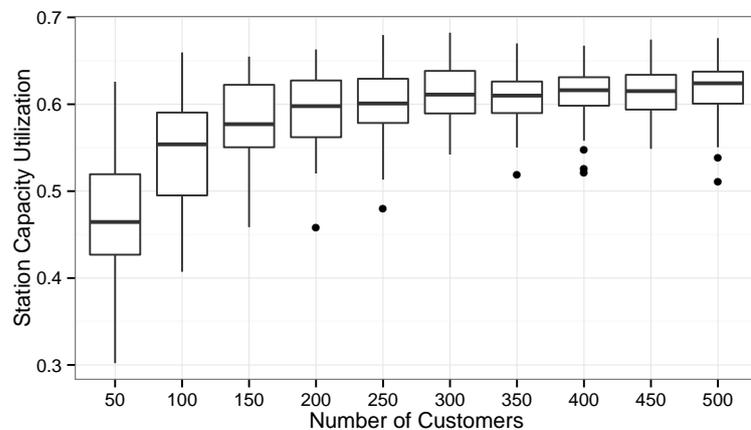


Figure 4: Station Utilization Level

5 Conclusion and Outlook

Battery switch stations can leverage a strong pooling effect with respect to the required number of batteries. Given a sufficient number of customers, station operators can greatly reduce the necessary amount of over-provisioning. This pooling effect is robust to changes of the scenario specifications. Furthermore, system efficiency also increases in the number of customers.

The switch station's highly periodic usage pattern points towards future research questions concerning "demand shaping". It would be interesting to analyze how different incentive structures, e.g., time-varying switching costs, can improve the system efficiency. Schneider et al. (2011) report that approximately 70% of customers would react to higher prices at peak times by shifting their swap requests. Revenue management models as described by Flath, Gottwalt, and Ilg (2012) can help assessing and leveraging customer incentivization approaches. Another interesting opportunity would be to move from a single station scenario to a setting with multiple, spatially dispersed charging stations (Robinson, 1990). Similarly, operators may want to elicit customers' temporal flexibility and subsequently optimize their operations accordingly (Fridgen, Mette, and Thimmel, 2014). Additionally, we will explicitly incorporate organizational aspects of switching station networks where tactical measures like battery transshipment or rerouting of interested drivers may turn out as promising levers.

In the context of power system management, the presented model can be enriched by integration of additional aspects. The provision of ancillary services to the grid presents another application for battery switching stations. With the paradigm shift towards decentral and intermittent power generation from renewable sources electrical storage plays a major role in achieving grid stability. A prominent idea is the usage of electric vehicles and their storage capacity in vehicle-to-grid concepts (Kempton and Kubo, 2000). A battery switch station can provide pooled access to multiple batteries and thus offer a more reliable control potential compared to the individual vehicle approach described by Dallinger, Krampe, and Wietschel (2011). This may provide additional revenue opportunities for charging station operators (Lombardi, Heuer, and Styczynski, 2010; Takagi et al., 2010). In this case, charging operations would be aligned with electricity market prices to minimize energy procurement costs or to facilitate arbitrage profits when feeding back energy to the grid (Schuller et al., 2014).

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