

GPS Data-Based Plug-in Hybrid Electric Vehicle Simulation

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Jürgen Wenig

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1. Gutachter: Prof. Dr. Thorsten Staake

2. Gutachter: Prof. Dr. Sven Overhage

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Preliminary remark

This thesis is a documentation of the result of the author's research activities at the chair of Information Systems and Energy Efficient Systems of the University of Bamberg and the Bits to Energy Lab. In this context, the broader field of data-based electric mobility scenario assessment is addressed. The ground-work for this thesis has been laid in (Wenig, 2014a) and elaborated in (Wenig, 2014b) and in (Wenig, Sodenkamp, and Staake, 2015).

Subsequently, major parts of this thesis have been developed within a research group, which led to the coauthored documents (Sodenkamp, Wenig, Thiesse, et al., 2019) and (Wenig, Sodenkamp, and Staake, 2019). They form crucial parts of the author's doctoral project and have thus been used and adapted within this thesis.

In consultation with my thesis advisor, for text from the manuscripts and (working) papers, direct quotes are not put in quotation marks. Instead these fragments (which include figures and tables) are referenced by endnotes.

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List of abbreviations

BMW	B ayerische M otoren W erke
CAMS	C opernicus A tmosphere M onitoring S ervice
CL	C ommuter (long)
CR	C ompany representative
CS	C ommuter (short)
DBSCAN	D ensity B ased S patial C lustering of A pplications with N oise
DL	D elivery (long)
DS	D elivery (short)
ECE-15	Urban driving cycle of the United Nations E conomic C ommission for E urope
EMPA T130	Driving cycle with 130 km/h average trip speed of the Swiss Federal Laboratories for Material Science and Technology (E idgenössische M aterial p rüfungs- und F orschungsanstalt)
EUDC	E xtra U rban D riving C ycle
FLD	F requent local d river
fpc	F lexible p rocedures for c lustering
GHI	G lobal H orizontal I rradiation
GPS	G lobal P ositioning S ystem
GSM	G lobal S ystem for M obile C ommunications
LDDV	L ong- d istance d elivery v ehicle
LDOD	L ong- d istance o ccasional d river
PHEV	P lug-in H ybrid E lectric V ehicle
SC	S tady c ommuter
SDDV	S hort- d istance d elivery v ehicle
SP	S ervice p rovider
TSV	T echnical s ervice v ehicle
UC	U nsteady c ommuter
UTC	C oordinated u niversal t ime

List of symbols

a	Acceleration
A_{car}	Frontal area of a car
A_{PV}	Surface area of photovoltaic cells
B	Battery capacity
C_d	Air drag coefficient
d	Parking duration
δ_{car}	Energy efficiency of a car
δ_{PV}	Energy efficiency of a photovoltaic system
E	Energy consumption of a car
e	Energy consumption of a car within pairs of consecutive measurement points
F	Tractive effort
F_{ad}	Aerodynamic drag
F_{la}	Linear acceleration force
F_{rr}	Rolling resistance force
g	Gravitational acceleration
G_{PV}	Energy generated by a photovoltaic system
j	Measurement point
k	Trip
l	Trip length
m	Mass of a vehicle
μ_{rr}	Rolling resistance coefficient
o	Energy fed at a charging facility
P	Charging power
P_S	Charging power when a load shifting strategy is applied
ρ	Air density
soc	State of charge
v	Vehicle speed
X	Charging location

Summary

The automotive sector, while being an example of a highly innovative industry driven by strong competitive pressure and constant technological progress, has never had to deal with truly disruptive changes regarding its products, processes, or value network structure. In this regard, the rise of electric mobility constitutes an unprecedented market change as it implies an extensive redefinition of the product architecture of cars, not only involving new technologies but also new market entrants from highly innovative industries, the anticipation of new business models, and a dependency on the electrical grid as an additional, essential infrastructure component.

In this context, decisions regarding both the capacity of batteries and the charging network play a major role as they determine the electric range of the vehicles as well as overall system costs. At the same time, the transition from combustion-based transportation to electric transportation has a considerable impact on the power grid that also depends on the trade-off between battery capacities and the density and power ratings of chargers.

In order to assess such important aspects as electric reachability, grid impact, and battery versus infrastructure trade-offs, the mobility behavior of individuals plays an essential role. Literature suggests that GPS driving data analysis constitutes a means of choice to assess the impact of battery capacities and charging opportunities on electric range and on power grid demand. Still, a great share of publications does either use synthetic mobility profiles (“driving cycles”) or self-reported data and thus does not utilize the wealth of information that is available in actual movement data. Moreover, literature research indicates that prior work that considers the entirety of car drivers as a coherent whole without describing different types of drivers in greater detail, rarely takes high electric range and variations in the availability of both private and public charging infrastructure facilities into account. Thus, such studies focus on average effects, which reduces the precision and utility of their assessments.

In this work, the high granularity of real-world GPS time series from 1,000 conventional vehicles is utilized to reflect the natural mobility behavior of drivers and to compare meaningful driver segments. Potential charging locations are automatically identified, and the electric energy consumption and charging behavior of plug-in hybrid electric vehicles is closely approximated. This enables the identification of appropriate vehicle and infrastructure parameters for electric mobility target groups and the assessment of their impact in terms of the electrification of mileage and energy demand. The consideration of household level solar systems and of a load shifting method as parts of a possible future charging infrastructure complements the work.

Results suggest that large but realistic battery capacities have the potential to dissipate concerns about the need for an all-encompassing charging infrastructure. Dense charge points are only needed for vehicles with short electric range or for small groups of fast long-range drivers. Both solar charging and load shifting considerably help alleviate stress on the power grid.

Decision makers may use the results and the methodology underlying this work to identify vehicle and infrastructure requirements of distinct segments and to estimate the grid impact of vehicle charging. Consequently, insights about benefits and obstacles of electric mobility adoption may facilitate better decisions in both vehicle development and infrastructure planning.

Zusammenfassung

Die Automobilindustrie ist traditionell durch starken Wettbewerb, technologischen Fortschritt und Innovationen geprägt. Jedoch waren ihre Produkte, Prozesse und Wertschöpfungsnetzwerke nie zuvor von einem disruptiven Wandel betroffen. In dieser Hinsicht stellt die zunehmende Verbreitung von Elektrofahrzeugen eine beispiellose Marktveränderung dar. Durch die Elektromobilität wird die Produktarchitektur von Fahrzeugen neugestaltet. Dieser Wandel geht über technische Fahrzeugeigenschaften hinaus, lässt neue Marktakteure auftreten und neue Geschäftsmodelle entstehen. Die elektrische Reichweite solcher Fahrzeuge wird durch die eingesetzten Batteriekapazitäten und durch die Gestaltung der Ladeinfrastruktur bestimmt. Zugleich führt die Umstellung von Verbrennungsmotoren zu Elektroantrieben zu einem erheblichen zusätzlichen Strombedarf.

Um jedoch zuverlässig beantworten zu können, welche Streckenanteile elektrisch fahrbar sind, welche zusätzliche Netzbelastung durch das Laden von Elektrofahrzeugen erwartet werden muss und inwiefern Batteriekapazitäten und Ladeinfrastrukturanforderungen voneinander abhängen, muss insbesondere auch das individuelle Mobilitätsverhalten berücksichtigt werden. Die Sichtung der Forschungsliteratur zeigt, dass insbesondere GPS-basierte Fahrdaten gut dazu geeignet sind, den Einfluss von Batteriekapazitäten und Lademöglichkeiten auf die elektrische Reichweite und auf den Strombedarf zu bewerten. Dennoch verwenden zahlreiche Studien entweder synthetische Geschwindigkeitsprofile („Fahrzyklen“) oder Umfragedaten und verzichten somit auf den Informationsreichtum detaillierter und realitätsnaher Bewegungsdaten. Ebenfalls lässt die Literaturrecherche erkennen, dass vorhergehende Forschungsarbeiten, die das Fahrverhalten der untersuchten Gesamtfahrzeugflotte beschreiben, ohne dabei jedoch auf die Verschiedenartigkeit einzelner Fahrergruppen detailliert einzugehen, nur selten die wechselseitige Abhängigkeit zwischen elektrischer Reichweite und unterschiedlich ausgebauten privaten und öffentlichen Ladeinfrastrukturen untersuchen. Bisherige Studien vermitteln also insbesondere zusammenfassenden Informationen mit in der Folge begrenzter Genauigkeit und Aussagekraft.

In der vorliegenden Arbeit werden hochgranulare GPS Zeitreihendaten von 1,000 konventionellen Autos verwendet, um deren wirklichkeitsnahes Bewegungsverhalten zu untersuchen und um verschiedenartige Fahrersegmente vergleichen zu können. Mögliche private und öffentliche Ladestandorte werden identifiziert und sowohl das Ladeverhalten als auch der Energieverbrauch von Plug-in-Hybridfahrzeugen werden geschätzt. Die Miteinbeziehung von Photovoltaikanlagen und einer Lastverschiebungsstrategie als Bestandteile einer Heimpladeeinrichtung rundet die Arbeit ab.

Die Ergebnisse zeigen, dass mit großen – aber dennoch realistischen – Batteriekapazitäten die Notwendigkeit einer flächendeckenden Ladeinfrastruktur deutlich verringert wird. Umfassende Ladeinfrastrukturmaßnahmen sind lediglich bei Fahrzeugen mit geringer elektrischer Reichweite oder bei einzelnen Fahrergruppen mit häufigen Langstreckenfahrten bei hoher Geschwindigkeit erforderlich. Sowohl Solarlademöglichkeiten als auch eine Lastverschiebestrategie können dabei helfen, die zusätzliche Netzbelastung durch Elektromobilität besser zu beherrschen. Die Ergebnisse und die der Arbeit zugrundeliegende Methodik ermöglichen es, gruppenspezifische Fahrzeug- und Infrastrukturanforderungen zu ermitteln und den zusätzliche Strombedarf durch Elektromobilität abzuschätzen. Dies erlaubt ein besseres Verständnis für die Vor- und Nachteile von Elektroautos und somit eine Entscheidungshilfe bei der Fahrzeugentwicklung und bei der Infrastrukturplanung.

1 Introduction

1.1 Background

A considerable share of energy demand can be attributed to the transportation sector. In the European Union, transport accounted for about one third of final energy consumption in 2015 (Eurostat, 2018). Similarly, in the United States of America, about 29% of energy was used for transportation in 2017 (U.S. Energy Information Administration, 2018). At the same time, mobility heavily depends on limited and non-renewable fossil energy sources (Eurostat, 2018; U.S. Energy Information Administration, 2018).

From a public health perspective, concerns are raised in relation to the local pollution caused by car exhaust emission (Zhang and Batterman, 2013) and also the global environmental consequences of vehicle exhaust are widely discussed (International Energy Agency, 2018; Schwanen, Banister, and Anable, 2011). Together with the growth of renewable energy generation, electric mobility could help mitigating these negative side effects of transportation (International Energy Agency, 2018).

Policy ambitions such as the “EV30@30” campaign, which was launched in 2017 at the Clean Energy Ministerial, indicate the intention of industrial nations to deal with electric mobility (International Energy Agency, 2018). In this campaign, member countries of the Electric Vehicles Initiative (including major economies from Europe, America, Asia, and New Zealand) collectively aim at an electric vehicle market share of 30% (including battery electric and plug-in hybrid electric passenger cars, buses, and trucks, but excluding two- and three-wheeled vehicles) by the year 2030 (International Energy Agency, 2018).

Table 1: Electric vehicle market share (here: percentage of new light-duty passenger car registrations), including both plug-in hybrid and battery electric vehicles from 2011 to 2017 for selected countries (International Energy Agency, 2018)

Year	Norway	Germany	China	United States	Japan
2011	1.3%	0.1%	0.0%	0.2%	0.3%
2012	3.3%	0.1%	0.1%	0.4%	0.5%
2013	6.0%	0.2%	0.1%	0.7%	0.6%
2014	13.7%	0.4%	0.4%	0.8%	0.7%
2015	22.4%	0.7%	1.0%	0.7%	0.6%
2016	29.0%	0.7%	1.4%	1.0%	0.5%
2017	39.2%	1.6%	2.2%	1.2%	1.0%

Currently, the electric vehicle market share varies greatly between different countries. In Table 1 the market trend over the course of time is summarized for selected countries. Respective figures for Norway are particularly prominent. Here, in 2017 the market share was about 39.2%, surpassing all other countries (International Energy Agency, 2018).

However, the overall examination of major economies also shows that – except for Norway – the electric vehicle market share was far below the aspired goal of 30% which indicates great potential for growth (International Energy Agency, 2018). For example the market share figure for Germany was only about 1.6% in 2017 (International Energy Agency, 2018).

Still, in absolute terms, 1.1 million electric vehicles were sold globally in 2017, including both PHEVs and battery electric vehicles (International Energy Agency, 2018). In the same year, the global electric car stock exceeded 3.1 million vehicles after having exceeded the one million mark in 2015 and having reached about two million in 2016 (International Energy Agency, 2018).

The growing interest in electric driving leads to the expectation of intensified competition in the automotive industry sector (Diehlmann and Häcker, 2013). In consequence, both Plug-in Hybrid Electric Vehicles (PHEVs) that can serve as a transition technology and battery electric vehicles have become essential parts of major automobile manufacturers' portfolios (Accenture, 2014; International Energy Agency, 2018).

Thus, the high overall energy demand of the transport sector (Eurostat, 2018; U.S. Energy Information Administration, 2018), transport-related environmental and health concerns (Schwanen, Banister, and Anable, 2011; Zhang and Batterman, 2013), ambitious goals aiming at a large-scale electrification of vehicles (International Energy Agency, 2018), rising electric vehicle sales figures (International Energy Agency, 2018), and the changes in the manufacturers' portfolios (Accenture, 2014; Diehlmann and Häcker, 2013; International Energy Agency, 2018) indicate an increasing interest in electric driving. Apart from this, currently still low global electric vehicle market share figures suggest that a notable future potential for growth exists (International Energy Agency, 2018).

Policy measures that aim at promoting the advancement in fleet electrification include, for example, tax and purchase incentives, but also bans for combustion-based cars have been announced (Carvalho, 2016; International Energy Agency, 2018). Moreover, infrastructure support is considered a suitable measure for electric mobility incentivization (International Energy Agency, 2018).

To further increase the electric car stock, also large investments in battery research seem to be crucial (National Academy of Sciences, 2015). After all, decreasing battery costs, increasing battery capacities, and infrastructure development measures support an increasing share of electric mobility in road traffic (International Economic Development Council, 2013; International Energy Agency, 2018).

A large-scale electrification of mileage also leads to the expectation of a major future electricity demand increase. This can be aptly illustrated by stating that the energy content of a 60-liter gasoline tank of a passenger car is roughly the same as the electric energy demand of a typical household over a period of two months. The comparison assumes that the energy content of gasoline is about 8.9 kWh per liter (Natural

Resources Canada, 2018) and that the annual electricity consumption of a world average household in the year 2014 is about 3,200 kWh – which is deemed realistic (World Energy Council, 2016).

However, the energy efficiency of a typical internal combustion engine can be assumed to be about 30% (Diehlmann and Häcker, 2013) such that only a small share of the energy that is stored in a fuel tank is actually used for propulsion of the vehicle. In comparison, the efficiency of an electric vehicle, depending on the efficiency of its components (particularly the electric engine, power electronics, and battery), is assumed to be about 90% (Diehlmann and Häcker, 2013; Karlsson and Kushnir, 2013; Mi, Masrur, and Gao, 2011).

Thus, the replacement of combustion-based vehicles by electric cars could significantly increase the energy efficiency of transportation (Diehlmann and Häcker, 2013). It must however be pointed out that in an assessment of the overall energy saving potential and environmental benefits of electric mobility, the broader context of well-to-wheels analysis, including, for example, the share of non-fossil sources in electricity generation, the efficiency of electricity generation, and the energy demand for fuel production would have to be taken into account (Ke, Zhang, He, et al., 2017).

Nevertheless, a greater number of electric vehicles on the streets could substantially decrease fossil fuel demand (i.e., gasoline and diesel consumption). At the same time, potentially cheaper electric energy could be used for transportation (Ipakchi and Albuyeh, 2009). This allows for a greater independence from crude oil (International Energy Agency, 2017).

To foster the use of renewable energy sources such as solar energy (Lund, 2007), vehicle charging stations could be placed at numerous locations with an electricity connection, both at home and at other private or public places (San Román, Momber, Abbad, et al., 2011). This facilitates the use of energy generated from photovoltaic systems available at frequently visited parking locations, such as the driver's residence for charging (Wenig, Sodenkamp, and Staake, 2015).

With respect to an intended electrification of transport, the electric range of vehicles – and in this context also the availability of charging opportunities – represent major challenges and should thus be particularly considered. While many short everyday trips only require a similarly short range to be driven electrically (Pasaoglu, Fiorello, Martino, et al., 2014), for longer trips the still limited electric range of PHEVs, together with expensive batteries, long charging times, and the limited availability of a public charging infrastructure are serious drawbacks of electric mobility (International Energy Agency, 2018; National Academy of Sciences, 2015).

As a consequence, the key elements of electric driving, namely electric range and charging infrastructure, have to be assessed together while taking into consideration the actual mobility requirements of individual drivers. From this, a reliable basis for effective decision making and realistic conclusions about the expected mileage

electrification potential and resulting power grid impact of electric mobility can be provided.

However, even with the impressive growth of global PHEV and battery electric vehicle sales figures in recent years, the overall share of electric cars on the roads remains low (International Energy Agency, 2018). This results in limited practical experience with electric driving.

The creation of practical conditions for electric mobility assessments is limited by high costs of long-range electric cars (International Economic Development Council, 2013) and charging infrastructure measures (National Academy of Sciences, 2015). However, important insights can be derived from computer simulations that are based on real-world data before making cost-intensive and possibly fault-prone decisions and investments in both charging infrastructure development and automotive manufacturing (Maia, Silva, Araújo, et al., 2011).

1.2 Electric mobility assessment based on behavioral data

Energy informatics plays an increasingly important role in the field of information systems and suggests the use of behavioral data of individuals (here: GPS based mobility data) to better understand energy consumption patterns (Goebel, Jacobsen, Del Razo, et al., 2014a, 2014b). The integrative approach aims at promoting an increasingly efficient use of energy, the utilization of renewable energy sources, and a future-proof energy supply (Goebel, Jacobsen, Del Razo, et al., 2014a, 2014b).

Consequently, this thesis utilizes mobility data that is based on GPS recordings to assess electric mobility scenarios. Here, particularly the prediction of the potential for mileage electrification (Pearre, Kempton, Guensler, et al., 2011; Wenig, Sodenkamp, and Staake, 2015), but also the quantification of the resulting additional stress to the power grid as a consequence of charging the vehicle's battery (Dong, Lin, Liu, et al., 2014; Wenig, Sodenkamp, and Staake, 2015) have a high relevance.

Driving cycles and survey studies can be considered as possible alternative foundations to analyze mobility patterns of drivers. However, driving cycles – i.e., specified driving speed profiles – provide a data basis that is often considered to be unrealistic and that assumes averages over a multitude of individual drivers and trips without taking into account variations in mobility needs (Smith, Shahidinejad, Blair, et al., 2011). Moreover, the lack of information on parking events limits their utility for electric mobility assessment, because longer lasting charging events coincide with the parking times of vehicles (Smith, Shahidinejad, Blair, et al., 2011). Survey studies (based, for example, on drivers' logbooks) typically provide short-term and often incomplete or inaccurate mobility data (De Gennaro, Paffumi, Martini, et al., 2014; Gonder, Markel, Simpson, et al., 2007; Wu, Aviquzzaman, and Lin, 2015).

Thus, GPS-based driving data is considered to be a more appropriate basis for the assessment of electric mobility scenarios than both driving cycles and survey studies

(De Gennaro, Paffumi, Martini, et al., 2014; Gonder, Markel, Simpson, et al., 2007; Smith, Shahidinejad, Blair, et al., 2011; Wu, Aviquzzaman, and Lin, 2015). Furthermore, in this thesis, GPS driving data from conventional combustion-based cars is preferred over already existing mobility data from electric vehicles. The latter might be highly biased by limitations of electric cars (Rezvani, Jansson, and Bodin, 2015) or unrepresentative mobility needs of early adopters (Anable, Skippon, Schuitema, et al., 2011; Plötz, Schneider, Globisch, et al., 2014), such that there exists a reasonable doubt that such data represents the objective mobility preferences of typical motorists.

The advantages of GPS driving data are further discussed in (Wenig, Sodenkamp, and Staake, 2019) and in chapter 3, respectively. Against this backdrop, in chapters 2, 3, and 4, respectively in (Sodenkamp, Wenig, Thiesse, et al., 2019; Wenig, Sodenkamp, and Staake, 2019), the state of the art of GPS driving data based electric mobility assessment is reviewed and four research questions arise. In the following, these questions are introduced, and their motivation and implications are described in a condensed way.

1.3 Research task

1.3.1 Driver segmentation

Literature suggests that a segmentation of drivers enables a more varied view on the automotive market by including the mobility behavior and preferences of vehicle users (Anable, 2005). Particularly with regard to electric mobility, the segmentation of automotive customers appears to be essential to appropriately consider distinct driver characteristics and thus facilitate the vehicle's market success (Hodson and Newman, 2009).

The related work on GPS driving data assessment provides results for different types of drivers by analyzing datasets from respective driver groups such as commuters (Björnsson and Karlsson, 2015) or primarily urban drivers (De Gennaro, Paffumi, Martini, et al., 2014; He, Wu, Zhang, et al., 2016). However, a data-driven distinction of driver groups according to their mobility behavior and based on extensive driving data allows for more comprehensive insights on the mobility needs of individual drivers and enables a direct comparison of groups.

Chapter 2 and (Sodenkamp, Wenig, Thiesse, et al., 2019), respectively, thus focus on the subject of driver segmentation for electric mobility scenario assessment. Here, the research question is: *How can cluster analysis be used to identify typical vehicle usage patterns?*

To address this question on how typical vehicle usage patterns can be identified, drivers are suggested to be segmented according to their mobility behavior. To do so, variations in the mobility behavior of individual drivers are analyzed. The segmentation approach reveals characteristic mobility patterns from GPS time series and discovers similar groups of drivers.

The resulting utility of the approach lies in the identification of driver groups that could more readily switch from a combustion-based vehicle to an electric car and that are thus highly relevant for electric mobility planning. Possibly false or vague assumptions that are based on the assessment of an average driver profile can be avoided and more reliable predictions on the usability and local grid impact of an individual driver become feasible.

Consequently, electric mobility requirements that influence the mileage electrification potential and the related electricity demand can be assessed separately for each group and for a variety of vehicle battery capacity and charging facility parameters. Resulting group-specific forecasts can make a more accurate forecast of the adoption potential and grid impact of PHEVs possible.

Note that in this thesis, the terms driver and vehicle are used interchangeably, although strictly speaking, the mobility behavior of a vehicle and not of a driver was measured. Thus, the behavior of an assumed driver is derived from the mobility patterns of an individual car. In the context of driver segmentation, also the terms segment, cluster, and group are used synonymously.

1.3.2 Battery versus infrastructure assessment

Both the mileage electrification potential and the resulting power grid impact due to charging depend on the electric range of the vehicle, but they are also affected by the availability of charging opportunities (Paffumi, De Gennaro, Martini, et al., 2015). Such charging facilities for PHEVs could be placed at both privately owned parking locations or at public spaces (San Román, Momber, Abbad, et al., 2011). Their utility for mileage electrification depends both on the charging power that is available at the facility (Paffumi, De Gennaro, Martini, et al., 2015) and the infrastructure development (Dong and Lin, 2012).

High expenses come along both with the production or acquisition of long electric range vehicles and with the development of the charging infrastructure (International Economic Development Council, 2013). However, in the course of technological advances, future costs for batteries are expected to decline (International Economic Development Council, 2013; Slowik, Pavlenko, and Lutsey, 2016), while costs for labor-intensive infrastructure measures can be expected to remain high (National Academy of Sciences, 2015).

Thus, knowing the mutual relation between vehicle battery and charging infrastructure characteristics from such a simulation-based assessment helps making well-funded decisions both for the individual driver and on a larger scale. This work suggests a comparison and assessment of vehicle battery capacities and charging infrastructure characteristics.

The subject is addressed in chapter 3 and in (Wenig, Sodenkamp, and Staake, 2019), respectively and leads to the formulation of the following research question: *To what extent do larger batteries relax the requirements regarding charging infrastructure and vice versa?*

A light is shed on the substitutability of electric range – resulting from a car’s battery capacity – and charging infrastructure characteristics. The work systematically analyses to what extent variations in electric vehicle characteristics (i.e., the vehicle’s battery capacity) and both the private and public charging infrastructure coverage and available charging power affect results. Furthermore, results are compared for distinct driver segments. The objective is to provide a profound assessment of the effect that electric range and charging opportunity variations have on the mileage electrification potential and to estimate and describe the resulting power grid impact that comes from the additional electric charging of cars.

1.3.3 Integration of vehicle charging into residential households

Charging electric cars at their assumed primary parking location (such as the home base) enables great shares of mileage to be driven electrically. As a consequence, the local power demand increases with peaks typically occurring in the evening, but also at noon. This observation is discussed in greater depth in (Sodenkamp, Wenig, Thiesse, et al., 2019; Wenig, Sodenkamp, and Staake, 2019, 2015), and in chapters 2 and 3, respectively.

Particularly for presumably private driver segments, the value of home charging for (private) electric driving is noticeable (c.f. (Sodenkamp, Wenig, Thiesse, et al., 2019; Wenig, Sodenkamp, and Staake, 2019) and chapters 2 and 3, respectively). Hence, an in-depth look at the grid impact of electric mobility at home locations is motivated.

The emphasis of the assessment is put on the integration of electric vehicle charging into residential households by comparing the typical load profile of a private household with the charging demand of a PHEV. In this integrated view of vehicle charging at residential locations, the overall energy demand is increased and particularly during peak times (most prominently in the evening, but also at noon), the additional stress to the grid can be illustrated.

In order to manage such an increased local energy demand, first, residential photovoltaic systems could be used for electric car charging to increase the self-consumption and thus reduce the grid demand, as was discussed in (Wenig, Sodenkamp, and Staake, 2015). It has to be analyzed how energy from distributed renewable energy sources (i.e., residential photovoltaic systems) can be utilized to change the electricity grid demand when PHEVs charge and to reduce stress on the grid. To do so, solar irradiation data is used to simulate the energy generation capability of residential photovoltaic systems. Consequently, the following question is addressed: *How does the electricity grid demand change when PHEVs charge from distributed renewable (i.e., solar) energy sources?*

Second, load shifting approaches for vehicle charging could help mitigating electricity demand during peak hours (Prüggler, 2013). Thus, the utility of managed charging (i.e., load shifting) for peak grid demand reduction has to be assessed. Here, a load shifting strategy is applied to evaluate the potential for shifting peak electricity demand to hours of less energy demand and to answer the question: *How could managed charging (i.e., load shifting) reduce peak grid demand?*

The suggested comparison of the electricity demand at private households with the home charging demand of PHEVs and both the assessment of residential photovoltaics and of a load shifting strategy for vehicle charging are addressed in the fourth chapter.

1.4 Outline of the methodology

To comprehensibly answer these raised questions, a data-based methodology has been developed and applied. An overview of this methodology is provided in Figure 1. The electric car simulation procedure from (Wenig, 2014a, 2014b; Wenig, Sodenkamp, and Staake, 2015) has been used as a groundwork.

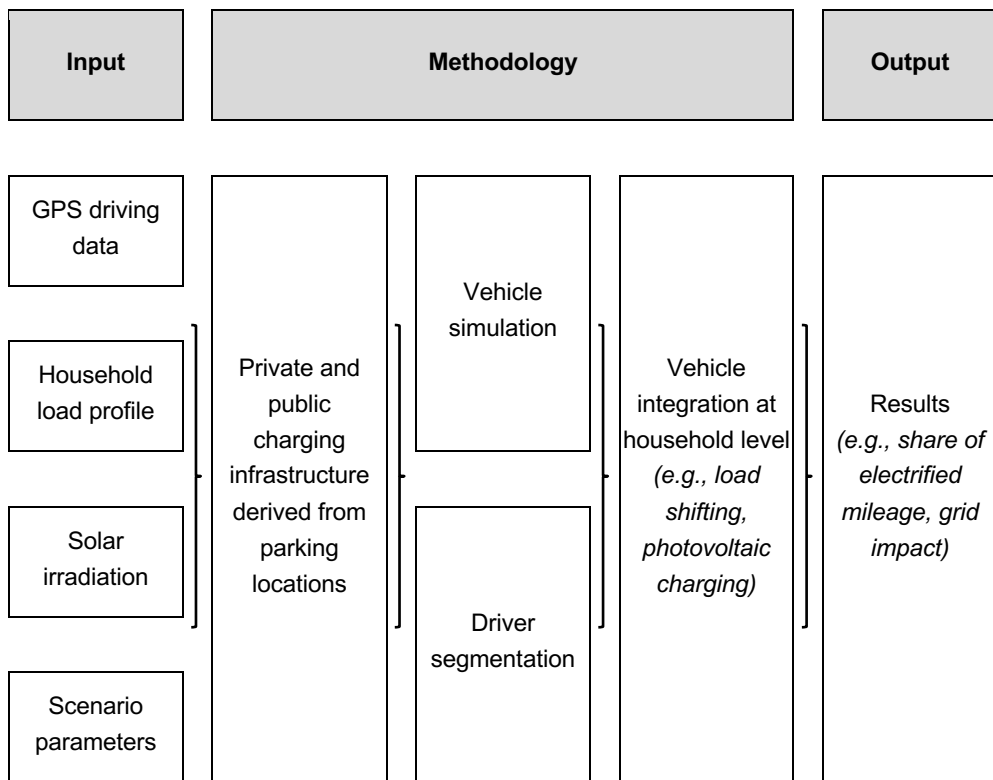


Figure 1: Overview of the data-based methodology

The approach uses GPS driving data, simulation techniques (i.e., a physical model of the electric vehicle energy consumption and charging behavior), and machine learning techniques (i.e., clustering approaches) to predict to what extent driver groups could drive electrically and to what extent such an additional electricity demand strains the power grid. From this, appropriate electric mobility parameters (i.e., electric vehicle and

charging infrastructure characteristics) that foster the electrification of transport can be identified.

1.4.1 Data input

First, a closer look at the input data is given. In this thesis, GPS time series data that represents the real-world mobility behavior of distinct drivers is processed using data analysis techniques. The GPS driving data set was provided by the chair of Information Systems and Energy Efficient Systems at the University of Bamberg, Germany and stems from a major European telematics service for pay-as-you-drive insurances (Ippisch, 2010; Octo Telematics Ltd., 2017). The data set contains driving data from 1,000 conventional vehicles over a period of two years. During trips, measurements have been recorded about every 2 km. The large majority of trips takes place in Northern Italy.

Moreover, standard household load profiles are utilized (Schellong, 2016) and are merged with the simulated home charging demand data of PHEVs and with time and place dependent solar irradiation data (MINES ParisTech and Transvalor S.A., 2017). Scenario parameters allow for the assessment of different electric mobility charging scenarios.

1.4.2 Charging infrastructure scenarios derived from parking locations

Potential private charging locations can be derived from GPS-based time series data. To do so, a procedure from (Wenig, Sodenkamp, and Staake, 2015) is applied. It particularly contains a method for the detection of potential primary (e.g., home) and secondary parking locations that is based on a density-based clustering algorithm (Ester, Kriegel, Sander, et al., 1996).

Frequent parking locations with the longest overall parking duration in a considered time period are assumed to be primary (e.g., home) parking locations (Krumm, 2007; Wenig, Sodenkamp, and Staake, 2015). Consequently, locations with the second longest parking duration are considered to be secondary parking locations (Wenig, Sodenkamp, and Staake, 2015).

A random assignment of charging opportunities at parking locations according to a specified public infrastructure coverage takes place to derive possible public charging opportunity locations. This is again addressed in (Wenig, Sodenkamp, and Staake, 2019) and in chapter 3, where different private and public charging infrastructure configurations are compared.

1.4.3 Vehicle simulation

The vehicle simulation model suggested in (Wenig, Sodenkamp, and Staake, 2015) is applied and contains both a vehicle energy consumption model and a charging model.

The electric vehicle energy consumption model uses GPS driving data (particularly the driven distance and speed at each measurement point) and estimates the energy consumption based on rolling resistance, aerodynamic drag, and acceleration. The charging model assumes a lithium-ion battery and considers both the charging duration and the available charging power. The usage of charging opportunities depends on the considered charging infrastructure (home, secondary, public) and on the respective parking times. From this, the state of charge of the battery at each location and timestamp can be derived.

In this work, PHEVs are assumed to be vehicles that allow plug-in charging and have a hybrid configuration of both an electric engine and an internal combustion engine (Amsterdam Roundtables Foundation and McKinsey & Company, 2014; National Academy of Sciences, 2015) More specifically, in the context of this thesis, a PHEV is considered to be a passenger vehicle that can be driven fully electrically, but that is potentially range extended by an internal combustion engine, if the battery runs out of charge (National Academy of Sciences, 2015).

Figure 2 shows the simplified layout of such a PHEV with an additional range extender. This range extender is a gasoline-based internal combustion engine that can recharge the lithium-ion battery if it is depleted. Due to this assumption, statements on the share of mileage that could be covered electrically – depending on the driving behavior and on the electric mobility scenario parameters – can be interpreted in a realistic and justifiable manner.

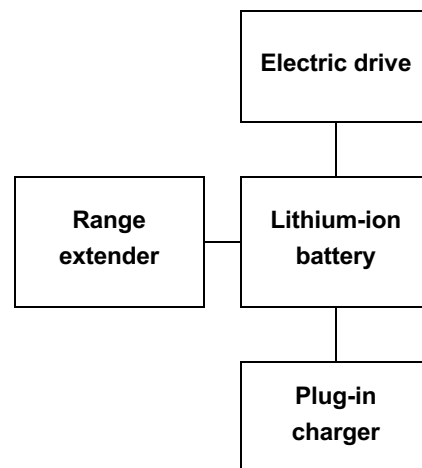


Figure 2: Simplified layout of a PHEV with range extender; inspired by (Amsterdam Roundtables Foundation and McKinsey & Company, 2014; National Academy of Sciences, 2015)

1.4.4 Driver segmentation

A partitioning based clustering algorithm (Han, Kamber, and Pei, 2012; Hartigan and Wong, 1979) is applied to find distinct groups of drivers based on the individuals' mobility behavior. In the segmentation approach, clustering variables that describe the driving

patterns and influence the energy consumption and charging behavior of a simulated PHEV are derived from the driving data.

These variables include information on the driven distance, duration, and speed and on parking durations – particularly at potential private charging facilities – such that drivers can be distinguished in terms of characteristics that are highly relevant for electric driving. Subsequently, discovered driver groups can be aptly described with regard to the vehicles' presumed main e.g., private or business purposes.

Moreover, the distinct mobility demand patterns of individual drivers and of derived driver groups are analyzed and compared for variations of electric mobility scenarios. Thereby, statements on the mileage electrification potential and grid impact for each group can be given for different vehicle characteristics (i.e., the battery capacity) and charging infrastructure parameters (i.e., the charging power and availability of charging facilities).

The segmentation procedure is described in (Sodenkamp, Wenig, Thiesse, et al., 2019) and in chapter 2, respectively and is further applied in subsequent chapters.

1.4.5 Vehicle integration at household level

The work also includes the assessment of residential photovoltaic charging and of the utility of a load shifting strategy for grid impact alleviation. This is discussed in detail in chapter 4.

The energy output of a residential photovoltaic system is simulated by using location- and time-specific solar irradiation data (MINES ParisTech and Transvalor S.A., 2017). The resulting power generation time series data is merged both with a typical standard household load profile that has been adapted to regional conditions (Schellong, 2016) and with the expected charging demand of presumably privately held electric cars at the primary (or home) parking location. The electricity demand of such a private household with an electric vehicle can be assessed and from this the potential for overall electricity demand reduction by utilizing locally generated solar energy can be estimated.

Peak charging demand at home locations typically occurs in the evening hours, while in the following nighttime hours and in the morning the average charging demand is much lower, as described both in (Wenig, Sodenkamp, and Staake, 2015) and in the course of the present work. Consequently, peak power demand could be reduced by means of a load shifting procedure (Palensky and Dietrich, 2011; Prügler, 2013; Shimizu, Ono, Hirohashi, et al., 2016).

The load shifting approach takes advantage of the entire home parking duration which is often considerably longer than the related time window that is required for unmanaged charging. During the parking period, the charging power can be reduced because of the extended charging duration (Shimizu, Ono, Hirohashi, et al., 2016). Thus, also the peak

power demand can be reduced without changing the state of charge of the battery at the end of the parking event.

1.4.6 Implementation

A GPS data-based simulation procedure (Wenig, 2014a, 2014b; Wenig, Sodenkamp, and Staake, 2015) constitutes the basis for this thesis and was further enhanced. The software was developed using the R software environment (R Core Team, 2018). The documented source code for the software from which the results of this thesis are derived is provided to the chair of Information Systems and Energy Efficient Systems of the University of Bamberg.

1.5 Structure of the thesis

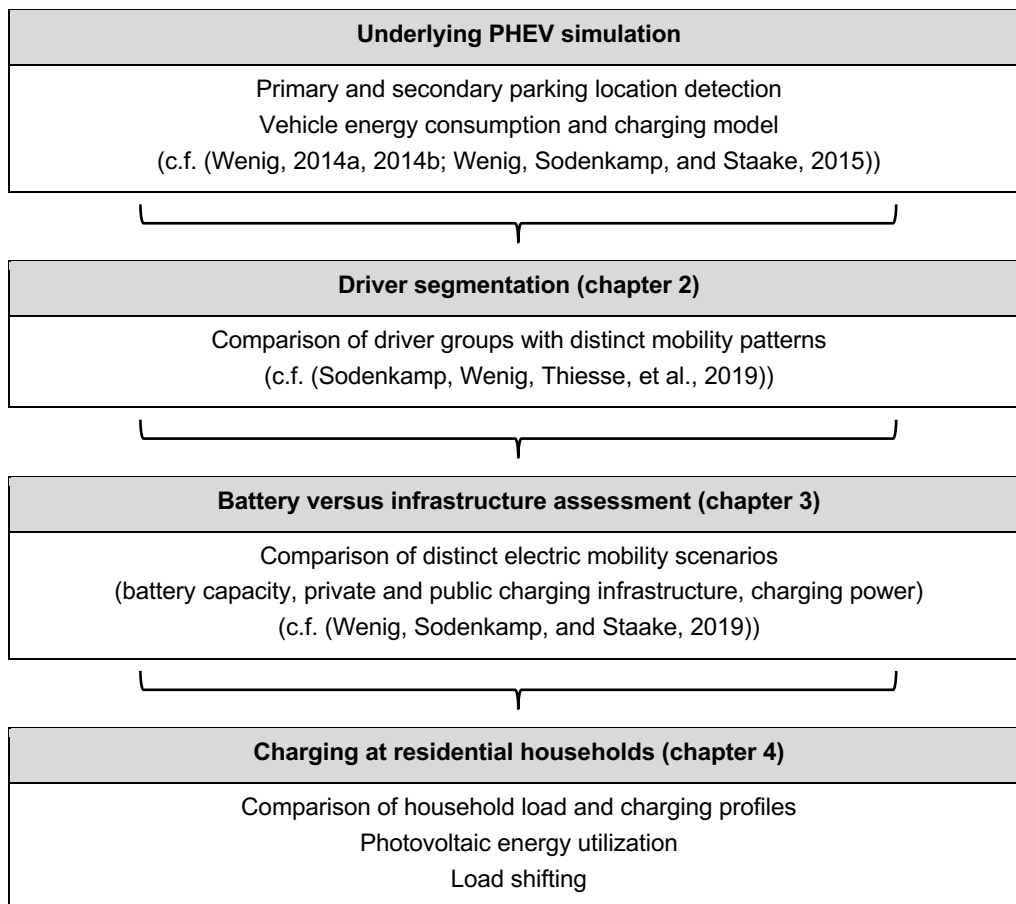


Figure 3: Content structure of the thesis

From the perspective of energy informatics, a contribution is made by generating insights based on the description and analysis of energy related behavioral data and the consequent prediction of the implications of the individual's driving behavior for electric mobility (Watson, Boudreau, and Chen, 2010). To do so, this thesis suggests the innovative utilization of GPS-based mobility behavior data in an approach that applies a

vehicle simulation model and data analytics techniques – including unsupervised machine learning.

In summary, the focus lies on the quantification and comparison of the mileage electrification potential and the resulting local grid impact of individual drivers for different electric vehicle configurations, charging infrastructure configurations, and different types of drivers (i.e., segments) while avoiding strong assumptions and mobility behavior adaptations.

In Figure 3, the content structure of this thesis is given. Preliminary work concerning the detection of private parking locations and the simulation of the energy consumption and charging behavior of an electric vehicle was documented in (Wenig, 2014a, 2014b; Wenig, Sodenkamp, and Staake, 2015).

The comparison of distinct driver segments according to their mobility patterns is addressed in (Sodenkamp, Wenig, Thiesse, et al., 2019) and in chapter 2, respectively. The key findings of this chapter are briefly summarized as follows:

Differences between groups of drivers are highly relevant for the assessment of electric mobility. Results thus suggest that different mobility patterns of driver groups should be included into the analysis of electric mobility scenarios to avoid an overly one-sided emphasis on the driving demand of an assumed average driver. The provided methodology allows for the identification of typical driver groups based on their driving behavior and for the comparison of these groups in terms of their readiness for electric mobility adoption and for the subsequent assessment of their expected impact to the power grid.

The subsequent comparison of electric mobility scenarios, particularly aiming at the assessment of battery capacity and charging infrastructure characteristics, is presented in (Wenig, Sodenkamp, and Staake, 2019) and in chapter 3, respectively. Again, key findings of this chapter can be summarized:

Even with limited electric range PHEVs and by home charging alone, a notable share of mileage could be electrified. This might be explained by the observation that many trips of conventional drivers are short and could thus be electrified in large parts with comparably modest equipment. However, even with small batteries equipped and with the availability of a single private charging facility, the impact to the power grid is considerable.

At the same time, for a large-scale electrification of mileage of a typical driver, large batteries appear to be indispensable. Extensive infrastructure measures alone hardly compensate for limited electric range. Naturally, with increasing shares of electrified mileage, large amounts of electricity are required. Here, particularly the consideration of demand peaks is essential.

With regard to the value and significance of home charging for PHEVs, in chapter 4, the energy demand profile of an average private household is compared with the energy demand of vehicle charging. A focus is set on the effect of vehicle charging at residential

households and further, residential photovoltaic charging and load shifting are addressed. The following main observations and conclusions can be drawn from the fourth chapter:

Both household electricity demand and charging demand peak in the evening, such that during these time windows most stress is put on the electric grid. However, when parked at their private home base, cars typically stand idle for an extended period of time (e.g., at night), such that a similarly extended time period could be used for load shifting. As a result, energy demand for charging can be distributed over a longer timeframe and peak power demand can be reduced.

The second largest power demand peak occurs around noon. With solar irradiation being highest at noon, an assessment of the potential for charging with energy generated from a residential photovoltaic system appears to be reasonable. In (Wenig, Sodenkamp, and Staake, 2015) it was discussed that home parking times during sunlight hours are limited and that cars are mostly parked during hours without sunlight (i.e., at night).

Consequently, only a smaller portion of energy generated by the photovoltaic system could be used for electric vehicle charging. Nevertheless, results show that the usage of locally generated photovoltaic energy for vehicle charging does reduce the demand peak at noon.

Finally, in chapter 5 a discussion of overall results takes place. Consequences derived from the findings, their practical implications, limitations, and possible future applications based on this work are addressed.

2 Driver segmentation for electric mobility assessmentⁱ

2.1 Introductionⁱⁱ

The automotive sector is an excellent example of a highly innovative industry driven by strong competitive pressure and constant technological progress (Holweg, 2008). However, the automotive industry also poses an example of an economic sector that has never had to deal with truly disruptive changes regarding its products, processes, or value network structure (Wollschlaeger, Foden, Cave, et al., 2015).

It was only recently that this situation has started to change with the rise of novel technologies beyond traditional core competencies (e.g., artificial intelligence for autonomous driving), major architectural innovations (e.g., fully electric drivetrains), new business models (e.g., internet-based ride sharing platforms), and dissolving industry boundaries (e.g., between automotive and information technology) (McKinsey & Company, 2016; Wollschlaeger, Foden, Cave, et al., 2015). As a consequence, automotive managers and policy makers are now confronted with a broader variety of fundamental strategic decisions than generations of decision makers in their domain before (McKinsey & Company, 2016; Wollschlaeger, Foden, Cave, et al., 2015).

In this context, the present study sets the focus on the replacement of conventional vehicles by cars equipped with electric engines and batteries. The electrification implies not only a redefinition of the product architecture of cars, but also comes along with questions surrounding the identification of key market segments for PHEVs and battery electric vehicles as well as issues regarding interdependent design choices of battery configurations and charging infrastructures. The primary lever – and major challenge – to achieve market success in fact lies in meeting the requirements of individual customer segments (Hodson and Newman, 2009) also with respect to factors that have previously been taken for granted, such as reachability of destination, or factors that are new, such as electric range under real-world conditions, and in foreseeing the resulting implications on technology choice and infrastructure design.

The transformation has implications beyond the automotive industry as it also concerns the utility sector. Many countries promote the electrification of individual mobility and at the same time support the use of renewable energy sources and the establishment of smart grids (Clastres, 2011). The grid impact of electric cars, however, depends not only on the technology but also on the drivers' profile (e.g., on distances traveled, place and time for re-charging, etc.). It is hence evident that car manufacturers as well as utility companies and public authorities require detailed analyses of car utilization behavior in order to make decisions in both vehicle development and infrastructure planning. Similarly, customers benefit from reports on the suitability of different electric vehicles with regard to their specific needs as support in their individual purchasing decisions.

Table 2. Prior studies using GPS data

Articles	Research focus		GPS analysis methodology		Data origin			Analyzed timeslots		Analyzed group of drivers
	Reachability	Network load	Descriptive	Simulation of energy consumption	North America	Europe	Other	24 hours	Multiple days	
(Khan and Kockelman, 2012; Wu, Aviquzzaman, and Lin, 2015)	x		x		x				x	urban / metropolitan
(Pearre, Kempton, Guensler, et al., 2011)	x	x	x		x				x	metropolitan
(Björnsson and Karlsson, 2015; Jakobsson, Gnann, Plötz, et al., 2016)	x		x			x			x	urban and rural
(De Gennaro, Paffumi, Martini, et al., 2014)	x	x	x			x			x	urban
(He, Wu, Zhang, et al., 2016)	x		x				x		x	metropolitan
(Gonder, Markel, Simpson, et al., 2007)	x			x	x			x		metropolitan
(Needell, McNerney, Chang, et al., 2016)	x			x	x			x		heterogeneous
(Greaves, Backman, and Ellison, 2014)	x			x			x		x	suburban
(Stark, Link, Simic, et al., 2015)	x			x		x			x	urban and rural
(Ashtari, Bibeau, Shahidinejad, et al., 2012; Dong, Lin, Liu, et al., 2014)		x	x		x				x	urban / metropolitan
(Shahidinejad, Bibeau, and Filizadeh, 2010)		x		x	x				x	urban
(De Gennaro, Paffumi, and Martini, 2015)		x	x			x			x	urban
(Wenig, Sodenkamp, and Staake, 2015)	x	x		x		x			x	heterogeneous

The datasets required to generate profile-related information have become available in recent years through the proliferation of real-time global positioning systems (GPS) used in cars and mobile devices, which automatically collect large amounts of location

data. Prior studies use such data for the estimation of key performance indicators (KPIs) of electric cars, including electric reachability, load to the electric grid, and the share of distances that can be driven electrically (see Table 2 for an overview).

Related empirical investigations and simulations have improved over time in terms of data quality and the level of detail in their model assumptions. Early research, for example, made strong assumptions regarding charging procedures, such as postulating that batteries are always fully charged once a day (Khan and Kockelman, 2012). Later studies included more comprehensive scenarios such as home and work charging (Wu, Aviquzzaman, and Lin, 2015) or differentiated between distinct usage scenarios such as first versus second car (Jakobsson, Gnann, Plötz, et al., 2016) and between vehicle sizes (Stark, Link, Simic, et al., 2015). The findings assert that a large share of the mileage can be electrified even with relatively small batteries of PHEVs and battery electric vehicles and at the same time reveal considerable differences regarding electrified mileage and reachability among different use cases. The findings nicely replicate in studies that focus on specific mobility needs of urban drivers (De Gennaro, Paffumi, Martini, et al., 2014; He, Wu, Zhang, et al., 2016) and commuters (Björnsson and Karlsson, 2015).

Alongside the focus on electric range and usability, a growing number of studies also pays attention to charging locations and electricity consumption (Ashtari, Bibeau, Shahidinejad, et al., 2012; Dong, Lin, Liu, et al., 2014; Gonder, Markel, Simpson, et al., 2007; Khan and Kockelman, 2012; Pearre, Kempton, Guensler, et al., 2011; Shahidinejad, Bibeau, and Filizadeh, 2010). The authors unanimously predict considerable demand peaks if return times are synchronized in neighborhoods and point out the necessity of charging control systems.

However, a GPS-based investigation of the usability and electricity consumption also allows for a comparison of individual driver segments against each other within one coherent model. The underlying conjecture is that the identification of driver segments can provide a more differentiated picture of electric vehicle usability and network load in comparison to prior research considering driver populations as a homogenous whole. Grouping of drivers according to their mobility behavior is already a widely discussed topic among mobility researchers (Anable, 2005). It was only recently that the issue of driver segmentation has gained a foothold in the electric vehicle usability community (Anable, Skippon, Schuitema, et al., 2011). However, investigated studies on reachability and electricity consumption do not capture the potential of driver segmentation based on real-world GPS travel data.

Against this backdrop, this research work extends the literature by proposing and applying a procedure for profiling the key segments of car drivers using GPS-based mobility data. Pattern recognition techniques help to identify distinct driver segments from GPS data sets and an exemplary analysis regarding usability and electricity consumption for 982 drivers over a two-year period reveals large differences regarding reachability and charging requirements between segments. Cluster analysis can be employed to identify typical vehicle usage patterns (e.g., by driving distance and duration, frequency and length of parking, etc.) from driving data. The results allow for segment-

specific vehicle requirements analyses regarding electric reachability, energy consumption, and recharging power over time and by location.

2.2 Data description and detection of parking locationsⁱⁱ

Starting point of the analysis is a dataset gathered from 1,000 cars that were equipped with on-board GPS sensors and GSM modules for data transfer (Ippisch, 2010). The primary location of the cars was Northern Italy and surroundings, including trips to Austria, Switzerland, France and across Italy. Information has been collected over the course of 24 months, originally to offer a usage-based insurance tariff (Ippisch, 2010). The cars' position was updated every few seconds and recorded in aggregated form with 2 km granularity; it contains additional information (e.g., state of ignition) as shown in Table 3. The collected data is of high quality. Still, for this chapter, 18 vehicles were excluded due to technical problems of the data recorders. A noteworthy property is that the data stems from regular drivers of conventional cars and is not, like in many previous studies, a convenience sample restricted to a smaller geographic area or a sample containing primarily early adopters of electric cars. Though a bias from insurance customers of a usage-based tariff cannot be ruled out, similar problems are also inherent to previous work, were self-selection biases of study participants and unclear characteristics of early electric car adopters cannot be precluded either.

Table 3. Data set and attributes (Ippisch, 2010)

Attribute	Description
Car number	Car/device number
Timestamp	Date and time on which the dataset was recorded
Latitude, Longitude	Vehicle position in decimal notation
Speed	Vehicle speed at recording time in km/h
Distance to previous point	Distance traveled since last recording point
Time since previous point	Time traveled since last recording point
Panel session	Data on <ul style="list-style-type: none"> - ignition turn-on - vehicle operation - ignition turn-off
Road type	Road type at recorded location <ul style="list-style-type: none"> - Urban - Highway - Extra urban

For the data set, each driver's primary and secondary parking location has been identified using location information (longitude and latitude) and panel session data (Wenig, Sodenkamp, and Staake, 2015). Following Krumm (2007), the place where most time is spent is henceforth referred to as the home location. The location where second-most time is spent can be considered a typical working place, even though some drivers may not have a workplace but may park, for example, at the grandchildren's house with the

second most pronounced frequency and duration (however, the notations *home* and *work location* are used to ease readability).

Based on similar arguments, numerous earlier methods of geospatial location clustering have been developed; (Gambs, Killijian, and del Prado Cortez, 2010) compare different segmentation algorithms and heuristics for the inference of points of interests from an individual's movement data. (Han, Lee, and Kamber, 2009) exemplify geographic location clustering using different algorithms of unsupervised machine learning. In the context of privacy preservation, (Krumm, 2007) review studies that deal with the extraction of individuals' home and identity from pseudonymous GPS traces. Information about the density of vehicle parking locations was utilized also by (Smith, Shahidinejad, Blair, et al., 2011) in order to categorize possible locations for charging infrastructure planning.

Leaning on previous work (Wenig, Sodenkamp, and Staake, 2015), a density-based clustering algorithm DBSCAN is used to identify the parking positions (Ester, Kriegel, Sander, et al., 1996)¹; DBSCAN is the algorithm of choice due to its ability to deal with arbitrary shaped clusters (Han, Lee, and Kamber, 2009) and thus allows slight deviation of parking positions around a base (as required for curbside parking). As two input parameters, the minimum number of points in a cluster is defined as three. The neighborhood radius of points is incrementally approximated, so that the parking area (i.e., its convex hull) is restricted to an area of about 316 x 316 m²; the relatively large area was necessary to capture the varying positions of cars parking on public streets in proximity to the point of interest (such as the home charging location). Analogously, the cluster with the second longest overall parking duration was selected as the secondary parking location.

Since primary and secondary parking locations may change over time (e.g., due to job changes, relocation, holiday times), such that the trips were grouped by calendar month and each group was considered separately. Table 4 shows the distribution of months with and without changes of the main and secondary parking locations. The results indicate that in 86.7% of all cases, the primary parking location remains stable over time whereas the same holds for 50.0% of the secondary parking locations. The numbers deem plausible and sufficiently stable given that cars are often used by more than one person and that the real-world data set might also include, for example, holiday and business trips.

Table 4. Stability of identified parking locations over time (n = 982)

Difference between months	Primary	Secondary
Location stays the same	86.7%	50.0%
Swaps between primary and secondary location	6.3%	5.5%
Location changes (excluding swaps)	3.9%	37.3%
No location detected	2.7%	6.7%
Insufficient data	0.6%	0.6%

¹ The R package "fpc" provides a density-based DBSCAN algorithm (Hennig, 2018).

Given that the data stems from conventional cars, the travel patterns include a number of trips that are too long to be driven non-stop by solely battery-powered vehicles. In a strict sense, the analysis is therefore highly accurate only for PHEVs with range extender (as it is the case in the later examples) and constitutes an approximation for solely battery-operated cars.

2.3 Driver segmentation

2.3.1 Methodologyⁱⁱ

In most markets, it is neither optimal to treat all customers alike nor to treat each individual uniquely (Dillon and Mukherjee, 2006). As a compromise between these two extremes, a variety of segmentation methods were developed with the aim of providing decision makers with information on who their customers are and what products or services these customers want and need (Dillon and Mukherjee, 2006). In the case of electric mobility, segmentations on the foundation of real-world behavioral data serve to better understand the actual suitability of PHEVs to the driving habits of individual drivers. For this purpose, segmentation methods can group driving data entries into coherent classes of vehicle usage patterns, which allows automotive manufacturers to better tailor their offerings to the actual needs of the respective customers.

In the context of the study, driver segments were identified on the foundation of the corresponding trip data. To this end, a backward segmentation approach (van Raaij and Verhallen, 1994) was chosen that assigns cars to groups by their similarity in one or more trip characteristics (i.e., segmentation variables), for example, the median distance of a roundtrip or the variance of speed. Consequently, the differences between the groups are related to behavioral differences of drivers. The segmentation variables were empirically defined and selected using correlation analysis.

Altogether, 12 segmentation variables were formulated: six of them describe trip and roundtrip drives (median distances, median driving durations, and speed variances), four variables reflect parking routines (median parking duration during a roundtrip, median parking durations at primary and non-primary locations, number of stops during a roundtrip), and two variables describing drive-to-park-time ratio during a roundtrip and number of roundtrips per month. Using Pearson's correlation coefficients, three variables could be excluded: roundtrip median parking duration (correlated with roundtrip median driving duration, coefficient 0.95), trip median drive duration (correlated with trip median distance, coefficient 0.92), and trip speed variance (correlated with roundtrip speed variance, coefficient 0.90). Data transformation (here: logarithmic transformation and min-max normalization) is applied, as suggested by literature, to improve the comprehensibility and usefulness of resulting segments (Han, Kamber, and Pei, 2012; McCune, Grace, and Urban, 2002).

Subsequently, given its robustness compared to hierarchical approaches, the k-means algorithm (Hartigan and Wong, 1979; Punj and Stewart, 1983) was employed² to assign cars to clusters. The plausibility of results for different numbers of clusters was checked by comparing them based on the Euclidean distances between cluster centers. As a final number of clusters (henceforth segments), seven allowed for a natural interpretation of the solution.

2.3.2 Resulting driver segmentsⁱⁱ

The outcome of the analysis procedure suggests three large segments, labelled (1) “frequent local driver” (FLD, n=246), (2) “commuter (short)” (CS, n=246), and (3) “commuter (long)” (CL, n=238) on the basis of the mean variable values depicted in Table 5. In total, almost 75% of cars in the data set belong to one of these clusters. The remaining drivers are associated with one of four smaller segments: (4) “delivery (short)” (DS, n=47), (5) “service provider” (SP, n=52), (6) “delivery (long)” (DL, n=54), and (7) “company representative” (CR, n=99). Additional data on the segments beyond the segmentation variables is given in Table 6.

Table 5. Profiles of the seven driver segments (segmentation variables)

Segment	1	2	3	4	5	6	7	All
Segment name	FLD	CS	CL	DS	SP	DL	CR	ALL
Segment size	246	246	238	47	52	54	99	982
% of fleet	25.1%	25.1%	24.2%	4.8%	5.3%	5.5%	10.1%	100.0%
Segmentation variables								
Median distance of a roundtrip [km]	11.43	24.50	41.47	0.73	90.95	94.14	225.06	51.77
Median duration of a roundtrip [h]	2.52	5.45	6.70	0.29	5.02	7.26	11.42	5.45
Ratio of driving to parking during a roundtrip	0.21	0.13	0.12	0.53	1.88	0.43	0.94	0.36
Variance of speed during a roundtrip	403.83	222.52	711.87	257.03	312.69	130.44	330.27	398.77
Average number of roundtrips per month	48.69	35.02	20.97	60.84	49.51	31.30	23.80	35.70
Average number of stops per roundtrip	3.84	3.93	5.19	7.98	6.58	15.62	8.87	5.69
Median distance of a trip [km]	3.03	6.24	7.28	1.71	11.16	2.28	14.84	6.38
Median parking duration at a primary parking location [h]	6.78	10.86	12.82	1.59	1.25	14.06	11.62	9.61
Median parking duration at a non-primary parking location [h]	0.38	0.90	0.86	0.18	0.23	0.16	0.27	0.59

² The R package “stats” provides a k-means algorithm (R Core Team, 2018).

Table 6. Profiles of the seven driver segments (non-segmentation variables)

Segment	1	2	3	4	5	6	7	All
Segment name	FLD	CS	CL	DS	SP	DL	CR	ALL
Segment size	246	246	238	47	52	54	99	982
% of fleet	25.1%	25.1%	24.2%	4.8%	5.3%	5.5%	10.1%	100.0%
Non-segmentation variables								
Mean distance of a roundtrip [km]	33.64	39.43	100.98	47.80	153.24	93.07	279.16	86.44
Mean duration of a roundtrip [h]	6.78	9.79	30.29	4.21	9.78	11.06	33.38	16.19
Mean distance of a trip [km]	8.72	10.18	19.36	8.58	26.53	6.17	33.07	14.92
Median duration of a trip [h]	0.13	0.20	0.25	0.10	0.34	0.10	0.46	0.22
Mean duration of a trip [h]	0.25	0.26	0.40	0.21	0.74	0.18	0.78	0.36
Average daily travels in km								
<i>Monday</i>	49	42	58	117	268	98	239	86
<i>Tuesday</i>	49	42	61	116	269	99	242	87
<i>Wednesday</i>	51	43	62	108	260	98	244	87
<i>Thursday</i>	52	44	66	121	272	97	253	91
<i>Friday</i>	53	48	70	115	278	96	241	92
<i>Saturday</i>	53	48	57	73	165	72	97	65
<i>Sunday</i>	48	41	51	7	15	5	24	38
<i>Mon-Fri</i>	51	44	63	115	269	98	244	89
<i>Sat-Sun</i>	51	44	54	40	90	39	60	52
Median parking duration at a secondary parking location [h]	2.93	4.84	4.71	0.98	1.42	0.87	1.87	3.45
Median daily parking duration at a primary parking location [h]	16.90	15.15	15.66	16.42	13.31	16.25	14.24	15.64
Median daily parking duration at a secondary parking location [h]	5.11	6.92	7.29	1.75	2.07	1.83	2.68	5.35
Portion of monthly mileage on urban roads	0.33	0.35	0.22	0.18	0.15	0.35	0.14	0.23
Portion of monthly mileage on extra-urban roads	0.38	0.44	0.29	0.39	0.35	0.45	0.28	0.35
Portion of monthly mileage on highways	0.30	0.21	0.49	0.43	0.51	0.21	0.58	0.42
Mean speed [km/h]	70.00	66.04	85.20	57.53	65.67	57.50	70.24	71.20
Monthly mileage [km]	1,539	1,331	1,830	2,822	6,527	2,451	5,763	2,359
Stability of locations on a monthly basis								
<i>Primary locations</i>	0.89	0.91	0.75	0.95	0.93	0.91	0.87	0.87
<i>Secondary locations</i>	0.48	0.67	0.41	0.50	0.42	0.48	0.39	0.50

Euclidian distances between cluster centers are given in Table 7. Additionally, to visualize differences between the seven segments, a hierarchical clustering algorithm with

Ward’s method as a distance metric (c.f. Murtagh and Legendre, 2014) was employed³. The resulting dendrogram in Figure 4 indicates that the three segments “frequent local driver”, “short-distance commuter”, and “long-distance commuter” resemble each other. The next three segments “long-distance delivery vehicle”, “service provider”, and “company representative” share similarities as well and are assumed to include cars used for business purposes. The last segment “short-distance delivery vehicle” has little in common with any other segment. In the following subsections, a detailed discussion of the average driver’s profile and each of the seven driver segments takes place.

Table 7. Euclidean distances between cluster centers

Cluster	1	2	3	4	5	6	7
1	0.00						
2	0.28	0.00					
3	0.38	0.26	0,00				
4	0.63	0.85	0.94	0.00			
5	0.54	0.61	0.66	0.76	0.00		
6	0.65	0.62	0.63	0.92	0.71	0.00	
7	0.61	0.49	0.44	1.04	0.56	0.45	0.00

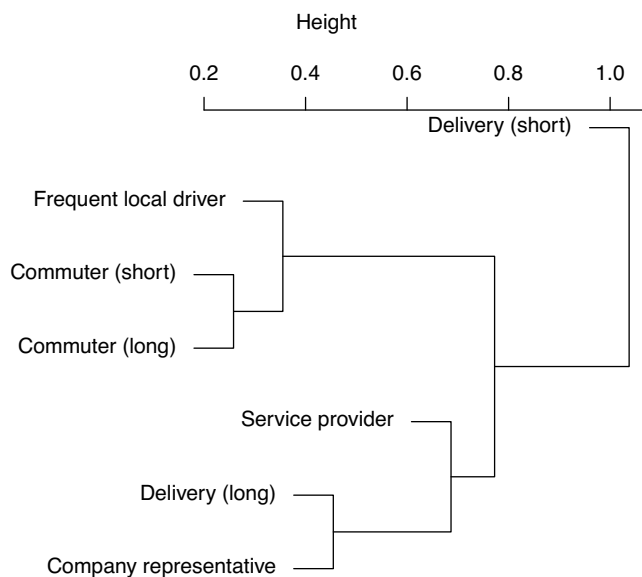


Figure 4. Dendrogram providing an overview of the cluster distances

2.3.2.1 Describing the average driver

The average driver (982 data sets, 100% of the sample) that represents all seven detected driver segments can be described as follows. In 50% of cases, the roundtrip distance is greater than 51.8 km and the roundtrip duration is greater than 5.5 hours (including stops). With a mean distance of 86.4 km and a mean duration of 16.2 hours

³ The R package “stats” provides a hierarchical clustering algorithm (R Core Team, 2018).

(including stops), the distribution is skewed. There are about 35.7 roundtrips per months – in other words: somewhat more than one roundtrip per day – with 5.7 stops per roundtrip.

The distance of individual trips is less than 6.4 km in 50% of cases and their median duration is 0.2 hours (or about 13 minutes). Again, the distribution is skewed with a mean trip distance of 14.9 km and a mean trip duration of 0.4 hours (or about 22 minutes).

Overall, drivers cover 2,359 km per month and the average speed is 71.2 km/h. The greatest share of mileage is covered on highways (42%) or on extra-urban roads (35%). A smaller share of mileage is covered on urban roads (23%).

Typically, most mileage is covered from Monday to Friday (89 km per weekday), while on weekends with 52 km the average daily mileage is lower. During weekdays, daily covered mileage is rather uniform. With about 92 km most mileage is covered on Fridays, while the shortest distance is covered on Mondays (86 km). During weekends, on Saturdays 65 km and on Sundays 38 km are covered.

The median parking duration at a primary location is 9.6 hours or 15.6 hours per day. At the secondary parking location, the median parking duration is 3.4 hours or 5.3 hours per day. In 87% of cases primary parking locations remain stable from month to month. Secondary locations remain stable in about 50% of cases.

2.3.2.2 Segment #1: Frequent local driverⁱⁱ

About 25.1% of the fleet belong to the segment of “frequent local drivers” (FLD). It is characterized by rather short roundtrips. 50% of their trips are shorter than 11.4 km and last less than 2.5 hours (30 min. driving time + stops). The distribution is skewed so that the mean roundtrip is 33.6 km with a mean duration of 6.8 hours (including stops). The segment shows many roundtrips per month (~48.7 on average) with about 3.8 stops per roundtrip. Individual trips have a median distance of 3.0 km and a median duration of 0.1 hours (or 8 minutes). The mean distance is 8.7 km and takes about 0.25 hours (or 15 minutes), which again indicates a skewed distribution. Overall, 1,539 km are covered each month.

Daily mileage is moderate (51 km on workdays, 51 km on weekends). During workdays, the shortest daily distance is covered on Mondays (49 km), while on Fridays the longest distance (53 km) is covered. On weekends, 53 km are covered on Saturdays and 48 km on Sundays.

Total daily parking duration at primary location is quite long (median: 16.9 hours), which may be interpreted such that the primary location poses a driver's home while the secondary location (median daily parking duration: 5.1 hours) is a frequent point of interest (e.g., half-day working place for some drivers). A typical parking event at the primary location takes about 6.8 hours (median), while at the secondary location the median

parking duration is 2.9 hours. The stability of primary/secondary locations over time is high: primary remains the same from month to month for 89% of cases. Secondary locations remain stable in 48% of all cases.

Road types and speeds include many urban drives (33%) and extra-urban drives (38%). Highway mileage is moderate (30%), which results in an equally moderate average speed (70.0 km/h). It can be assumed that these vehicles are most likely used by private car users, such as local workers (possibly part-time employed), parents that stay at home, or retirees who frequently make shorter trips. The figures indicate that members of this segment could live in the suburbs, live or work in a town/city, and actively drive from area to area via highways.

2.3.2.3 Segment #2: Commuter (short)ⁱⁱ

The second segment contains 25.1% of the fleet and shows medium-length roundtrips with 50% being shorter than 24.5 km and lasting less than 5.5 hours (including stops). The distribution is highly skewed so that the mean roundtrip is 39.4 km and 9.8 hours, respectively. The typical car drives 35.0 roundtrips per month and during each roundtrip there are about 3.9 stops. During an average trip, there are about 6.2 km covered (median; respectively 10.2 km mean distance) and each trip takes about 0.2 hours (median; respectively 0.3 hours mean duration) or 12 minutes (median; respectively 16 minutes mean duration). The monthly driven mileage is 1,331 km and the average speed is 66.0 km/h. Daily mileage is almost equal on workdays (44 km during the week; smallest value of 42 km on Mondays and largest value of 48 km on Fridays) and weekends (44 km during the weekend, 48 km on Saturday and 41 km on Sunday). Most mileage is covered on extra-urban (44%) or on urban (35%) roads. A smaller portion of mileage is covered on highways (21%).

Daily parking duration at the primary location is moderate (median: 15.2 hours). The car parks 6.9 hours per day (median) at a secondary location. The median duration of an individual parking event is 10.9 hours at the primary and 4.8 hours at the secondary location.

These vehicles might belong to employed persons who travel about once a day from their home to their workplace and back. Primary and secondary parking locations are very stable over time (91% vs. 67%).

2.3.2.4 Segment #3: Commuter (long)ⁱⁱ

Drivers from segment 3 (24.2%) drive more than 41.5 km in 50% of cases and half of the roundtrips last more than 6.7 hours. With a mean distance of 100.1 km and a mean duration of 30.3 hours (including stops), results are highly skewed. Roundtrips do not occur every day (21 roundtrips per month) and there are about 5.2 stops per roundtrip. With a median distance of 7.3 km and a median duration of 0.25 hours (15 minutes), respectively with a mean distance of 19.4 km and a mean duration of 0.4 hours (24

minutes), results for trip distance and duration are highly skewed as well. Each month, 1,830 km are driven, and the mean speed is 85.2 km/h.

Average daily mileage on weekdays (63 km) and on weekends (54 km; 57 km on Saturday and 51 km on Sunday) is rather similar. Again, during weekdays on Mondays, shortest distances are covered (58 km) while on Fridays daily mileage is higher (70 km).

Daily parking duration at the primary location is moderate (median: 15.7 hours) and a typical parking event at the primary location takes 12.8 hours. The car is parked for 7.3 hours per day (median) at a secondary location, or for 4.7 hours per parking event at the secondary location. The primary location is relatively unstable (75%) with many switches with the secondary location (9%), which may indicate longer business trips or the existence of a second household near the working location. The secondary location is stable in only 41% of cases.

These data may be associated to employed people, who travel larger distances, and either are not at home every day or do not travel every day. Their trips take place mostly on highways (49%), followed by urban (22%) and extra-urban (29%) roads. Average speed (85.2 km/h) is significantly higher than for segments 1 and 2.

2.3.2.5 Segment #4: Delivery (short)ⁱⁱ

With only 4.8%, the fourth segment poses the smallest group of drivers. 50% of roundtrips in this segment are very short (i.e., smaller than 0.7 km) and last about 0.3 hours or 17 minutes. The distribution is highly right skewed with a mean roundtrip length of 47.8 km and a duration of 4.2 hours (including stops). There are about 61 roundtrips per month and during each roundtrip there are roughly 8 stops. Individual trips cover about 1.7 km (median) and take about 0.1 hours (median; or 6 minutes). The comparison with mean figures (8.6 km distance, 0.2 hours or 13 minutes duration) again reveals a highly skewed distribution. Overall, 2,822 km are covered, and the average speed is 57.5 km/h. Daily mileage on workdays is high (115 km; longest on Thursdays with 121 km and shortest on Wednesday with 108 km) and drops substantially on weekends (40 km with 73 km on Saturday and 7 km on Sunday).

Median parking time between trips is short, both at the primary and the secondary location (median: 1.6 vs. 1 hours), which indicates that cars return to these locations several times a day. During the entire day, the parking duration at the primary location is about 16.4 hours and at the secondary location it is about 1.8 hours. The stability of the two types of locations is high (95% vs. 50%) with almost no switches.

Mileage is typically covered on highways (43%) and on extra-urban roads (39%). A smaller portion (18%) is covered on urban roads. This pattern might be typical for commercial service or delivery vehicles.

2.3.2.6 Segment #5: Service providerⁱⁱ

This small segment (5.3%) includes drivers that are assumed to be, for instance, field service employees or express parcel carriers. The corresponding roundtrips are rather long (median values: 91 km and 5.0 hours). The mean roundtrip is 153.2 km with a mean duration of 9.8 hours (including stops). The number of roundtrips per month is 49.5 on average (i.e., 1-2 per day) with 6.6 stops per roundtrip. Individual trips cover about 11.2 km (median) and take 0.3 hours (median; or 21 minutes). Related mean values are 26.5 km and 0.74 hours (or 45 minutes). Each month, 6,527 km are covered, and the mean speed is 65.7 km/h. The majority of mileage is driven on highways (51%), followed by extra-urban roads (35%) and urban roads (15%).

Daily mileage is very high and differs between weekdays (269 km) and weekends (90 km or 165 km on Saturday and 15 km on Sunday). Longest distances are covered on Fridays (278 km) and on Mondays daily driven distances are typically shorter (268 km). More than 50% of parking periods at a primary location are extremely short (1.3 hours). This segment is hence the only group of cars that spends more time driving than parking. The median daily parking duration at the primary location is 13.3 hours; cars park 2.1 hours per day (median) at a secondary location and each parking event at the secondary location takes about 1.4 hours. While the primary location is very stable (93%), the secondary is not (42%).

2.3.2.7 Segment #6: Delivery (long)ⁱⁱ

In contrast to the fourth segment, the vehicles referred to as “delivery (long)” (DL) (5.5%) are used for long trips. Roundtrips cover about 94.1 km (median) and take 7.3 hours (median). Mean values (93.1 km and 11.1 hours) are relatively comparable. The mean number of roundtrips per month is 31.3, which equals about one per day and there are about 15.6 stops per roundtrip. The median distance of individual trips is 2.3 km (mean: 6.2 km) and their median duration is 0.1 hours or 6 minutes (mean: 0.2 hours or 11 minutes). The average monthly driven mileage is 2,451 km with an average speed of 57.5 km/h. The longest distances are covered on workdays (98 km with a maximum of 99 km on Tuesdays and a minimum of 96 km on Fridays) while shorter distances are covered during the weekend (39 km or 72 km on Saturday and 5 km on Sunday).

The median duration of the parking periods at the primary parking location is rather long (14.1 hours per parking event or 16.3 hours per day), whereas parking at the secondary location (median: 0.9 hours per parking event or 1.8 hours per day) as well as all other stops are very short. In sum, the profile of this driver group is characterized by frequent regional roundtrips with many intermediate stops. The primary parking location is stable on a monthly basis (91%), the secondary location is stable in 48% of cases. 45% of all trips are made in extra-urban areas, followed by urban areas (35% of mileage) and highways (21%).

2.3.2.8 Segment #7: Company representativeⁱⁱ

The last segment accounts for 10.1% of the fleet; it differs from the others with regard to the length of the roundtrips: 50% of them are longer than 225.1 km and last more than 11.4 hours. The mean length of roundtrips is 279.2 km and they take about 33.4 hours (mean). On average, there are about 8.9 stops per roundtrip. Drivers make these roundtrips about 23.8 times per month and mostly on weekdays (244 km vs. 60 km on weekends or 97 km on Saturday and 24 km on Sunday). During the work week, a minimum of 239 km is covered on Mondays and a maximum of 253 km is covered on Thursdays. Individual trips cover 14.8 km (median; mean: 33.1 km) and take 0.46 hours or 28 minutes (median; mean: 0.78 hours or 47 minutes).

The median parking time at a primary location is rather long (11.6 hours per parking event or 14.2 hours per day), but the median at the secondary location is 1.9 hours per parking event (or 2.7 hours per day). The primary location is stable (87%), whereas the secondary location is stable in only 39% of cases, which may be due to the extensive number of meetings with customers. These characteristics are in line with the high fraction of highway mileage (58%) compared to extra-urban (28%) and urban (14%) areas. The average speed is high with 70.2 km/h and each month 5,763 km are driven. This driving profile may be considered typical for company representatives who visit far distant customers.

The usability of electric vehicles for each segment and the implications to the grid are presented hereafter.

2.4 Usability analysis

2.4.1 Simulation modelⁱⁱ

Based on segment-specific driving patterns of the vehicle fleet, the resulting electric energy consumption and charging processes are derived by utilizing the simulation procedure from (Wenig, Sodenkamp, and Staake, 2015)⁴. Energy consumption E during a trip k is the sum of energy consumptions $e_{j,k}$ within the pairs of consecutive measurement points j : $E_k = \sum e_{j,k}$. The car energy consumption model by Larminie and Lowry (2003) was adopted, which implies that $e_{j,k}$ depends on the tractive effort F needed to move the vehicle, energy efficiency δ_{car} of the car, and the trip length $l_{j,k}$: $e_{j,k} = \frac{F \cdot l_{j,k}}{\delta_{car}}$.

The tractive effort F is the sum of three forces: aerodynamic drag F_{ad} , rolling resistance force F_{rr} , and linear acceleration force F_{la} . Aerodynamic drag F_{ad} largely depends on the frontal area and the shape of the vehicle, and is defined by: $F_{ad} = \frac{1}{2} \cdot \rho \cdot A_{car} \cdot C_d \cdot v^2$, where ρ is the air density, A_{car} is the car's frontal area, C_d is the air drag coefficient, and v is the vehicle speed. Rolling resistance F_{rr} is caused by friction of the wheel on the road and primarily depends on the mass of the vehicle: $F_{rr} = \mu_{rr} \cdot m \cdot g$, where μ_{rr}

⁴ In (Wenig, 2014a) an earlier version of this model is described.

is the rolling resistance coefficient, m is the vehicle's mass, and g is the gravitational acceleration. Finally, acceleration force F_{la} is defined by: $F_{la} = m \cdot a$, where m is the mass of the vehicle, and a is its acceleration. Due to the low granularity of the data, the acceleration a was not calculated. Instead, standard values from ECE-15, EUDC, and EMPA T130 driving cycles (Barlow, Latham, McCrae, et al., 2009), as provided in (André and INRETS, 2009), were used. Furthermore, Larminie and Lowry (2003) suggest that m can be increased by 5% in the calculation of F_{la} to include the wheel force needed to provide the angular acceleration, and assume that with a negative total tractive effort caused by deceleration, 50% of energy is recuperated when braking.

The energy fed at a charging location X depends on the parking time d and charging power P : $o_{j,x} = P_x \cdot d_{j,x}$. Losses of the energy transfer from and to the battery are included in the energy efficiency δ_{car} of the car. Thus, the state of battery charge $soc_{j,k}$ between two consecutive measurements is: $soc_{j,k} = soc_{j-1,k} + o_{j,k} - e_{j,k}$, $0 \leq soc \leq B$, where B is the battery capacity. The non-linear nature of battery charging time is considered as follows: the first 80% of the total required charge is made linearly while the remaining 20% of the charge require triple time (Hsieh, Chen, and Huang, 2001). In this study, it is assumed that the PHEV is driven electrically if the battery is not empty. If the battery is empty, the car is powered by an internal combustion engine, such as is the case with the BMW i3 range extender (BMW AG, 2013), until the next charging facility is reached.

Driving patterns might be different between a conventional car and an electric car, yet it is assumed that mobility habits of individuals are rather stable. Furthermore, the behavior of a large number of conventional car drivers might be better suited to predict general electric mobility patterns than the behavior of today's early electric vehicle adopters.

The trip data and the simulation model described above are used to compare 18 different electric mobility scenarios, based on different assumptions for charging power, charging locations, and vehicle type. Regarding charging power, the following three levels were considered: (i) 3.7 kW (maximum load of the typical European wall outlet), (ii) 7.4 kW (typical configuration for faster chargers at home), and (iii) 50 kW (typical fast charger in public infrastructures) (Wenig, Sodenkamp, and Staake, 2015). Charging locations may (i) either be limited to primary locations (ii) or include primary and secondary locations (e.g., at work).

Moreover, three different types of electric vehicles were simulated. Following the categorization of vehicles by curb weight according to the National Highway Traffic Safety Administration (NHTSA, 2017), a "passenger car compact", inspired by a BMW i3 (a PHEV with range extender) was considered. The vehicle is also simulated with battery capacity variations of 6.3 kWh, being one third of the capacity of the regular model, and 56.4 kWh, which poses three times the capacity. The car weight is kept constant regardless of the battery size; this is done to ease comparability and can be justified by expected battery improvements over time. Table 8 summarizes the corresponding vehicle characteristics.

Table 8: Simulated car profiles (BMW AG, 2013; De Haan and Zah, 2013)

Vehicle parameters	Compact car
Weight [kg]	1,270
Frontal area [m ²]	2.8
Rolling resistance coefficient	0.011
Air resistance coefficient	0.31
Battery capacity [kWh]	6.3 / 18.8 / 56.4

2.4.2 Results and discussion

2.4.2.1 Electric reachabilityⁱⁱ

Using the simulation model and the empirical data, two indicators of electric reachability for each of the seven driver segments were computed: the portion of trips that can be driven in a fully electric fashion and the share of the overall distance that can be completed electrically. The corresponding results are depicted in Figure 5 and Figure 6, respectively.

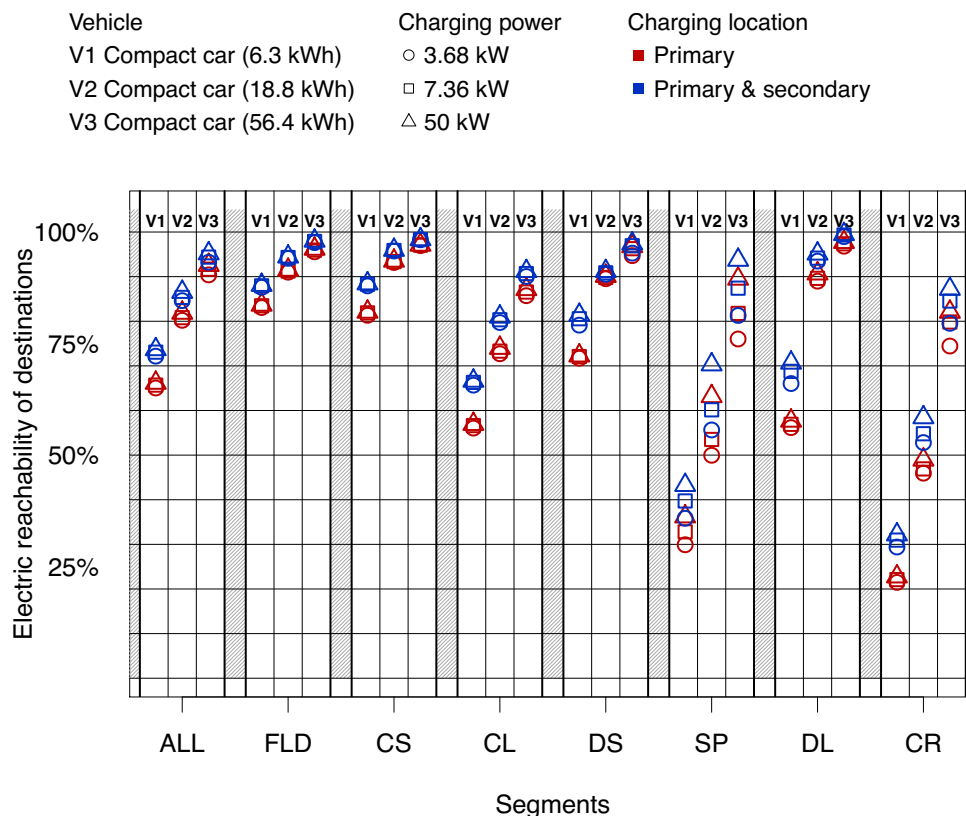


Figure 5. Trips that can be completed electrically (share of electrically reachable destinations)

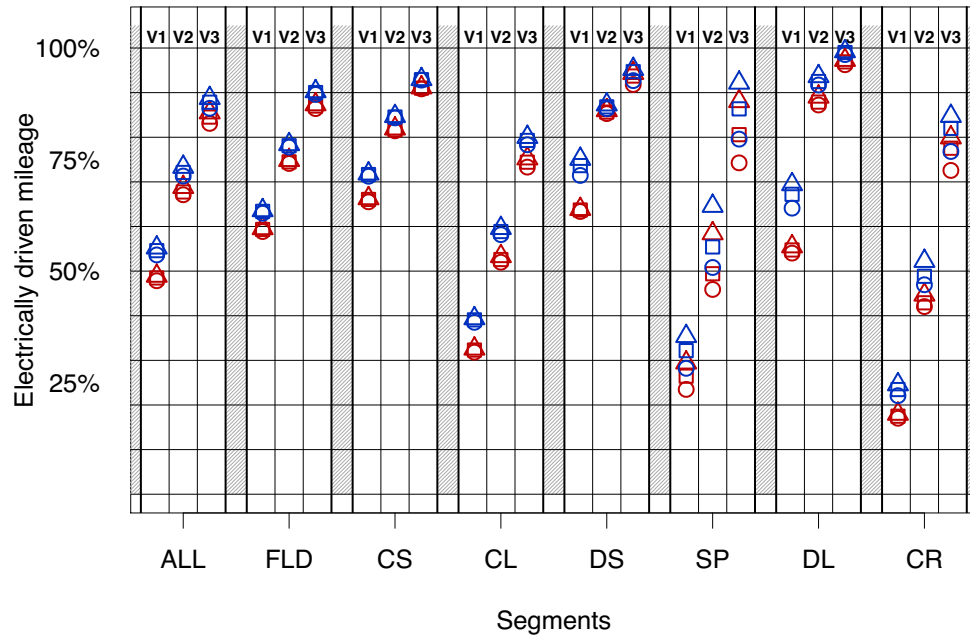


Figure 6. Distances that can be completed electrically (share of electrically driven mileage)

The results reveal that all performance indicators vary drastically between different driver segments and deviate considerably from the overall average values; the findings thus highlight the necessity to conduct segment-specific assessments. The differences are large for all car configurations but are especially pronounced for cars with small battery capacities.

Taking a segment-specific perspective, segments 1 and 2 (FLD and CS) are especially well suited for an electrification: even with the smallest battery size (6.3 kWh) and 3.7 kW home charging only, they can complete above 80% of the trips electrically and drive more than 60% of the mileage electrically. Segments 1 and 2 together account for about half of the fleet. On the other side of the spectrum, segments 5 and 7 (SP and CR) can complete only 30% and 21% of the trips without the help of a range extender and travel only about 20% of the mileage electrically.

Furthermore, advances in the charging infrastructure regarding the maximum power output show only a marginal impact in segments 1 to 4 (FLD, CS, CL, DS), which together include almost 80% of the fleet. Fast charging makes some difference to “service providers” (SP) and “company representatives” (CR) with together about 15% of the fleet and to a limited extent also to the special case of long-distance delivery vehicles with small batteries. Regarding the three largest segments, segment 3 (CL) benefits the most from additional charging opportunities at the work place, whereas for segments 1 and 2 (FLD and CS), the advances from the extended charger density are rather limited both regarding the electric reachability and the electrified mileage.

Third, for all segments, larger batteries outperform more sophisticated charging infrastructures: even for the case of low power home charging only, the next-larger battery

yields better KPIs for electric reachability and electrified mileage. The effect is especially pronounced for “company representatives” (CR) with their long trips at high average speed. Fast charging has the smallest effect on driving performance indicators. On average, the impact is marginal (~2%), being most relevant for 15% of the fleet in case of medium- and large-battery vehicles in segments 5 and 7 (SP and CR). For almost 75% of the fleet (i.e., FLD, CS, CL) fast charging does not show significant improvements.

Fourth, the two segments 5 and 7 (SP and CR) represent use cases that are especially challenging with respect to an electrification. This phenomenon can be attributed to the fact that roundtrip distances in these two segments are by far the longest among the whole driver population. They show the lowest electric reachability and the lowest share of electrified mileage. Moreover, charging power and charging location play a more important role in segment 5 (SP) than in any other segment owing to short parking times at the primary location.

Finally, segments 4 and 6 (DS and DL; representing a small part of the fleet of 10.3%) appear to have a distinct battery capacity threshold after which an electrification leads to very good performance indicators: reachability and share of electrified mileage increase dramatically when a battery with a capacity of 18.8 kWh is used.

From a policy maker’s perspective, the amount of overall electrified distance is of high relevance as well. Drivers that could cover the greatest share of mileage electrically do not necessarily electrify the greatest overall distance in absolute terms. Table 9 and Table 10 contrast the relative share and the absolute mileage that can be electrified in different segments and for different charging parameters. The figures reveal a contradicting nature of the relative share and the absolute electrified mileage.

Table 9. Proportional and absolute electrified mileage: average over all vehicle types; 7.4 kW charging power

Segment	1	2	3	4	5	6	7	All
Segment name	FLD	CS	CL	DS	SP	DL	CR	ALL
Segment size	246	246	238	47	52	54	99	982
% of fleet	25.1%	25.1%	24.2%	4.8%	5.3%	5.5%	10.1%	100.0 %
Primary charging								
Mileage electrified	74%	80%	53%	81%	52%	80%	46%	67%
Mileage electrified [km]	1,133	1,059	972	2,286	3,404	1,957	2,650	1,578
Primary & secondary charging								
Mileage electrified	77%	83%	59%	85%	58%	86%	51%	72%
Mileage electrified [km]	1,188	1,105	1,081	2,400	3,785	2,114	2,964	1,687

Table 10: Proportional and absolute electrified mileage: primary location charging only; 7.4 kW charging power

Segment	1	2	3	4	5	6	7	All
Segment name	FLD	CS	CL	DS	SP	DL	CR	ALL
Segment size	246	246	238	47	52	54	99	982
% of fleet	25.1%	25.1%	24.2%	4.8%	5.3%	5.5%	10.1%	100%
6.3 kWh compact size passenger car								
Mileage electrified	59%	66%	32%	64%	26%	55%	17%	48%
Mileage electrified [km]	913	879	591	1,797	1,727	1,342	1,008	1,143
18.8 kWh compact size passenger car								
Mileage electrified	74%	82%	53%	86%	49%	88%	43%	68%
Mileage electrified [km]	1,146	1,087	963	2,417	3,225	2,154	2,472	1,598
56.4 kWh compact size passenger car								
Mileage electrified	87%	91%	74%	94%	81%	97%	78%	85%
Mileage electrified [km]	1,339	1,211	1,362	2,645	5,260	2,375	4,469	1,994

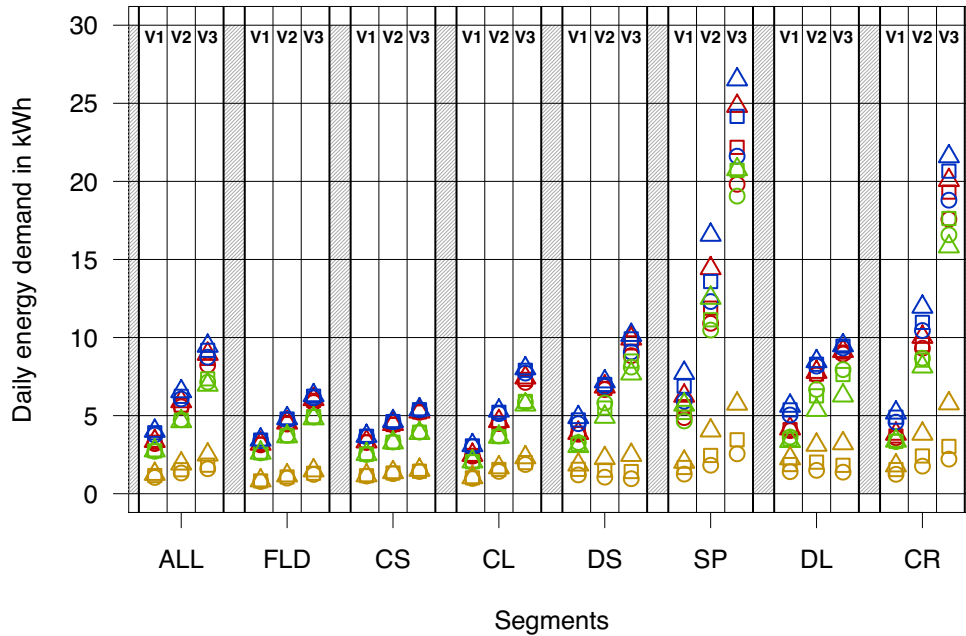
2.4.2.2 Impact of vehicle charging on the electric power networkⁱⁱ

An analysis of the network load for different electric mobility scenarios follows. First, overall daily energy demand is considered. Figure 7 a) illustrates the average daily electricity demand for the whole sample as well as for individual segments. Detailed results for weekdays and weekends are given in Figure 7 b) and c).

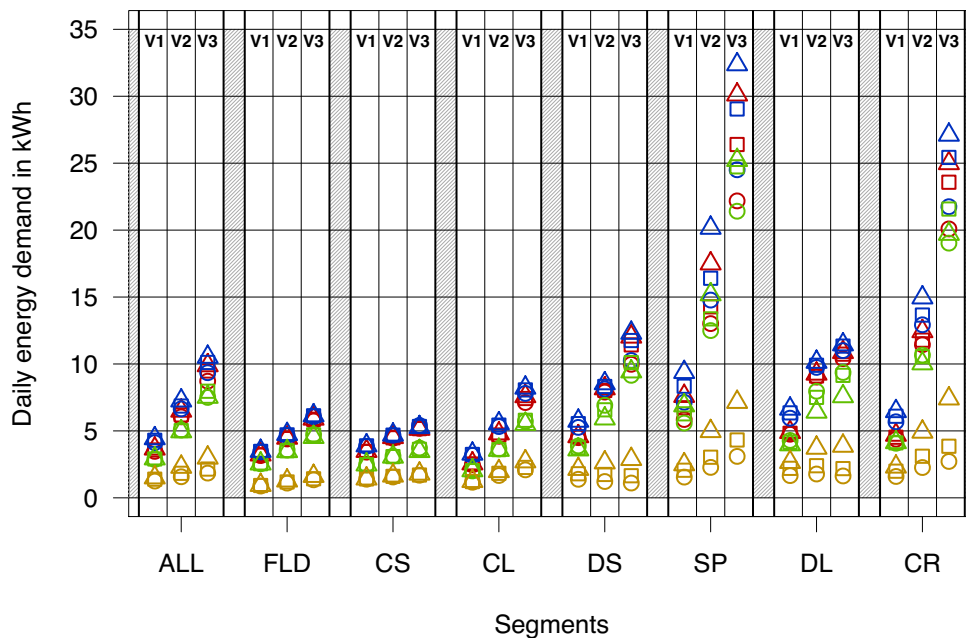
When looking at the fleet as a whole, the expected interrelations become evident: first, electricity demand increases considerably with larger batteries and a more potent charging infrastructure. Compared to the case of a vehicle with a small battery (6.3 kWh) and 3.7 kW charging power at a primary parking location only, energy demand increases by a factor of 2.9 on average if a large battery (56.4 kWh), a secondary charging location, and fast charging (50 kW) become available. In this case, the network load at the primary location increases from on average 0.3 kW to 0.5 kW during the late morning and from 0.3 kW to 0.7 kW in the late afternoon peak times.

As is the case for electric reachability and share of electrified mileage, the grid impact varies considerably between segments. First, over all battery and infrastructure configurations, segments 1 to 3 (FLD, CS and CL; together about 75% of the fleet) show an electric energy demand that is lower than average, whereas segments 4 to 7 (DS, SP, DL, CR; which can most likely be subsumed as commercial vehicles that in the sample account for about 25%) consume above average.

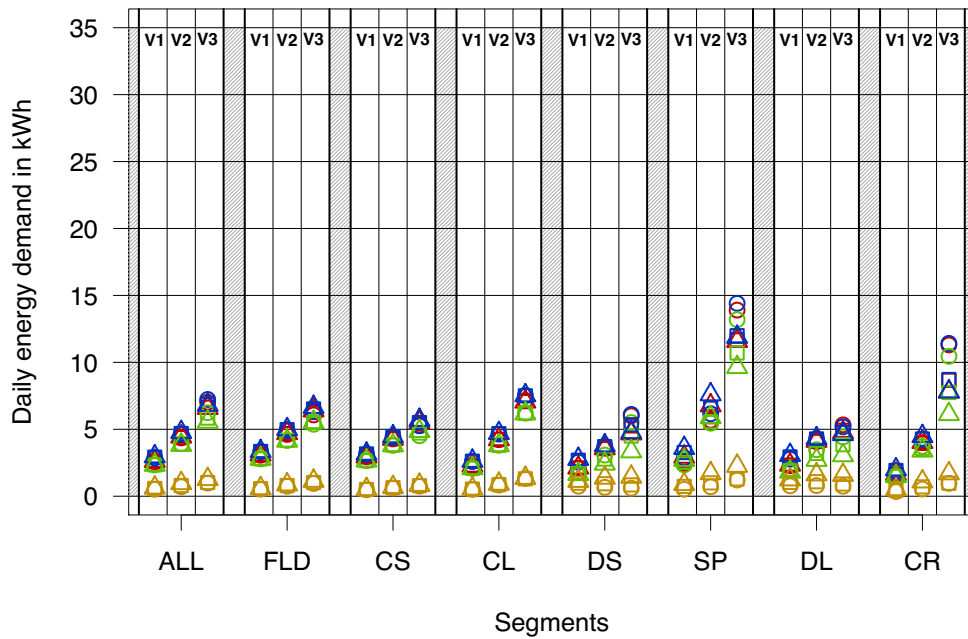
- | | | |
|---------------------------|-----------------------|---|
| Vehicle | Charging power | Charging location |
| V1 Compact car (6.3 kWh) | ○ 3.68 kW | ■ Primary |
| V2 Compact car (18.8 kWh) | □ 7.36 kW | ■ Primary & secondary |
| V3 Compact car (56.4 kWh) | △ 50 kW | ■ Primary & secondary
(Demand at primary only) |
| | | ■ Primary & secondary
(Demand at secondary only) |



(a) Average daily energy demand from PHEV charging



(b) Energy demand from PHEV charging on weekdays (Monday-Friday)



(c) Energy demand from PHEV charging on weekends (Saturday-Sunday)

Figure 7. Daily energy demand at the charging locations under different PHEV scenarios

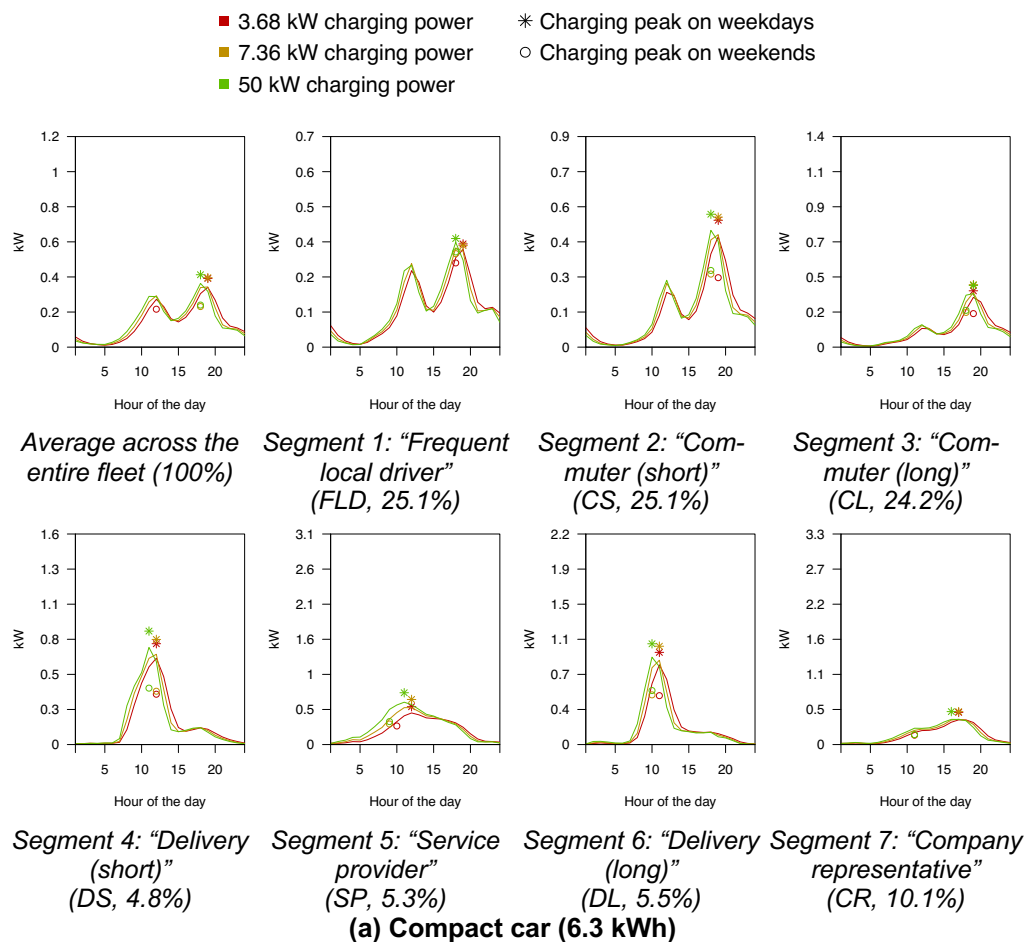
Second, the results show that the impact of battery capacity on energy demand is moderated by segment membership. Larger batteries lead to a much higher electricity demand especially for “service providers” (SP) and “company representatives” (CR) than for “frequent local drivers” (FLD), “commuters (short)” (CS), and “commuters (long)” (CL). The implications are two-fold. When considering absolute electricity demand and not the potential peaks over time, “service providers” (SP) and “company representatives” (CR) are especially burdensome for the grid. Moreover, these segments show the highest potential per car to substitute large amounts of fossil fuels by electricity. In contrast, “frequent local drivers” (FLD), “commuters (short)” (CS), and “commuters (long)” (CL) have a limited effect on fossil fuel use with increasing battery capacities.

The data also indicate that, if charging is possible at primary and secondary locations, the energy demand at the primary location is by far the dominant one. Demand at the secondary location is relatively stable, independent from the segment and, to a lesser extent, even from battery capacities.

Among the individual segments, “commuters (short)” (CS) show the lowest demand volatility under scenario changes. Here, maximum parameter improvements lead to a network load increase of approximately 60%. For segments 1, 4, and 6 (FLD, DS, and DL), the same improvements more than double the load, mainly at the primary location. For segment 3 (CL), energy demand is increased approximately by a factor of three, while segments 5 and 7 (SP and CR) are most sensitive to the parameter changes with an increase by factors of about five and six between the minimum and the maximum val-

ues. In contrast, on average the network load drops considerably on weekends, particularly for the smaller segments 4-7 (DS, SP, DL, CR). At the secondary location, energy demand on weekends is about 1 kWh per day for all segments.

The grid load over time in fact varies considerably between the different segments. Figure 8 a) illustrates the case “small 6.3 kWh battery vehicle with home charging only”; Figure 8 b) and c) present detailed 24-hour load profiles for cases with 18.8 kWh and 56.4 kWh battery vehicles. Figure 9 a) to c) present detailed 24-hour load profiles of the other charging infrastructure cases. A closer look at these plots reveals that for the three large segments (FLD, CS, CL), the peak charging times are in the late afternoon. A second smaller demand peak occurs in the late morning. In contrast, segments 4 to 6 (DS, SP, DL) exhibit single prolonged peaks, typically at noon. Segment 7 (CR), again, peaks in the late afternoon. A comparison among all segments suggests that cars in segments 1 to 3 and 7 (FLD, CS, CL, CR) tend to be charged in the evening or at night, while cars in segments 4 to 6 (DS, SP, DL) tend to be charged during the day. This finding is consistent with the interpretation of the segments: cars in segments 1 to 3 and 7 (FLD, CS, CL, CR) leave their primary location in the morning and return in the evening, whereas cars in segments 4 to 6 (DS, SP, DL) could be company-held vehicles, which return to the primary location several times a day.



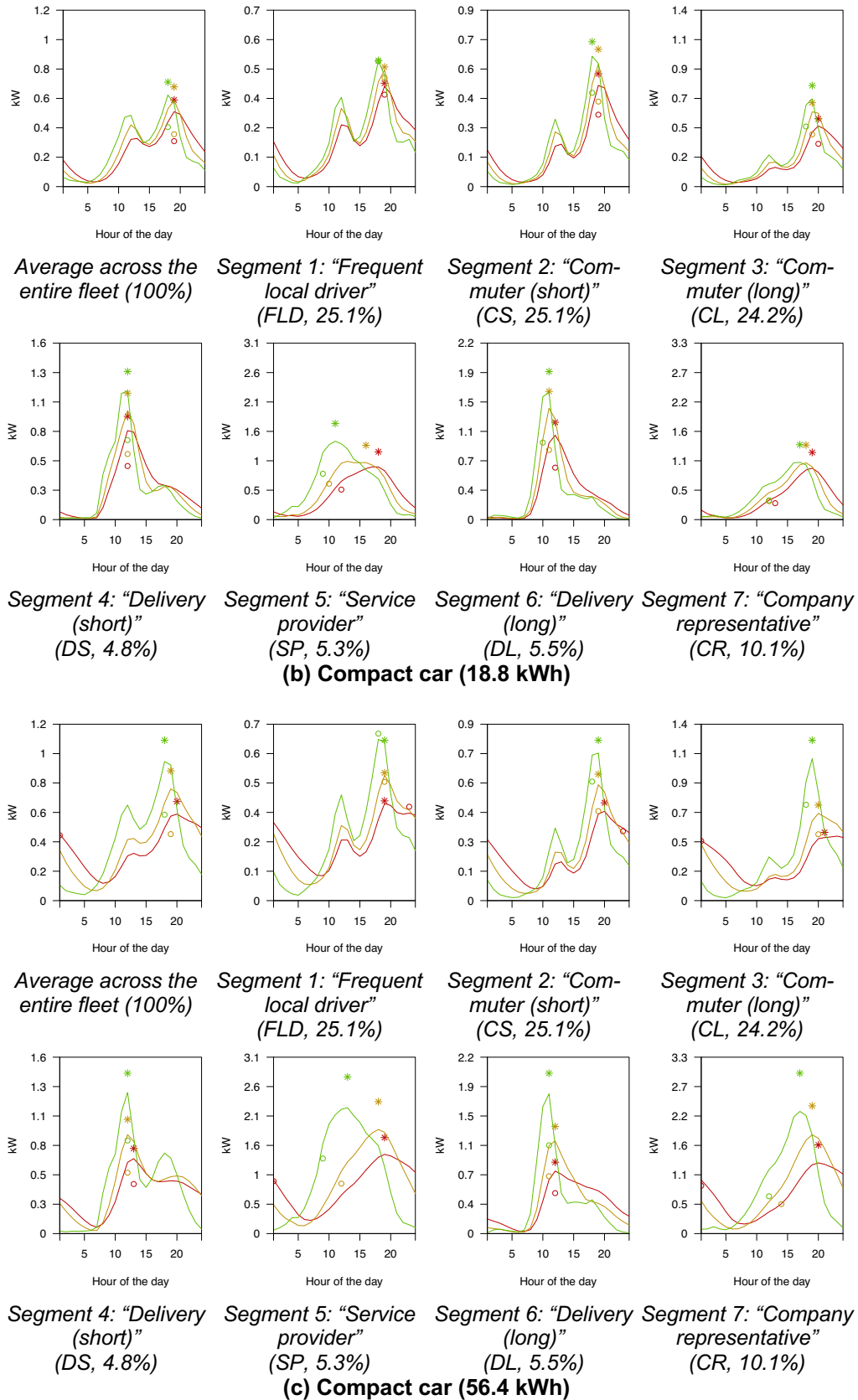
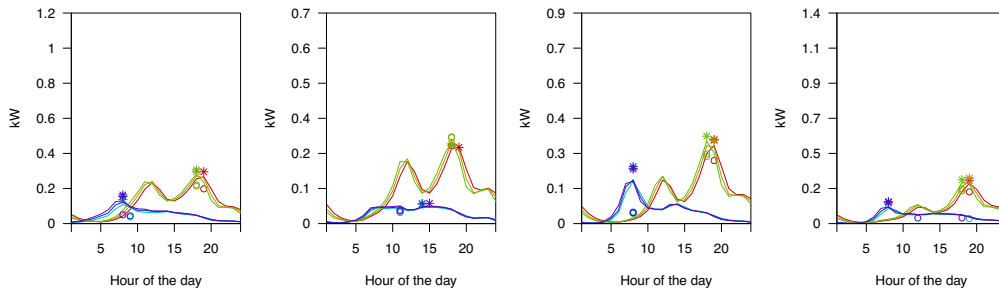


Figure 8. Impact of PHEV charging on the electric power network under primary location charging

Primary location charging Secondary location charging * Charging peak on weekdays
 ■ 3.68 kW charging power ■ 3.68 kW charging power ○ Charging peak on weekends
 ■ 7.36 kW charging power ■ 7.36 kW charging power
 ■ 50 kW charging power ■ 50 kW charging power

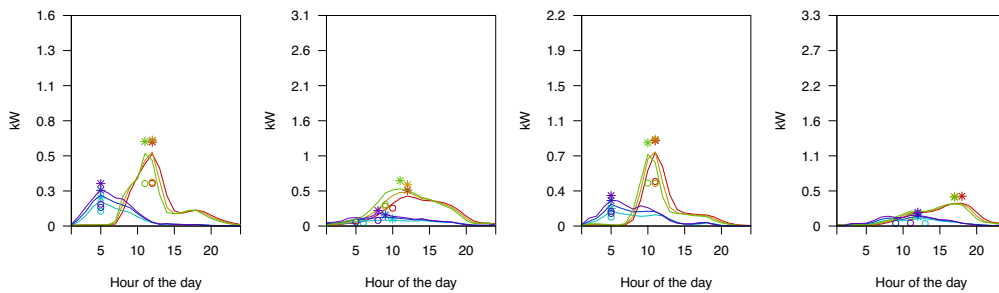


Average across the entire fleet (100%)

Segment 1: "Frequent local driver" (FLD, 25.1%)

Segment 2: "Commuter (short)" (CS, 25.1%)

Segment 3: "Commuter (long)" (CL, 24.2%)



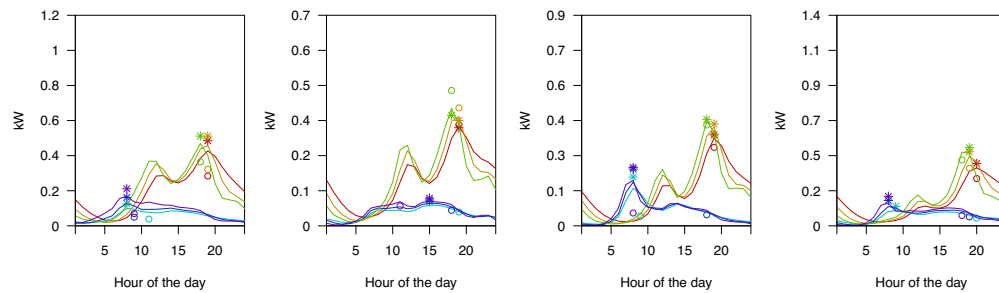
Segment 4: "Delivery (short)" (DS, 4.8%)

Segment 5: "Service provider" (SP, 5.3%)

Segment 6: "Delivery (long)" (DL, 5.5%)

Segment 7: "Company representative" (CR, 10.1%)

(a) Compact car (6.3 kWh)

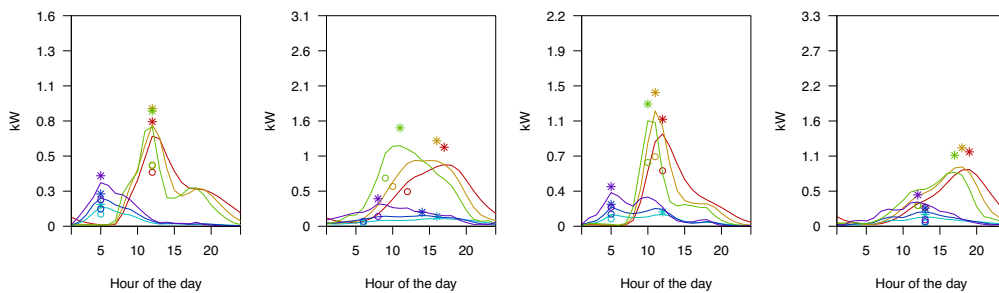


Average across the entire fleet (100%)

Segment 1: "Frequent local driver" (FLD, 25.1%)

Segment 2: "Commuter (short)" (CS, 25.1%)

Segment 3: "Commuter (long)" (CL, 24.2%)



Segment 4: "Delivery (short)" (DS, 4.8%)

Segment 5: "Service provider" (SP, 5.3%)

Segment 6: "Delivery (long)" (DL, 5.5%)

Segment 7: "Company representative" (CR, 10.1%)

(b) Compact car (18.8 kWh)

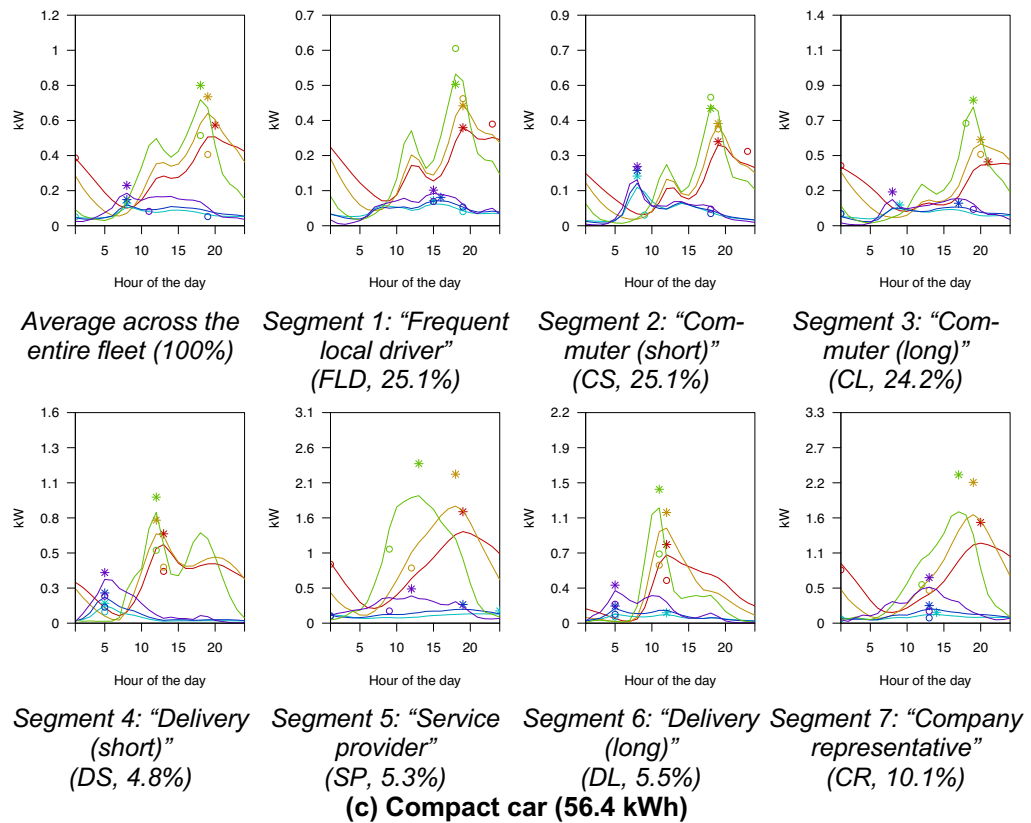


Figure 9. Impact of PHEV charging on the electric power network under primary and secondary location charging

Moreover, the analysis also shows that, as expected, larger batteries cause higher demand peaks and shift the peaks to the later hours because charging of the battery takes more time. Load profiles for the combination of large batteries and slow chargers show higher energy demand at night for all individual segments and are much smoother than if fast chargers are available. Usually demand peaks are higher on weekdays and lower on weekends. This is particularly evident for segments 4-7 (DS, SP, DL, and CR). On the other hand, a higher charging power slightly shifts the demand peak to the left (i.e., to the earlier hours) and increases peaks as well while charging times are shortened. Compared to the base case (compact car with 6.3 kWh battery, charging at a primary parking location with 3.7 kW), maximum battery and charger improvements together increase the daily demand peak by a factor of about 2.8.

If a secondary charging opportunity is given, load profiles at the primary charging facility are roughly comparable to the primary charging scenario; however, demand peaks are alleviated. Demand at the secondary parking location peaks on average in the early morning around 7-8 am. However, the overall network impact at the secondary parking location is smaller and the demand profile curve is smoother than for the primary location for all segments.

2.5 Conclusionⁱⁱ

The main objectives of this chapter were to develop a procedure for the identification of car driver segments on the foundation of their real-world driving behavior and to show the segment-specific usability and impact to the grid regarding PHEV and battery electric vehicles. For this purpose, the use of a cluster analysis approach to detect vehicle usage patterns in a geographic area from fine-grained time series of GPS location measurements was proposed.

The specific profile of each segment regarding trip length, parking times, etc. allows for evaluating the practical utility of different electric vehicles to the respective driver segments measured by the percentage of roundtrips and total mileage that can be completed electrically. To this end, a simulation model, which takes several car characteristics into account and allows for comparing the impact of different car configurations regarding, for example, battery size and charging power, was utilized. Seven driver segments were identified and compared and subsequently evaluated in terms of their compatibility to electric mobility adoption. Furthermore, the model allows for estimating the segment-specific impact of vehicle charging and individuals' driving behavior on electricity distribution networks (i.e., electricity load at common parking locations such as homes and workplaces).

This chapter (together with (Sodenkamp, Wenig, Thiesse, et al., 2019)) contributes to the literature in three ways. First, instead of restricting estimates to a pre-defined group of drivers, the segmentation approach considers the entirety of heterogeneous car usage habits and automatically divides these into meaningful and easy-to-interpret similarity groups.

A second contribution refers to the automatic and periodic identification of major vehicle parking locations (e.g., at home or at work), which allows for processing even large datasets with distinct driver segments. Knowledge about major vehicle parking locations is key to accurate forecasts of charging times and the corresponding network load as well as to effective planning of charging facilities.

Third, the utilized model accurately simulates energy consumption of individual cars during the trips as well as the process of unmanaged battery charging (i.e., charging begins when the vehicle is plugged in). With the help of this simulation model, different configurations of electric vehicle parameters along with information on different types of charging facilities allow for investigating vehicle usability for different groups of drivers. Values for three electric mobility scenario characteristics were varied, namely the availability of private charging facilities (primary or primary & secondary); the charging power (slow 3.7 kW, medium 7.4 kW, or fast 50 kW); and the vehicle type (compact size passenger car: 6.3 kWh, 18.8 kWh, and 56.4 kWh).

The proposed procedure and its implications were demonstrated by the example of a large heterogeneous dataset collected over 24 months from real-world drivers in Italy.

In sum, the resulting performance estimates draw a much more detailed picture of electric vehicle usability and network load (especially on a per-transformer station level) than prior aggregated studies considering driver populations as a coherent whole.

This study and the proposed procedure could be used by car manufacturers in the identification of segment-specific vehicle requirements and targeted marketing strategies to increase the vehicles' attractiveness for customers (Hodson and Newman, 2009). Moreover, the segment specific insights about benefits and obstacles of PHEV or battery electric vehicle adoption may help end customers take more informed purchasing decisions.

In this section, a discussion regarding the results' implications for the design of charging facilities and for battery choices is provided and the key findings for policy makers are summarized.

2.5.1 Implications with respect to charging powerⁱⁱ

For the discussion of the impact of charging power on the electrification of mileage, charging is assumed to be possible at the primary location only, and charging power values of 3.7 kW, 7.4 kW, and 50 kW are compared. The numbers represent an average over all vehicle types, if not otherwise stated.

If only slow 3.7 kW charging was possible, 66% of mileage could be electrified. With 7.4 kW, 67% of mileage could be electrified. With fast 50 kW charging, this value would increase to 68%. Thus, on average, the impact of charging power is limited. Thus, even conventional wall outlets are sufficient to electrify a considerable share of the mileage in a scenario with PHEVs with range extender.

Taking a segment specific perspective, an increase in charging power hardly improves the electrified mileage for drivers in most groups (for 3.7 kW / 7.4 kW / 50 kW of segments 1 (FLD): 73% / 74% / 74%, segment 2 (CS): 79% / 80% / 80%, segment 3 (CL): 52% / 53% / 54%, segment 4 (DS): 80% / 81% / 81%, and segment 6 (DL): 79% / 80% / 81%). Still, if relative changes are considered, drivers with the greatest average mileage profit most from higher charging power, potentially due to limited parking times at charging facilities (segments 5 (SP): 48% / 52% / 59%, segment 7 (CR): 44% / 46% / 48%).

If instead all vehicles were compact size cars with large 56.4 kWh batteries, the share of electrified mileage would increase from 83% (3.7 kW) to 86% (50 kW) for the average driver, such that in both scenarios, figures would increase by about 3-4% on average. In particular, with such vehicles, improvements due to charging power would be slightly lower for "service providers" (SP) (74% / 81% / 88%), compared to the average over all vehicle types. At the same time, for "company representatives" (CR), improvements would be slightly higher (73% / 78% / 80%), compared to the average over all vehicle types.

The findings show that charging power is of limited importance in the considered cases in terms of electrified mileage and electric reachability. Consequently, the extension of individual wall outlets should not be a key priority.

2.5.2 Implications of charging facilities at the secondary parking locationⁱⁱ

In order to discuss the impact of the availability of charging facilities on the electrification of mileage, the charging power is assumed to be 7.4 kW. The availability of charging opportunities at the primary location is compared to a scenario with charging opportunities at the primary as well as the secondary location. Again, the numbers represent an average over all vehicle types.

Considering the driver population as a whole, the results show that if charging was possible at the primary location only (e.g., at home), 67% of mileage could be electrified and 1,578 km from a total of 2,359 km per month could be driven electrically. If an additional secondary charging facility became available, this value would increase to 72%; in this case, 1,687 km (+7%) could be driven electrically per month. Thus, the availability of a secondary charging facility leads to moderate average improvements.

Taking a segment specific perspective, the impact of secondary charging facilities becomes clearer. For drivers in segments with limited roundtrip distances, the implications are rather small (primary / primary & secondary for segment 1 (FLD): 74% / 77%, for segment 2 (CS): 80% / 83%, and for segment 4 (DS): 81% / 85%). Long roundtrip distance drivers, however, yield a larger benefit from the additional charging opportunity (segment 3 (CL): 53% / 59%, segment 5 (SP): 52% / 58%, segment 6 (DL): 80% / 86%, and segment 7 (CR): 46% / 51%).

Despite of their relatively small share of electrified mileage, drivers in segments with the highest total mileage per month can electrify the highest number of kilometers in a home charging scenario (segments 5 (SP): 3,404 km of 6,527 km, 7 (CR): 2,650 km of 5,763 km). With an additional secondary charging facility, the number of electrified kilometers is further increased by 381 km to 3,785 km (SP) and by 314 km to 2,964 km (CR). Overall, charging opportunities at the secondary charging location increase the electric mileage considerably for the important segment of long-range drivers. Thus, charging facilities at the work place are helpful for the respective segments and at the same time, due to moderate loads to the grid, can be expected to induce limited stress to the network.

2.5.3 Battery capacityⁱⁱ

Finally, the impact of the battery capacity on the electrification of mileage is outlined by comparing a compact size passenger car with an 18.8 kWh battery and a compact size passenger car with a 56.4 kWh battery. It is assumed that a 7.4 kW charging opportunity is available at the primary location.

Considering the non-segmented view on the fleet, an increase in battery capacity from 18.8 kWh to 56.4 kWh greatly increases the percentage of mileage that could be electrified from 68% to 85%. If a PHEV with an 18.8 kWh battery was available, 1,598 km of 2,359 km could be electrified. For a PHEV with a 56.4 kWh battery, this value increases by about 25% to 1,994 km. This underlines that, on a macro perspective, battery size is more important than the availability of a secondary charging facility.

A segment-specific assessment reveals who benefits most from larger batteries: considering a PHEV with 18.8 kWh, most drivers (segments 1, 2, 3, 4, 6) can electrify more than half of their mileage. With a larger battery, the results improve at different magnitudes for different segments; high improvements can be shown for segment 1 (FLD) (74% / 87% for 18.8 kWh / 56.4 kWh), segment 2 (CS) (82% / 91%), segment 3 (CL) (53% / 74%), segment 4 (DS) (86% / 94%) and for segment 6 (DL) (88% / 97%). Drivers with long roundtrip distance (SP and CR) profit most considerably from the increased battery capacity (SP: 49% / 81%, CR: 43% / 78%).

Drivers in the segment with the highest total mileage per month can electrify the highest number of kilometers (SP: 3,225 km of 6,527 km for an 18.8 kWh battery). If a PHEV with a 56.4 kWh is available, drivers in long-distance segments 5 and 7 (SP and CR) could again electrify the greatest number of kilometers. The number of electrified kilometers rises by 2,035 km from 3,225 km to 5,260 km for “service providers” (SP) and by 1,997 km from 2,472 km to 4,469 km for “company representatives” (CR).

Overall, it can be stated that battery capacity plays the greatest role in terms of vehicle mileage electrification. Both the availability of a secondary charging facility and charging power are considerably less important. On average, the availability of a secondary charging facility is slightly more important than charging power. The most difficult segments to electrify are at the same time the groups where the gains per kWh of battery capacity are most pronounced.

2.5.4 Policy implicationsⁱⁱ

From the perspective of policy makers, the chapter allows for drawing a number of conclusions on future strategies for managing the transition from combustion engines to electromobility. So far, governmental incentives that promote an adoption of electric drivetrains for example via tax reductions, purchase incentives, financial support for the deployment of charging stations, and priority lanes – are still indispensable for market growth (International Energy Agency, 2018). However, policy makers must also consider the future phase-out of incentives while avoiding subsequent drawbacks such as lower electric vehicle adoption figures (Slowik, Pavlenko, and Lutsey, 2016). Against this backdrop, the segmentation approach allows for identifying those driver segments whose requirements are met best by electric cars, defining more targeted incentives, reconsidering the efficiency of incentives for each group, and optimizing the respective phase-out steps.

In addition, the same approach helps delineating those driver segments that pose the largest challenge for the electric grid and, in turn, lead to substantial decreases in total fuel consumption. More accurate estimates on the spatiotemporal distribution of network load (for example at domestic or commercial regions) also allow policy makers to make more accurate plans for grid enhancements.

Not least, knowledge about electric mobility requirements of distinct groups could be used to give a more realistic outlook on the expected adoption and grid impact of electric vehicles. On this foundation, policy makers may derive more realistic goals for electric mobility adoption, allocate resources more efficiently (e.g., for charging infrastructure implementation), and focus their incentive measures on driver segments with less challenging electric range and charging requirements. Among others, analyses like the one presented herein that are based on empirical data and differentiate between relevant driver groups may lead to a better understanding of the benefits of home charging, fast charging infrastructures, and the importance of greater battery capacities.

ⁱ Major parts of this chapter (also including figures and tables) have been taken from an earlier version of the coauthored work (Sodenkamp, Wenig, Thiesse, et al., 2019) and were adapted where applicable.

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3 Battery versus infrastructure assessmentⁱⁱⁱ

3.1 Introduction^{iv}

Although the development of the market for PHEVs and battery electric vehicles failed to meet expectations, sales figures have significantly risen in recent years (Grünig, Witte, Dominic, et al., 2011; International Energy Agency, 2018). Notably, policy efforts to incentivize electric mobility (Bjerkan, Nørbech, and Nordtømme, 2016; Lévy, Drossinos, and Thiel, 2017), bans on vehicles with particularly high pollution levels (Carvalho, 2016), and announcements to restrict combustion-based vehicle sales (International Energy Agency, 2018) foster the adoption of PHEVs and battery electric vehicles.

Market research indicates that in the coming years world leading car manufacturers will market high range electric vehicles at prices that are competitive with conventional cars (Slowik, Pavlenko, and Lutsey, 2016). However, the existing public charging infrastructure coverage is considered to be one of the main obstacles to an electro mobile future (Eurelectric, 2016). Moreover, with respect to customer requirements, charging time has to be taken into account as an additional barrier to electric mobility (National Academy of Sciences, 2015).

This shows that both battery capacity and charging infrastructure characteristics must be regarded in an integrated perspective to evaluate their impact on the viability of electric driving. Despite of the importance of available charging facilities, expenses for large-scale infrastructure deployment - including equipment and skilled workforce - remain high (National Academy of Sciences, 2015). Nevertheless, cost-intensive charging infrastructure investments have been announced (International Energy Agency, 2018). At the same time, high battery costs cause high prices of PHEVs and battery electric vehicles (International Economic Development Council, 2013; Lévy, Drossinos, and Thiel, 2017). However, economies of scale and the general technical progress are expected to lead to decreasing future costs for batteries (International Economic Development Council, 2013; Slowik, Pavlenko, and Lutsey, 2016).

Thus, the question arises: To what extent do larger batteries relax the requirements regarding charging infrastructure and vice versa? Consequently, a better understanding of the effect of variations in vehicle characteristics (battery capacity) and infrastructure characteristics (infrastructure coverage and charging power) on electric mobility key figures (particularly, the share of electrically driven mileage and the location and time specific grid impact of vehicle charging) is essential.

For this purpose, data from conventional combustion-based vehicles can be used to replicate both the energy consumption and the charging behavior of – potentially range extended – PHEVs. Such data represents the current mobility need of drivers and is not highly biased by restrictions of limited range electric vehicles (Franke, Neumann,

Bühler, et al., 2012; Rolim, Gonçalves, Farias, et al., 2012) or specific characteristics of early adopters of electric cars (Saarenpää, Kolehmainen, and Niska, 2013).

Standard driving cycles do not provide a realistic data foundation that is necessary for a comprehensive electric mobility assessment (Adornato, Patil, Filipi, et al., 2009). Neither information on parking events nor variations in driving events are included in such data (Smith, Shahidinejad, Blair, et al., 2011). Also, travel survey data fails at providing the level of detail required for electric vehicle simulations (Gonder, Markel, Simpson, et al., 2007). Particularly, short term travel surveys within a period of one day do not consider the daily variation in realistic mobility behavior of a driver (Wu, Aviquzzaman, and Lin, 2015). In addition, the overall quality of travel survey data can be affected by misinterpretation and error on the part of the respondents (De Gennaro, Paffumi, Martini, et al., 2014).

To mitigate these problems, researchers have recently started to employ GPS driving data (Adornato, Patil, Filipi, et al., 2009; De Gennaro, Paffumi, Martini, et al., 2014; Gonder, Markel, Simpson, et al., 2007; Smith, Shahidinejad, Blair, et al., 2011; Wu, Aviquzzaman, and Lin, 2015). Still, a sufficiently large data basis is desirable to represent differences in driver profiles (Adornato, Patil, Filipi, et al., 2009).

Recent studies analyze real-world GPS driving data to discuss different aspects of electric mobility scenarios and suggest that both the available charging infrastructure and the electric range of the vehicle are essential for practical use, as shown in Table 11. In the following, these references are described in context:

Table 11: Research literature on battery versus infrastructure assessment

Vehicles	Charging scenarios	Studies
One vehicle type	Private and public charging facilities	(Asamer, Reinthaler, Ruthmair, et al., 2016; Cai, Jia, Chiu, et al., 2014; Dong, Liu, and Lin, 2014; Paffumi, De Gennaro, and Martini, 2016; Wenig, Sodenkamp, and Staake, 2015; Wood, Neubauer, and Burton, 2015; Yang, Dong, and Hu, 2017; Yang, Dong, Lin, et al., 2016)
Multiple vehicle types	Home charging or simple time-based charging rules	(De Gennaro, Paffumi, Martini, et al., 2014; Gonder, Markel, Simpson, et al., 2007; Greaves, Backman, and Ellison, 2014; Jakobsson, Gnann, Plötz, et al., 2016; Khan and Kockelman, 2012; Pearre, Kempton, Guensler, et al., 2011; Wang, Zhang, and Ouyang, 2015)
Multiple vehicle types	Home and secondary or workplace location charging	(Shahidinejad, Filizadeh, and Bibeau, 2012; Smith, Shahidinejad, Blair, et al., 2011; Sodenkamp, Wenig, Thiesse, et al., 2019; Wu, 2018; Wu, Aviquzzaman, and Lin, 2015)

Multiple vehicle types	Private or public charging at pre-defined locations	(Ashtari, Bibeau, Shahidinejad, et al., 2012; Betz, Walther, and Lienkamp, 2017)
Multiple vehicle types	Charging strategies based on parking time	(Björnsson and Karlsson, 2015; Bryden, Hilton, Cruden, et al., 2018; De Gennaro, Paffumi, and Martini, 2016, 2015; De Gennaro, Paffumi, Scholz, et al., 2014; Denholm, Kuss, and Margolis, 2013; Fraile-Ardanuy, Castano-Solis, Álvaro-Hermana, et al., 2018; He, Wu, Zhang, et al., 2016; Paffumi, De Gennaro, Martini, et al., 2015; Smith, Morison, Capelle, et al., 2011)
Multiple vehicle types	Public charging infrastructure derived from parking locations	(Andrenacci, Ragona, and Valenti, 2016; Hu, Dong, Lin, et al., 2018)
Multiple vehicle types	Public charging infrastructure variations	(Dong and Lin, 2012; Ko, Kim, Nam, et al., 2017; Li, Jia, Shen, et al., 2017; Shahraki, Cai, Turkay, et al., 2015; Shen, Li, He, et al., 2016; Yang, Dong, and Hu, 2018)

(Asamer, Reinthaler, Ruthmair, et al., 2016; Cai, Jia, Chiu, et al., 2014; Dong, Liu, and Lin, 2014; Paffumi, De Gennaro, and Martini, 2016; Wood, Neubauer, and Burton, 2015; Yang, Dong, and Hu, 2017; Yang, Dong, Lin, et al., 2016) assess private and public charging infrastructure configurations, given a constant electric range of the vehicle. (Wenig, Sodenkamp, and Staake, 2015) apply a vehicle simulation model to consider the impact of driving behavior on range for one vehicle and quantify the benefits of additional secondary charging facilities that complement home charging.

Compared to this, below-mentioned studies vary electric range figures of vehicles. (De Gennaro, Paffumi, Martini, et al., 2014; Gonder, Markel, Simpson, et al., 2007; Greaves, Backman, and Ellison, 2014; Jakobsson, Gnann, Plötz, et al., 2016; Khan and Kockelman, 2012; Pearre, Kempton, Guensler, et al., 2011; Wang, Zhang, and Ouyang, 2015) estimate the benefit of increased range to electric mobility and expect that the battery can be charged at home (Greaves, Backman, and Ellison, 2014) or make strong assumptions, such as that it is fully charged once a day (Gonder, Markel, Simpson, et al., 2007; Jakobsson, Gnann, Plötz, et al., 2016; Khan and Kockelman, 2012; Pearre, Kempton, Guensler, et al., 2011; Wang, Zhang, and Ouyang, 2015), or that a charging opportunity exists during a specific overnight time window once per day (De Gennaro, Paffumi, Martini, et al., 2014).

(Smith, Shahidinejad, Blair, et al., 2011) show that an additional charging opportunity at work that complements home charging allows battery size to be reduced for urban commuters. (Wu, Aviquzzaman, and Lin, 2015) extend the assumption that vehicles are fully charged at night by providing a study that considers individual home to home roundtrips and workplace charging. They vary vehicle range and find that workplace charging is particularly beneficial to the share of electrically driven mileage, if the electric range is

limited. Similarly, (Sodenkamp, Wenig, Thiesse, et al., 2019) (and chapter 2, respectively) consider charging opportunities at primary and secondary parking locations for each driver and demonstrate that results and therefore the utility of range and charging infrastructure parameters greatly vary for different groups of drivers. Also (Wu, 2018) addresses the impact of additional charging opportunities at work places and discusses potential benefits, such as reduced range anxiety and failure rate during electrically driven trips. (Shahidinejad, Filizadeh, and Bibeau, 2012) emulate a driver's charging decision behavior at home and at work, using a fuzzy-logic inference system and find that larger batteries lead to less urgent charging requirements and therefore relax the grid impact.

Still, these studies limit charging opportunities to private locations without considering public charging facilities. (Ashtari, Bibeau, Shahidinejad, et al., 2012) extend such basic charging scenarios by adding charging opportunities at work or at shopping places, stating that an increased battery capacity limits the effect of charging scenarios on electric reachability. However, due to its exemplary nature, such a restriction of public charging opportunities to shopping places constitutes an inadequate basis for comparing possible public charging infrastructure expansion measures. (Betz, Walther, and Lienkamp, 2017) evaluate the potential of the existing charging infrastructure – including public, employee, customer, and company charging – for a small sample of commercial vehicles and they discuss a future charging infrastructure expansion.

A noteworthy alternative approach derives charging scenarios from time-based charging strategies. In (Björnsson and Karlsson, 2015; Denholm, Kuss, and Margolis, 2013; He, Wu, Zhang, et al., 2016; Smith, Morison, Capelle, et al., 2011), charging time windows during the day extend overnight charging. For example, (Björnsson and Karlsson, 2015) assume that charging is possible if parking time exceeds a certain threshold and state that more charging opportunities significantly reduce the recommended battery size. They reason that time windows that allow charging not only over night at home, but also at the workplace can significantly reduce suggested battery costs for commuters.

Also (Fraile-Ardanuy, Castano-Solis, Álvaro-Hermana, et al., 2018) assume that public charging is possible if parking time exceeds a certain threshold and they discuss the mileage electrification improvement of taxis enabled by a larger battery. (Bryden, Hilton, Cruden, et al., 2018) suggest that charging is possible both at home and at work or if parking time exceeds a certain threshold and they derive the drivers' public fast charging demand depending on battery size. (De Gennaro, Paffumi, and Martini, 2016, 2015; De Gennaro, Paffumi, Scholz, et al., 2014; Paffumi, De Gennaro, Martini, et al., 2015) put the comparison of different time-based charging strategies into focus and discuss both vehicle characteristics and charging infrastructure development.

(Andrenacci, Ragona, and Valenti, 2016) derive the public charging infrastructure from trip destinations and utilize driving behavior data to quantify the energy demand at each charging station. (Hu, Dong, Lin, et al., 2018) discuss the feasibility of electric taxis with different electric range parameters while considering both the current public charging

infrastructure and a possibly expanded charging infrastructure at frequent dwell locations of taxis.

(Dong and Lin, 2012) compare variations in both electric range and public charging infrastructure coverage to assess electric driving share and energy demand for one day and to demonstrate the fuel saving and energy cost reduction benefits of public charging. Also (Ko, Kim, Nam, et al., 2017; Li, Jia, Shen, et al., 2017; Shahraki, Cai, Turkay, et al., 2015; Shen, Li, He, et al., 2016; Yang, Dong, and Hu, 2018) gradually increase the charging infrastructure coverage and electric range of the vehicle to estimate the potential and requirements for the electrification of a large taxi fleet. In (Dong and Lin, 2012; Li, Jia, Shen, et al., 2017; Shen, Li, He, et al., 2016; Yang, Dong, and Hu, 2018) parking locations form the basis for public charging infrastructure siting, while (Ko, Kim, Nam, et al., 2017) relocate charging demand locations to nearby road network nodes and (Shahraki, Cai, Turkay, et al., 2015) assume that existing gas stations present an adequate foundation.

This work employs long-term GPS driving data (2 years) from conventional vehicles and aims at systematically assessing both vehicle and charging infrastructure parameters and drawing a realistic picture of the potential of electric mobility. Only a limited number of discussed papers (Betz, Walther, and Lienkamp, 2017; Bryden, Hilton, Cruden, et al., 2018; De Gennaro, Paffumi, and Martini, 2016; De Gennaro, Paffumi, Martini, et al., 2014; Hu, Dong, Lin, et al., 2018; Jakobsson, Gnann, Plötz, et al., 2016; Paffumi, De Gennaro, Martini, et al., 2015) takes high electric range vehicles into account. Thus, in this electric mobility study, battery capacity parameters from 9.4 kWh to 112.8 kWh are compared.

Furthermore, the majority of studies apply predefined range values or derive range from the battery capacity and predetermined vehicle efficiency values. However, the high resolution of GPS data allows to take driving characteristics (e.g., speed and acceleration) at each measurement point into account in order to estimate energy consumption (Andrenacci, Ragona, and Valenti, 2016; Betz, Walther, and Lienkamp, 2017; Fraile-Ardanuy, Castano-Solis, Álvaro-Hermana, et al., 2018; Greaves, Backman, and Ellison, 2014; Shahidinejad, Filizadeh, and Bibeau, 2012; Smith, Shahidinejad, Blair, et al., 2011; Sodenkamp, Wenig, Thiesse, et al., 2019; Wenig, Sodenkamp, and Staake, 2015) (and chapter 2, respectively). Therefore, a physical energy consumption and charging model (Wenig, Sodenkamp, and Staake, 2015) is applied again to provide results, including the grid impact and the share of electrically reachable destinations of the average driver.

The heterogeneity of mobility behavior is exploited to segment drivers into distinct groups, as demonstrated in (Sodenkamp, Wenig, Thiesse, et al., 2019) and in chapter 2, such that the evaluation of simulation results takes into consideration individual differences in electric mobility requirements. Finally, private and public charging facilities are distinguished (San Román, Momber, Abbad, et al., 2011). The private charging infrastructure consists of one or two most frequently visited parking locations that can only be accessed by their respective vehicle, while the public charging infrastructure can be

accessed by every vehicle and supplements private charging. Charging scenarios range from home charging to a 100% public charging infrastructure coverage.

3.2 Method^{iv}

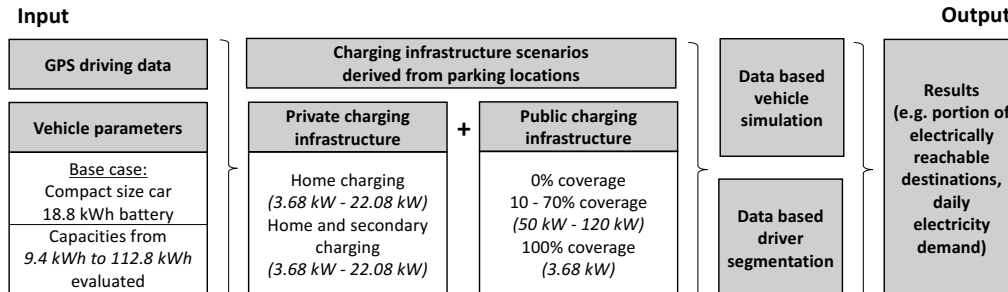


Figure 10: Methodology to systematically create, analyze, and compare realistic electric mobility scenarios

The underlying methodology from (Sodenkamp, Wenig, Thiesse, et al., 2019; Wenig, Sodenkamp, and Staake, 2015) and the previous chapter was applied and extended in this chapter. First, the range of potential battery capacity parameters was increased to compare the impact of electric range for one otherwise unchanged vehicle type. Second, public charging opportunities cover 0 to 100% of parking locations as an addition to private charging facilities at home and potentially at secondary locations. Third, viable charging power parameters, ranging from slow to fast charging, are compared for private and public facilities. Finally, realistic electric mobility scenarios, considering variations in battery capacity, charging infrastructure coverage, and charging power, were systematically created, analyzed, and compared to assess the impact of PHEVs on the electric grid and to assess their utility in terms of the portion of mileage that is electrically drivable and the portion of destinations that are electrically reachable. The methodology is summarized in Figure 10 and explained in detail in the following subchapters.

3.2.1 GPS driving data^{iv}

GPS time series data from 1,000 conventional vehicles provided by Octo Telematics (Octo Telematics Ltd., 2017) is used. A larger area of both urban and extra-urban environment on the European continent with a focus on Northern Italy is covered within a timeframe of two years from summer 2007 to summer 2009. Measurements at engine ignition, engine stop, and roughly every 2 km while driving are considered.

Data includes location, date, time, heading, speed, engine state and road type (urban, extra-urban, and highway) at each measurement point and both distance and duration related to the previous measurement data entry. Data from 91 vehicles has noticeable deficiencies – presumably caused by measurement inaccuracy (i.e., considerable gaps in data, implausible GPS location or vehicle status updates) – and is removed. 909 vehicles pass the data quality control and therefore provide the data basis underlying this study.

Literature suggests that the sample size should be large when partitioning based clustering is applied (Dolnicar, 2003). This particularly holds true for clustering applications with many segmentation variables (Dolnicar, 2003). Therefore, in the previous chapter (and in (Sodenkamp, Wenig, Thiesse, et al., 2019)) one objective of data cleansing was to preserve a large sample size and thus to keep the number of vehicles represented by the data set high when introducing the segmentation method.

Overall, in the previous chapter, 18 data sets were excluded from the overall sample, leading to a dataset that represents a fleet of 982 vehicles. In this chapter, the focus lies on a comparison of vehicle and charging infrastructure parameters, such that a stricter data cleansing approach appears to be reasonable.

3.2.2 *Charging infrastructure scenarios derived from parking locations^{iv}*

The charging infrastructure is characterized by the availability of charging facilities and by charging power. Charging facilities are geographically associated with parking locations that are in close proximity to each other.

A density based clustering (Ester, Kriegel, Sander, et al., 1996) approach from (Sodenkamp, Wenig, Thiesse, et al., 2019; Wenig, Sodenkamp, and Staake, 2015) and chapter 2 is applied to compare scenarios where charging is possible at a primary parking location (frequent and most long-time parking cluster, probably the home location, parking for at least 15 minutes and less than 5 days) or both at a primary and at a secondary parking location (frequent and second most long-time parking cluster, parking for at least 15 minutes and less than 5 days). Charging powers of 3.7 kW (e.g., domestic socket, 230 V * 16 A), 7.4 kW (e.g., domestic socket, 230 V * 32 A), 11.0 kW (e.g., three-phase current, 3.7 kW * 3), and 22.1 kW (e.g., three-phase current, 7.4 kW * 3) are compared at private locations (Legrand S.A, 2010).

Public charging facilities complement private charging opportunities and were randomly distributed among non-primary parking locations in close proximity. Charging at secondary facilities is preferred over public charging facilities. The public charging power is 50 kW (e.g., Combined Charging System) or 120 kW (e.g., Tesla Super Charger) (Jar, Watson, and Miller, 2016). A realistic public charging infrastructure coverage of 10% is compared with extreme 40% and 70% coverages by randomly assigning charging facilities to parking locations. The public charging infrastructure distribution approach with its random component has been carried out several times and overall results appeared to be appropriately comparable.

To complement the study, a ubiquitous charging scenario is considered as well. Here, at every parking location a 3.7 kW charging facility is available. Recent developments like charging at street lights with charging sockets (Fraunhofer IWM, 2016) make such a scenario thinkable. This study assumes that each parking spot at a charging facility is potentially equipped with a charger. Queuing, respectively the occupation of one

charger by multiple cars, is not possible, because charging events are derived from actual and therefore separate parking events.

3.2.3 *Data based vehicle simulation*^{iv}

An energy consumption and charging model from (Larminie and Lowry, 2003; Sodenkamp, Wenig, Thiesse, et al., 2019; Wenig, Sodenkamp, and Staake, 2015), and chapter 2 is applied to estimate the state of charge of the battery of a (range extended) electric vehicle. It takes the rolling resistance, aerodynamic drag, acceleration, and regenerative braking of the car into account. The amount of energy required to overcome the rolling resistance and aerodynamic drag is derived from the GPS time series' distance and speed values between two measurement points. High-resolution speed profiles from urban (ECE-15), extra-urban (EUDC), and highway (EMPA T130) driving cycles (André and INRETS, 2009; Barlow, Latham, McCrae, et al., 2009) substitute low-resolution speed measurements from the GPS data set and are used to provide distance-dependent values for acceleration and regenerative braking.

The charging model simulates the charging behavior of a lithium-ion battery. It is a function of charging power at a charging location and respective parking time and assumes that charging power drops to 1/3 as soon as the state of charge of the battery exceeds 80% (Hsieh, Chen, and Huang, 2001). Energy demand and charged energy are continually offset against each other to derive the state of charge of the battery at each measurement point under the restriction that it can never be negative and never exceed 100%.

The PHEV considered in this study represents a compact size car (NHTSA, 2017), inspired by a BMW i3, weighting 1,270 kg (BMW AG, 2013; De Haan and Zah, 2013). A battery capacity of 18.8 kWh (BMW AG, 2013) is assumed and multiplied by factors of 0.5 (9.4 kWh), 2 (37.6 kWh), 3 (56.4 kWh), and 6 (112.8 kWh) to also capture different car configurations and show the sensitivity of the results. Furthermore, it is assumed that a gasoline-based range extender is installed and enables a continuation of the trip without adaptations of driving behavior if the battery runs out of energy (BMW AG, 2013; Hidrue and Parsons, 2015).

3.2.4 *Data based driver segmentation*^{iv}

Compared to the previous chapter and (Sodenkamp, Wenig, Thiesse, et al., 2019), the adapted data basis leads to slightly different, yet comparable segmentation results. A number of eight clusters was chosen for the present chapter as it allows for a meaningful interpretation of results.

On the basis of the more strictly cleansed data, one additional presumably private driver segment (i.e., four instead of three private groups) comes into view, when assuming

seven clusters for the k-means segmentation approach. Thus, a number of eight clusters was chosen to also preserve all four presumably business-related driver groups, identified in the previous chapter (i.e., keep the “technical service vehicle” (TSV) group).

To take variations in driving behavior of individuals into consideration, drivers are segmented into different groups by using a procedure based on a k-means clustering algorithm (Hartigan and Wong, 1979), as suggested in (Sodenkamp, Wenig, Thiesse, et al., 2019) and in chapter 2. It is assumed that each vehicle represents one driver, even though the use of one car by multiple persons is possible. The reason is that allowing the utilization of a car by several secondary drivers lies within the sphere of influence of the car holder and therefore directly influences mobility requirements.

Segmentation variables that represent each driver’s mobility behavior (i.e., driving and parking) were derived from the GPS time series data and Pearson’s correlation coefficients were compared to exclude highly correlated variables, such that the final clustering approach includes nine segmentation variables, as depicted in Table 12. In an iterative process, eight clusters lead to stable and meaningfully interpretable results and is therefore accepted.

Table 12: Characteristics of eight driver groups and the average driver (segmentation variables)

Segment	1	2	3	4	5	6	7	8	ALL
Segment name	FLD	LDOD	SC	UC	SDDV	LDDV	TSV	CR	ALL
Segment size	149	103	172	276	40	49	36	84	909
% of fleet	16.4%	11.3%	18.9%	30.4%	4.4%	5.4%	4.0%	9.2%	100%
Segmentation variables									
Median roundtrip distance [km]	10.18	57.22	29.03	21.10	0.65	98.88	66.71	207.55	47.23
Median roundtrip duration [h]	2.15	9.92	6.29	4.36	0.29	7.34	4.33	9.28	5.43
Ratio of driving to parking during a roundtrip	0.22	0.07	0.13	0.15	0.49	0.46	1.22	0.85	0.29
Variance of speed during a roundtrip	347.89	754.81	242.86	495.68	207.33	122.83	367.06	357.53	402.33
Average number of roundtrips per month	56.31	11.91	34.74	32.40	60.37	32.21	50.06	24.22	35.61
Average number of stops per roundtrip	3.58	5.84	3.67	4.60	8.41	16.10	6.70	8.70	5.65
Median trip distance [km]	3.01	9.51	7.73	3.87	1.59	2.33	9.58	12.85	5.97
Median parking duration (home) [h]	4.77	14.90	10.49	11.24	1.56	14.06	1.51	11.80	9.84
Median parking duration (not home) [h]	0.36	1.18	1.16	0.48	0.18	0.15	0.23	0.28	0.61

For a better illustration of segmentation results, the segments are given adequate descriptions, based on their characteristics. It is suggested that these segments can best be understood by assuming that they represent typical private or business purposes. Thus, in four groups, vehicles are assumed to be privately held. These groups are called 'frequent local driver' (FLD, n=149), 'long-distance occasional driver' (LDOD, n=103),

'steady commuter' (SC, n=172), and 'unsteady commuter' (UC, n=276). The other four groups are assumed to be business related and are called 'short-distance delivery vehicle' (SDDV, n=40), 'long-distance delivery vehicle' (LDDV, n=49), 'technical service vehicle' (TSV, n=36), and 'company representative' (CR, n=84). Segment names were inspired by (Sodenkamp, Wenig, Thiesse, et al., 2019) and by respective names given in chapter 2. The characteristics of all eight driver segments are depicted in Table 12 (segmentation variables) and in Table 13 (non-segmentation variables).

Table 13: Characteristics of eight driver groups and the average driver (non-segmentation variables)

Segment	1	2	3	4	5	6	7	8	ALL
Segment name	FLD	LDOD	SC	UC	SDDV	LDDV	TSV	CR	ALL
Segment size	149	103	172	276	40	49	36	84	909
% of fleet	16.4%	11.3%	18.9%	30.4%	4.4%	5.4%	4.0%	9.2%	100%
Non-segmentation variables									
Mean roundtrip distance [km]	29.14	144.98	43.97	51.04	43.40	97.27	116.84	254.77	80.34
Mean roundtrip duration [h]	5.45	65.44	10.43	11.02	4.12	10.04	8.35	17.76	16.32
Mean trip distance [km]	8.15	24.01	11.94	11.15	7.20	6.31	22.96	30.53	14.09
Median trip duration [h]	0.13	0.30	0.23	0.16	0.09	0.10	0.29	0.41	0.20
Mean trip duration [h]	0.21	0.47	0.29	0.28	0.18	0.18	0.61	0.74	0.34
Average daily travel in km									
<i>Mon-Fri</i>	51.97	48.89	47.50	52.42	100.08	103.23	224.10	227.79	78.86
<i>Sat-Sun</i>	50.19	45.86	46.26	51.80	38.88	39.59	71.67	52.58	49.45
Median parking duration (secondary) [h]	2.74	5.30	5.49	3.78	1.00	0.87	1.76	1.76	3.56
Median daily parking duration (home) [h]	16.93	16.47	14.58	16.17	16.66	16.16	13.93	14.46	15.80
Median daily parking duration (secondary) [h]	4.76	7.85	7.45	6.25	1.56	1.83	2.42	2.74	5.49
Portion of mileage on urban roads	0.34	0.19	0.33	0.30	0.19	0.34	0.15	0.15	0.25
Portion of mileage on extra-urban roads	0.41	0.29	0.44	0.33	0.42	0.45	0.35	0.27	0.35
Portion of mileage on high-ways	0.25	0.52	0.24	0.38	0.39	0.21	0.50	0.58	0.40
Mean speed [km/h]	67.81	86.48	67.98	75.93	55.95	57.98	64.07	69.35	71.37
Monthly mileage [km]	1,563	1,453	1,434	1,587	2,514	2,583	5,491	5,402	2,140

In the following, all eight identified segments are described in detail and differences to the seven segments from the previous chapter are briefly discussed. Energy demand figures and the share of electrifiable mileage greatly differ for different driver segments, which can be shown in the following subchapters.

3.2.4.1 Describing the average driver

There are 909 vehicles in the observed fleet and the average driver can be described as follows. The average driven roundtrip covers less than 47.2 km and takes less than 5.4 hours in about 50% of cases. The mean roundtrip distance is 80.3 km and it has a

mean duration of 16.3 hours, which indicates a skewed distribution. There are typically 35.6 roundtrips per month with 5.6 stops per roundtrip. Individual trips have a median distance of 6.0 km (mean: 14.1 km) and a median duration of 0.2 hours (or 12 minutes; mean: 0.3 hours or 20 minutes).

Each month, roughly 2,140 km are covered at an average speed of 71.4 km/h. Most mileage is driven from Monday to Friday (78.9 km per day). On weekends, daily mileage is lower (49.4 km). The greatest share of mileage is covered on highways (40%) and extra-urban roads (35%). The remaining 25% of mileage are driven on urban roads. Vehicles are parked for about 9.8 hours (15.8 hours per day) at primary – or home – locations and for about 3.6 hours (5.5 hours per day) at secondary locations. At non-primary locations, parking events take about 0.6 hours (or 36 minutes).

3.2.4.2 Segment #1: Frequent local driver

16.4% of the fleet belong to the first segment (FLD). Here, about 50% of the roundtrips cover less than 10.2 km and take less than 2.2 hours. The distribution is skewed with a mean roundtrip distance of 29.1 km and a duration of 5.4 hours. Each month, about 56.3 roundtrips can be observed, which is rather frequent and there are about 3.6 stops per roundtrip. The distribution of trips is skewed as well. Here the median distance is 3.0 km and the median duration is 0.1 hours (or 8 minutes). The mean distance of a trip is 8.1 km with a mean duration of 0.2 hours (or 13 minutes).

Mileage covered during weekdays and weekend days is rather similar with about 52.0 km per day covered during the week and 50.2 km per day covered during the weekend. Each month about 1,563 km are driven and the average speed is 67.8 km. Most mileage is covered on extra-urban roads (41%), followed by urban roads (34%) and highways (25%). Each day, the vehicle is parked at the primary location for 16.9 hours and each parking event takes 4.8 hours. At the secondary location the daily parking time amounts to 4.8 hours with about 2.7 hours per parking event. A typical non-primary parking event takes about 0.4 hours or 21 minutes. This group shows many similarities with the "frequent local driver" (FLD) segment from the previous chapter and they share most vehicles, such that reusing this name is reasonable.

3.2.4.3 Segment #2: Long-distance occasional driver

This second segment (LDOD) consists of 11.3% of the fleet. The median distance and duration are 57.2 km and 9.9 hours. Corresponding mean values are 145.0 km and 65.4 hours, which indicates skewed distributions. With an average number of 11.9 roundtrips per month, apparently the vehicle is used infrequently for longer journeys. There are about 5.8 stops per roundtrip. A trip has a median distance of 9.5 km (mean: 24.0 km) and a median duration of 0.3 hours (or 18 minutes; mean: 0.5 hours or 28 minutes).

The mean speed is relatively high (86.5 km/h) and 1,453 km are covered each month, mostly on highways (52%), followed by extra-urban (29%) and urban (19%) roads. Daily

driven distances are rather similar on weekdays (48.9 km) and weekends (45.9 km). At the home location the vehicles parks for 14.9 hours on average (16.5 hours per day). At the secondary location, parking times are 5.3 hours per parking event and 7.9 hours per day. At non-primary locations parking time is about 1.2 hours.

Many drivers in this segment also exist in the long-distance commuter group from the previous chapter and many similarities can be seen. However, particularly their noticeably less frequent long-distance roundtrips inspire the name "long-distance occasional drivers" (LDOD).

3.2.4.4 Segment #3: Steady commuter

Segment 3 (SC) consists of 18.9% of the fleet and 50% of roundtrips cover less than 29 km or take less than 6.3 hours. With 44.0 km and 10.4 hours, mean values are somewhat higher. Each month there are 34.7 roundtrips with an average of 3.7 stops per roundtrip. About 50% of individual trips cover less than 7.7 km and take less than 0.2 hours (or 14 minutes). Again, with 11.9 km and 0.3 hours (or 17 minutes), mean values are higher. Vehicles cover about 1,434 km per months. The average speed is 68.0 km/h.

During typical weekdays 47.5 km are covered. On the weekend the traveled distance is 46.3 km per day. The greatest portion of mileage is covered on extra-urban (44%) and urban (33%) roads. Less mileage is covered on highways (24%). The vehicle is parked at the home location for 14.6 hours per day (10.5 hours per parking event). The corresponding value for the secondary location is 7.5 hours per day (or 5.5 hours per parking event). Parking at non-primary locations takes about 1.2 hours.

This segment roughly resembles the short distance commuter group from the previous chapter both in terms of mean figures and similar vehicles. However, in the following it is called "steady commuter" (SC) to highlight differences to the subsequent segment 4.

3.2.4.5 Segment #4: Unsteady commuter

With 30.4% the largest portion of the fleet belongs to the fourth segment (UC). Here the median distance per roundtrip is 21.1 km (mean: 51 km) and the median duration is 4.4 hours (mean: 11.0 hours). There are 32.4 roundtrips each month with about 4.6 stops each. The median distance for individual trips is 3.9 km (mean: 11.1 km) and their median duration is 0.2 hours (or 9 minutes; mean: 0.3 hours or 17 minutes). The monthly mileage is 1,587 km with a mean speed of 75.9 km/h.

Daily mileage is rather similar on weekdays and weekends (52.4 km versus 51.8 km) and most mileage is covered on highways (38%), followed by extra-urban (33%) and urban (30%) roads. In this group, vehicles are parked for 16.2 hours each day at the home location (11.2 hours per parking event) and for 3.8 hours each day at the secondary location (6.3 hours per parking event). At non-primary locations, parking takes about 0.5 hours (or 29 minutes).

This segment almost exclusively consists of drivers from the short and long-distance commuter group and the frequent local driver group from the previous chapter. In comparison to the previously identified “steady commuter” (SC) segment, larger trip speed and roundtrip distance variations indicate a less uniform driving behavior, such that the term “unsteady commuter” (UC) appears to be a descriptive name for this group of drivers.

3.2.4.6 Segment #5: Short-distance delivery vehicle

4.4% of the fleet belong to segment 5 (SDDV). With 0.7 km the median roundtrip distance is very short and with a mean distance of 43.4 km the distribution is highly skewed. The median and mean duration of roundtrips are 0.3 hours (or 18 minutes) and 4.1 hours. There are about 60.4 roundtrips per month and during each roundtrip the vehicle stops 8.4 times. 50% of individual trips cover less than 1.6 km (mean: 7.2 km) and take less than 0.1 hours (or 6 minutes; mean: 0.2 hours or 11 minutes).

With 56.0 km/h the mean speed is relatively low, compared to the other segments and each month about 2,514 km are covered. Vehicles are usually driven from Monday to Friday (100.1 km per day) and less mileage is covered during the weekend (38.9 km per day). Usually, vehicles drive on extra-urban roads (42% of mileage) and on highways (39% of mileage). About 19% of mileage are driven on urban roads.

Vehicles are parked at the primary location for 16.7 hours per day, however the parking duration of individual parking events at such locations is only 1.6 hours. At secondary locations, the daily parking duration is 1.6 hours (1 hour per parking event). At non-primary locations, vehicles park for 0.2 hours (or 11 minutes) on average.

This group exclusively consists of drivers from the short-distance delivery vehicle segment from the previous chapter and thus shares many similarities with them, such that the name “short-distance delivery vehicle” (SDDV) is adopted.

3.2.4.7 Segment #6: Long-distance delivery vehicle

The sixth segment (LDDV) consists of 5.4% of the fleet. 50% of roundtrips cover more than 98.9 km (mean: 97.3 km) and last more than 7.3 hours (mean: 10.0 hours). Roundtrips take place about 32.2 times per month and have many stops (16.1). Individual trips have a median distance of 2.3 km (mean: 6.3 km) and a median duration of 0.1 hours (or 6 minutes; mean: 0.2 hours or 11 minutes).

2,583 km are covered each month at an average speed of 58.0 km/h. This distance is driven mostly from Monday to Friday (103.2 km per day versus 39.6 km on days of the weekend) on extra-urban (45%) and urban (34%) roads, while only 21% of mileage is covered on highways. Vehicles park for 16.2 hours per day (14.1 hours per parking event) at the primary location and for 1.8 hours per day (0.9 hours or 52 minutes per

parking event) at the secondary location. At non-primary locations, a parking event takes about 0.2 hours (or 9 minutes).

This group is roughly comparable with the long-distance delivery vehicle segment from the previous chapter and results from both segmentation approaches share the same vehicles. Thus, the name “long-distance delivery vehicle” (LDDV) is reused.

3.2.4.8 Segment #7: Technical service vehicle

With 4.0%, segment 7 (TSV) is the smallest. The median roundtrip distance is 66.7 km (mean: 116.8 km) and the median roundtrip duration is 4.3 hours (mean: 8.3 hours). There are about 50.1 roundtrips per month with 6.7 stops each. Individual trips cover 9.6 km (median; mean: 23.0 km) and take 0.3 hours or 18 minutes (median; mean: 0.6 hours or 37 minutes).

Each month, 5,491 km are covered, and the average speed is 64.1 km/h. About 50% of the mileage is covered on highways, followed by extra-urban (35%) and urban (15%) roads. Longest distances are covered from Monday to Friday (224.1 per day versus 71.7 km per day at the weekend). The vehicle is parked for 13.9 hours per day (1.5 hours per parking event) at the home location and for 2.4 hours per day (1.8 hours per parking event) at the secondary parking event. At non-primary locations, the vehicle is parked for about 0.2 hours or 14 minutes.

There are some dissimilarities between this group and the service provider segment, described in the previous chapter – particularly the average roundtrip distance and monthly mileage. Yet, the overall picture is comparable, and most vehicles belong to the same segment, such that using the cluster name “technical service vehicle” (TSV) is considered appropriate.

3.2.4.9 Segment #8: Company representative

Finally, 9.2% of the fleet belong to segment 8 (CR). Here, roundtrips are particularly long (median: 207.6 km, mean: 254.8 km) and they take about 9.3 hours (median; mean: 17.8 hours). Roundtrips take place 24.2 times per month and during each roundtrip there are about 8.7 stops. Individual trips cover a median distance of 12.8 km (mean: 30.5 km) and have a median duration of 0.4 hours or 24 minutes (mean: 0.7 hours or 44 minutes).

5,402 km are covered each month. The longest daily distances are driven during work-days (227.8 km per day versus 52.6 km per day at the weekend). The majority of mileage is covered on highways (58%), followed by extra-urban (27%) and urban (15%) roads. The mean speed is 69.4 km/h. Median parking times at the primary location are 14.5 hours per day (11.8 hours per parking event). At secondary locations the median parking duration per day is 2.7 hours (1.8 hours per parking event). At non-primary locations vehicles remain parked for about 0.3 hours or 17 minutes.

The general impression from these figures and many similarities with the "company representative" (CR) segment from the previous chapter, including a majority of similar drivers suggest keeping this name. A considerably shorter mean roundtrip duration is noteworthy but does not complicate the interpretation of the segment.

3.3 Results

3.3.1 *Share of electric mileage and reachability of destinations^{iv}*

The following section presents electric mobility key figures – share of electric mileage and reachability of destinations – as average values for all driver. In the considered scenarios, we compare battery capacities from small 9.4 kWh to large 112.8 kWh and a range of both private and public charging infrastructure configurations with different charging power values. Table 14 and Table 15 show the portion of destinations that are electrically reachable (Table 14), respectively the portion of mileage that is electrically drivable (Table 15).

Results indicate that even if batteries are limited to 9.4 kWh and charging is only possible at home with 3.7 kW, about 73% of destinations can be reached electrically, respectively 57% of mileage can be covered electrically. Table 14 and Table 15 also indicate that the coverage of the public charging infrastructure is particularly beneficial for vehicles with a limited battery capacity.

For example, a vehicle with a 9.4 kWh battery and 3.7 kW charging facilities at the primary and secondary parking locations can provide for an average portion of 62% of electrically drivable mileage. With a 70% coverage of a 50 kW public charging infrastructure, this value is increased to 78%.

With larger batteries, the benefit of an extended charging infrastructure diminishes. For example, with a large 112.8 kWh battery and with 3.7 kW charging facilities at the primary and secondary parking locations, 94% of mileage could be covered electrically. A public 50 kW charging infrastructure at 10% of parking locations is sufficient to reach about 98% of destinations electrically or to cover about 96% of mileage electrically when using a 112.8 kWh battery.

If a public 50 kW charging opportunity is available at 70% of parking locations, about 99% of mileage could be electrified. It can also be shown exemplarily that a vehicle with a 56.4 kWh battery and a single 3.7 kW primary charging facility can reach roughly the same portion of destinations electrically as a 9.4 kWh vehicle with a ubiquitous 3.7 kW public charging infrastructure.

Charging power appears to be less critical if common parking events are considered for charging. For example, a private charging power increase from 3.7 kW to 22.1 kW improves the electric reachability figure by up to 2% and a public charging power increase

from 50 kW to 120 kW improves reachability figures by less than 0.5%, if public charging opportunities exist at 10% of parking locations. If the ubiquitous 3.7 kW public charging infrastructure was replaced by 120 kW chargers at 70% of parking locations, the portion of electrically reachable destinations would increase by up to 2%.

Table 14: Portion of destinations that are electrically reachable (%)

Portion of destinations that are electrically reachable (%).																				Battery Cap. (kWh)
9.4				18.8				37.6				56.4				112.8				
3.7	7.4	11.0	22.1	3.7	7.4	11.0	22.1	3.7	7.4	11.0	22.1	3.7	7.4	11.0	22.1	3.7	7.4	11.0	22.1	Charging pow. (kW)
73	74	74	75	82	82	83	83	88	89	89	90	91	92	93	93	95	96	97	97	Home charging
79	80	80	81	86	87	87	88	92	92	93	93	94	95	95	95	97	98	98	98	Home charging
84	84	84	84	89	90	90	90	94	94	95	95	96	97	97	97	98	99	99	99	+ secondary
90	90	90	90	94	94	94	94	97	97	97	97	98	99	99	99	100	100	100	100	+10% public (50kW)
93	93	93	93	96	96	96	96	98	98	98	98	99	99	99	99	100	100	100	100	+40% public (50kW)
84	84	84	85	90	90	90	91	94	95	95	95	96	97	97	97	99	99	99	99	+70% public (50kW)
90	90	90	90	94	95	95	95	97	98	98	98	99	99	99	99	100	100	100	100	+10% public (120kW)
93	93	93	93	96	96	96	96	99	99	99	99	99	99	99	99	100	100	100	100	+40% public (120kW)
91	91	91	92	94	95	95	95	97	97	97	97	98	99	99	99	99	100	100	100	+70% public (120kW)
																				+100% public (3.68kW)

Table 15: Portion of mileage that is electrically drivable (%)

Portion of mileage that is electrically drivable (%).																				Battery Cap. (kWh)
9.4				18.8				37.6				56.4				112.8				
3.7	7.4	11.0	22.1	3.7	7.4	11.0	22.1	3.7	7.4	11.0	22.1	3.7	7.4	11.0	22.1	3.7	7.4	11.0	22.1	Charging pow. (kW)
57	57	58	58	68	69	69	70	79	79	80	80	84	85	85	85	91	93	93	93	Home charging
62	63	63	63	73	73	74	74	82	83	83	84	87	88	88	89	94	95	95	95	Home charging
66	67	67	67	76	77	77	77	86	86	86	86	90	91	91	91	96	97	97	97	+ secondary
73	74	74	74	83	83	83	83	91	91	91	91	95	95	95	95	98	98	98	99	+10% public (50kW)
78	78	78	78	86	87	87	87	93	94	94	94	96	96	97	97	99	99	99	99	+40% public (50kW)
67	67	67	68	77	77	77	78	86	87	87	87	91	91	91	92	96	97	97	97	+70% public (50kW)
74	74	74	74	84	84	84	84	92	92	92	92	95	95	96	96	99	99	99	99	+10% public (120kW)
78	78	78	78	87	87	88	88	94	95	95	95	97	97	97	97	99	99	99	99	+40% public (120kW)
74	75	75	75	82	83	83	83	90	90	90	91	94	94	94	94	98	98	98	98	+70% public (120kW)
																				+100% public (3.68kW)

3.3.2 Energy demand and grid impact^{iv}

A comparison of Table 15 and Table 16 verifies that the daily total electric energy demand rises with a greater portion of electrically drivable mileage. A PHEV with a 9.4 kWh battery that could be charged with 3.7 kW at the home charging facility requires about 3.9 kWh per day to cover 57% of mileage. With an additional extensive fast 120 kW charging infrastructure at 70% of parking locations, this value rises to 6.8 kWh per day and 78% of mileage could be covered. If instead of a 9.4 kWh battery, a 112.8 kWh battery was available, these figures would rise to 8.8 kWh (91% of mileage) and 10.3 kWh (99% of mileage) per day.

In Table 17, the daily peak power demand is given. In the home charging scenario, the power demand peak increases from 0.4 kW to 0.6 kW if instead of a 9.4 kWh battery capacity, 112.8 kWh were available. With the additional public charging opportunities, respective figures increase from 0.5 kW to 0.7 kW. With greater charging power at primary charging facilities, energy demand peaks further increase. Additional secondary or public charging opportunities can mitigate electrical peak demand (for batteries with a capacity of 37.6 kWh or more and charging power greater than 3.7 kW at the primary charging facility). The demand peak hours for each scenario are compared in Table 18. Energy demand was examined on an hourly granularity. Peak demand usually occurs in the late morning and in the evening with figures indicating the highest peak hour.

Table 16: Daily total energy demand (kWh)

Daily total energy demand (kWh)																				
9.4				18.8				37.6				56.4				112.8				Battery Cap. (kWh)
3.7	7.4	11.0	22.1	3.7	7.4	11.0	22.1	3.7	7.4	11.0	22.1	3.7	7.4	11.0	22.1	3.7	7.4	11.0	22.1	Charging pow. (kW)
3.9	4.0	4.0	4.1	5.3	5.4	5.5	5.5	6.9	7.0	7.1	7.2	7.7	8.0	8.0	8.1	8.8	9.2	9.3	9.3	Home charging
4.4	4.5	4.6	4.7	5.8	5.9	6.0	6.1	7.3	7.5	7.6	7.7	8.1	8.4	8.5	8.6	9.2	9.5	9.6	9.7	Home charging + secondary
5.0	5.1	5.1	5.2	6.4	6.5	6.5	6.6	7.9	8.0	8.1	8.1	8.7	8.9	8.9	8.9	9.6	9.8	9.8	9.9	+10% public (50kW)
6.1	6.1	6.1	6.1	7.5	7.5	7.6	7.6	8.9	8.9	8.9	9.0	9.5	9.6	9.6	9.6	10.1	10.2	10.2	10.2	+40% public (50kW)
6.7	6.7	6.7	6.7	8.1	8.2	8.2	8.2	9.4	9.4	9.4	9.4	9.9	9.9	9.9	9.9	10.3	10.3	10.3	10.3	+70% public (50kW)
5.1	5.1	5.2	5.2	6.5	6.6	6.6	6.7	8.0	8.1	8.2	8.2	8.8	9.0	9.0	9.0	9.7	9.9	9.9	9.9	+10% public (120kW)
6.2	6.2	6.2	6.2	7.7	7.7	7.7	7.8	9.1	9.1	9.1	9.1	9.7	9.7	9.7	9.7	10.2	10.2	10.2	10.2	+40% public (120kW)
6.8	6.8	6.8	6.8	8.3	8.3	8.3	8.4	9.5	9.5	9.6	9.6	10.0	10.0	10.0	10.0	10.3	10.3	10.3	10.3	+70% public (120kW)
6.0	6.0	6.1	6.1	7.2	7.3	7.3	7.4	8.6	8.6	8.7	8.7	9.2	9.4	9.4	9.4	10.0	10.1	10.1	10.1	+100% public (3.68kW)

Table 17: Daily demand peak (kW)

Daily demand peak (kW)																				Battery Cap. (kWh)
9.4				18.8				37.6				56.4				112.8				
3.7	7.4	11.0	22.1	3.7	7.4	11.0	22.1	3.7	7.4	11.0	22.1	3.7	7.4	11.0	22.1	3.7	7.4	11.0	22.1	Charging pow. (kW)
0.4	0.4	0.4	0.4	0.5	0.6	0.6	0.6	0.5	0.7	0.7	0.8	0.5	0.7	0.8	0.9	0.6	0.7	0.8	0.9	Home charging
0.4	0.4	0.4	0.4	0.4	0.5	0.5	0.5	0.5	0.6	0.6	0.7	0.5	0.6	0.7	0.8	0.5	0.6	0.7	0.8	Home charging + secondary
0.4	0.4	0.4	0.4	0.4	0.5	0.5	0.5	0.5	0.6	0.6	0.7	0.5	0.6	0.7	0.7	0.5	0.6	0.7	0.8	+10% public (50kW)
0.4	0.4	0.4	0.4	0.5	0.5	0.5	0.5	0.5	0.6	0.6	0.6	0.5	0.6	0.6	0.7	0.6	0.6	0.6	0.7	+40% public (50kW)
0.5	0.5	0.5	0.5	0.5	0.5	0.6	0.6	0.6	0.6	0.6	0.6	0.6	0.6	0.6	0.7	0.6	0.6	0.6	0.7	+70% public (50kW)
0.3	0.4	0.4	0.4	0.4	0.5	0.5	0.5	0.5	0.6	0.6	0.6	0.5	0.6	0.7	0.7	0.5	0.6	0.7	0.8	+10% public (120kW)
0.4	0.4	0.4	0.4	0.5	0.5	0.5	0.5	0.5	0.6	0.6	0.6	0.6	0.6	0.6	0.6	0.6	0.6	0.6	0.7	+40% public (120kW)
0.5	0.5	0.5	0.5	0.5	0.6	0.6	0.6	0.6	0.6	0.6	0.6	0.6	0.6	0.6	0.7	0.7	0.6	0.6	0.7	+70% public (120kW)
0.4	0.4	0.4	0.4	0.5	0.5	0.5	0.5	0.5	0.6	0.6	0.6	0.5	0.6	0.7	0.7	0.5	0.6	0.7	0.8	+ 100% public (3.68kW)

Table 18: Demand peak hour

Demand peak hour																				Battery Cap. (kWh)
9.4				18.8				37.6				56.4				112.8				
3.7	7.4	11.0	22.1	3.7	7.4	11.0	22.1	3.7	7.4	11.0	22.1	3.7	7.4	11.0	22.1	3.7	7.4	11.0	22.1	Charging pow. (kW)
18.0	18.0	18.0	17.0	18.0	18.0	18.0	17.0	19.0	18.0	18.0	18.0	19.0	18.0	18.0	18.0	19.0	18.0	18.0	18.0	Home charging
18.0	17.0	17.0	17.0	18.0	18.0	17.0	17.0	18.0	18.0	18.0	17.0	18.0	18.0	18.0	17.0	18.0	18.0	18.0	18.0	Home charging + secondary
18.0	17.0	17.0	17.0	18.0	18.0	17.0	17.0	18.0	18.0	18.0	17.0	18.0	18.0	18.0	17.0	18.0	18.0	18.0	18.0	+10% public (50kW)
10.0	10.0	10.0	10.0	10.0	10.0	10.0	10.0	11.0	11.0	11.0	11.0	11.0	18.0	17.0	17.0	11.0	18.0	18.0	17.0	+40% public (50kW)
8.0	10.0	10.0	10.0	10.0	10.0	10.0	10.0	10.0	10.0	10.0	10.0	10.0	10.0	10.0	10.0	10.0	11.0	11.0	11.0	+70% public (50kW)
18.0	17.0	17.0	17.0	18.0	17.0	17.0	17.0	18.0	18.0	18.0	17.0	18.0	18.0	18.0	17.0	18.0	18.0	18.0	18.0	+10% public (120kW)
10.0	10.0	10.0	10.0	10.0	10.0	10.0	10.0	10.0	10.0	10.0	10.0	10.0	10.0	10.0	10.0	10.0	10.0	11.0	17.0	+40% public (120kW)
8.0	10.0	10.0	10.0	9.0	10.0	10.0	10.0	8.0	10.0	10.0	10.0	8.0	10.0	10.0	10.0	8.0	10.0	10.0	10.0	+70% public (120kW)
11.0	11.0	10.0	10.0	18.0	11.0	11.0	11.0	18.0	18.0	18.0	17.0	18.0	18.0	18.0	17.0	18.0	18.0	18.0	18.0	+ 100% public (3.68kW)

3.3.3 *Distinct characteristics of driver segments*^{iv}

A base case is created to provide a basis for comparing the influence of scenario parameter changes for eight different driver segments. This way, the influence of three scenario parameters – battery capacity, charging power, and charging infrastructure coverage – can be assessed. The base case scenario comprises an 18.8 kWh battery capacity with a 7.4 kW home charging infrastructure.

In Figure 11, the portion of electrically reachable destinations are depicted as an average for all vehicles (ALL) and for eight segments. The grey color indicates the base case. At least 51% of destinations are reachable for every segment. All but “long-distance occasional drivers” (LDOD), “technical service vehicles” (TSV), and “company representatives” (CR) reach at least 86% of destinations electrically.

A vehicle with limited range (18.8 kWh battery capacity) and limited charging opportunities (7.4 kW at a primary charging facility) is well suited for private car holders who drive within a limited area (FLD) or who commute without exceeding the vehicle’s electric range (SC and UC). Private car holders who use the vehicle occasionally to cover long-distances (LDOD) require more range or a better charging infrastructure. Given car and infrastructure configuration is well suited for business vehicles if covered distances rarely exceed the electric range of the vehicle (SDDV, LDDV). If large distances are covered and great variations in trip length exist (TSV, CR), larger batteries and better infrastructure coverage may be required.

3.3.3.1 **Influence of battery capacities**^{iv}

It appears likely that the battery capacity has a great impact on the electric reachability target value for all segments, as it directly influences the electric range of the vehicle. Therefore, we modify the base case scenario in Figure 11 (grey color) by decreasing and increasing the battery capacity value to 9.4 kWh (red color) and to 37.6 kWh (blue color) respectively.

With a smaller 9.4 kWh battery, the “long-distance delivery vehicle” (LDDV) segment’s reachability value drops from 89% to 70%. For the “technical service vehicle” (TSV) this value drops from 62% to 47% and for the “company representative” (CR) segment it drops from 51% to 34%.

With a larger 37.6 kWh battery, reachability values rise to 79% for the “technical service vehicle” (TSV) segment and to 71% for the “company representative” (CR) segment. The “long-distance occasional drivers” (LDOD) reach 75% of destinations electrically. Both “technical service vehicles” (TSV) and the “company representatives” (CR) benefit the most from larger 37.6 kWh batteries.

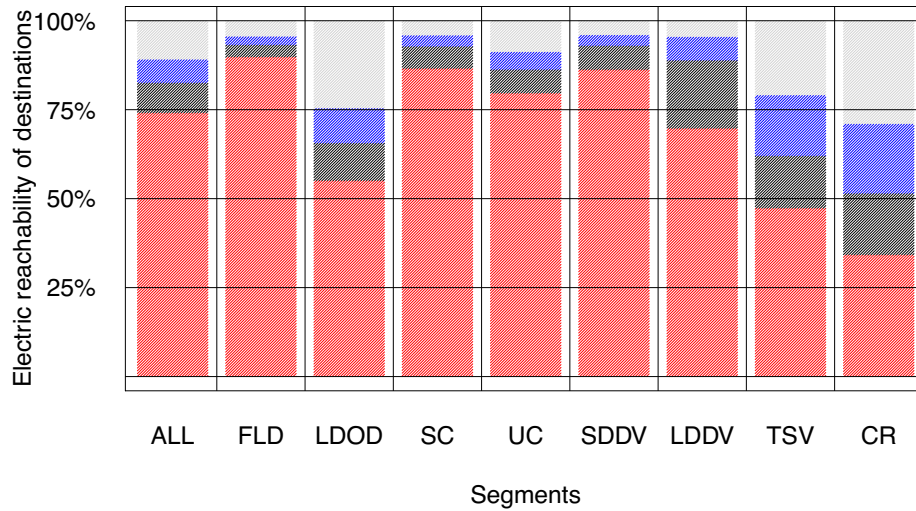


Figure 11: Base case versus 9.4 kWh and 37.6 kWh battery capacity

Figure 12 compares results for 5 different battery capacity values from 9.4 kWh to 112.8 kWh. The generally high reachability figure for all segments when using very large 112.8 kWh batteries is noteworthy. Every segment electrically reaches 90% of destinations (“long-distance occasional drivers”, LDOD) or more. Long-distance drivers (LDOD, LDDV, TSV, and CR) profit the most from having larger batteries.

Still, the benefit from battery capacities greater than 18.8 kWh is relatively low for drivers in the “long-distance delivery vehicle” (LDDV) group. This limited battery capacity demand can be explained by a comparatively low average driving speed and variance in roundtrip distances. For drivers with shorter roundtrip distances (FLD, SC, UC, SDDV) the battery parameter is generally less important.

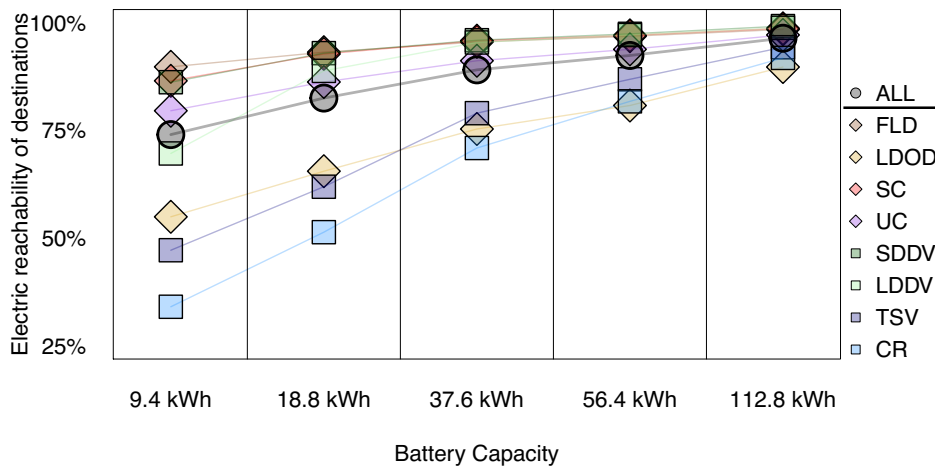


Figure 12: Comparison of electric reachability figures for different battery capacities when charging is possible with 7.4 kW at the primary charging facility

3.3.3.2 Influence of charging infrastructure^{iv}

In the base case scenario, a charging facility at the primary parking location is assumed. This infrastructure can be extended by adding an additional private secondary charging facility. Such an infrastructure expansion increases the portion of electrically reachable destinations, as shown in Figure 13 (blue color). “Frequent local drivers” (FLD), “steady commuters” (SC), and “short-distance delivery vehicles” (SDDV) only slightly benefit from the additional charging opportunity, with an increase of 3%, 3%, and 1% respectively. With an increase of 12%, 11%, and 15%, “long-distance occasional drivers” (LDOD), “technical service vehicles” (TSV), and “company representatives” (CR) benefit the most.

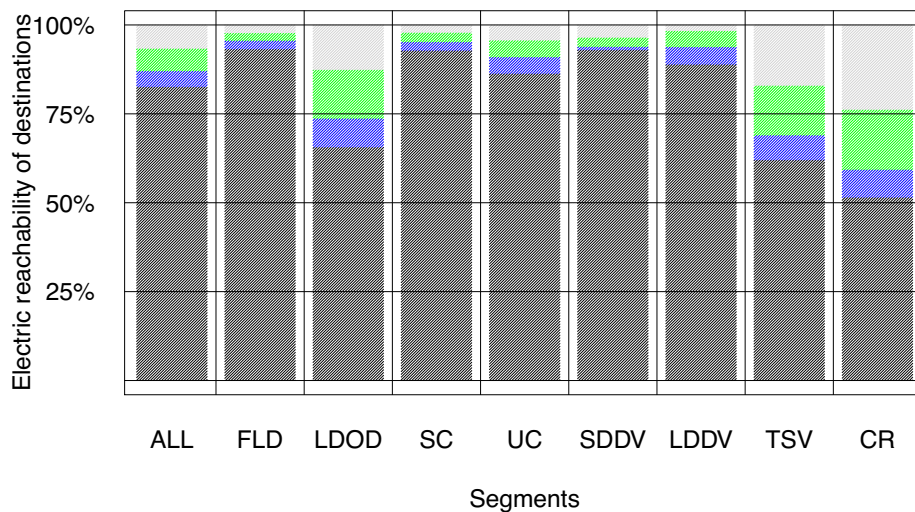


Figure 13: Base case versus additional charging at the secondary charging facility (blue color) or at both the secondary charging facility and at 70% of parking locations (green color)

Such a private charging infrastructure can be further extended by adding public charging facilities. With an extensive 50 kW public charging infrastructure that covers 70% of parking locations, every segment reaches at least 89% of destinations electrically, as depicted in Figure 13 (green color). Again, this infrastructure expansion is particularly beneficial to “long-distance occasional drivers” (LDOD), “technical service vehicles” (TSV), and “company representatives” (CR).

Figure 14 compares five infrastructure coverage scenarios, including two private charging scenarios (“primary”, “both primary and secondary”) and three scenarios that combine private and public charging (both locations plus 10%, 40%, or 70% public charging coverage). An extensive charging infrastructure coverage would indeed make a great share of destinations reachable electrically. However, the expectedly great expenses for such an infrastructure measure (National Academy of Sciences, 2015) make its realization unlikely. Although each infrastructure improvement also increases the reacha-

bility key figure, the increase from a 40% public charging infrastructure to 70% is comparatively small. Ultimately, an increase in battery capacity, as depicted in Figure 12 creates similar benefits.

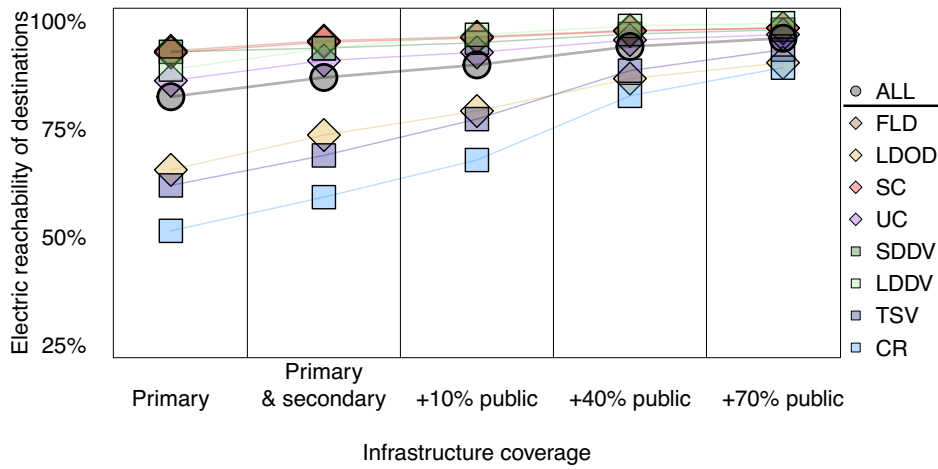


Figure 14: Comparison of electric reachability figures for different charging infrastructure coverages when an 18.8 kWh battery capacity is available. Private charging power is set to 7.4 kW and public charging power is set to 50 kW

3.3.3.3 Influence of charging power^{iv}

Besides battery capacity and charging infrastructure coverage, an increase in charging power can potentially improve the portion of electrically reachable destinations, as illustrated in Figure 15. However, the comparison of four different charging power values from 3.7 kW to 22.1 kW indicates that the benefit from an increase in charging power in a home charging scenario is very low.

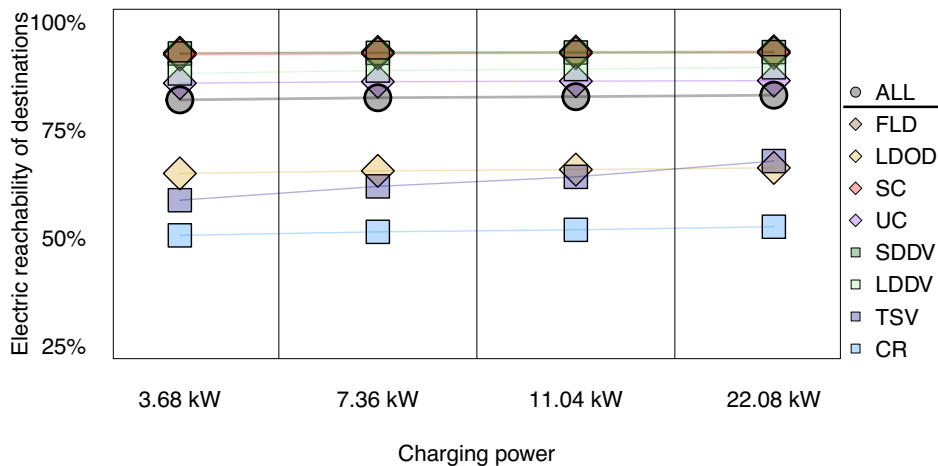


Figure 15: Comparison of electric reachability figures for different charging power parameters when an 18.8 kWh battery capacity is available and charging is possible at the primary charging facility

Also in a public charging scenario the benefit of increased charging power is limited, as Figure 16 shows. Here, 7.4 kW private chargers are available both at the primary and secondary charging facility. In addition, 10% of parking locations provide public charging opportunities with a charging power of 50 kW or 120 kW.

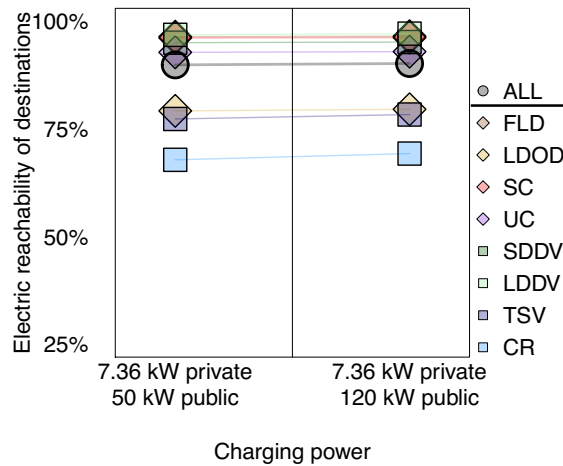


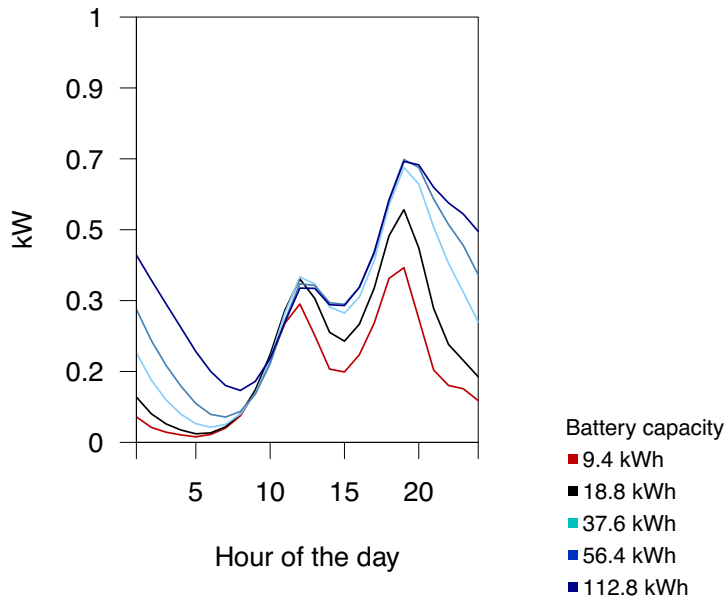
Figure 16: Comparison of electric reachability figures for different charging power parameters when an 18.8 kWh battery capacity is available and charging is possible at both the primary and secondary charging facility and at 10% of parking locations

3.3.3.4 Detailed description of the grid impact

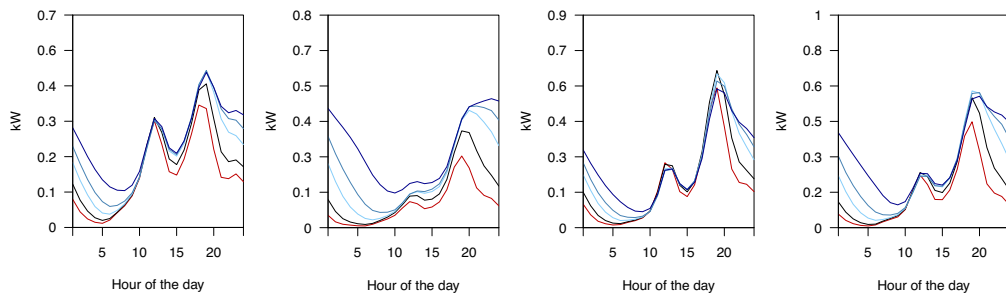
In the following Figure 17 to Figure 25, 24-hour charging demand profiles are depicted that give detailed information on the expected grid impact of PHEV charging for infrastructure and battery capacity variations. It is assumed that the charging power at private locations is 7.4 kW. The black line indicates an 18.8 kWh battery capacity. The red line indicates a 9.4 kWh battery capacity. The three blue lines indicate 37.6 kWh, 56.4 kWh, and 112.8 kWh with darker color shades for larger batteries.

A public charging infrastructure, particularly with higher charging power, tends to shift energy demand from evening hours to daytime hours. Even though a public infrastructure leads to an overall increase in energy demand and in electrified mileage, peak demand is decreased in average charging demand profiles.

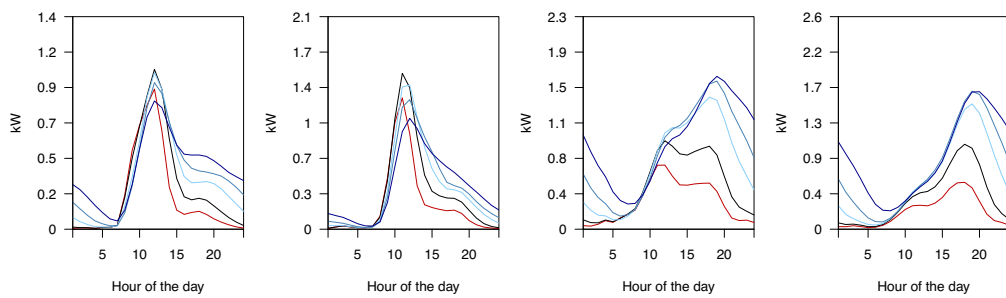
An increased battery capacity typically increases energy demand and peak demand. In that regard it is particularly noteworthy that the overall demand is shifted to the right, because it takes more time to charge larger batteries (e.g., during night hours). Interestingly, a close examination of demand profiles reveals that in some cases the peak power demand for smaller batteries is higher than for very large batteries. This is due to the assumption that charging power is reduced after the battery is charged to 80%, as explained in (Sodenkamp, Wenig, Thiesse, et al., 2019; Wenig, Sodenkamp, and Staake, 2015), and in chapter 2, respectively.



(a) Average across the entire fleet (100%)



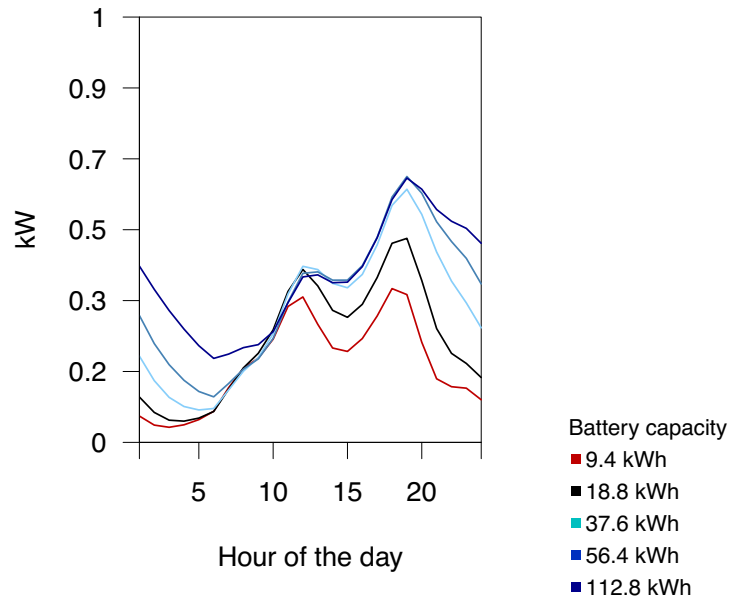
Segment 1: "Frequent local driver" (FLD, 16.4%) Segment 2: "Long-distance occasional driver" LDOD, 11.3%) Segment 3: "Steady commuter" (SC, 18.9%) Segment 4: "Unsteady commuter" (UC, 30.4%)



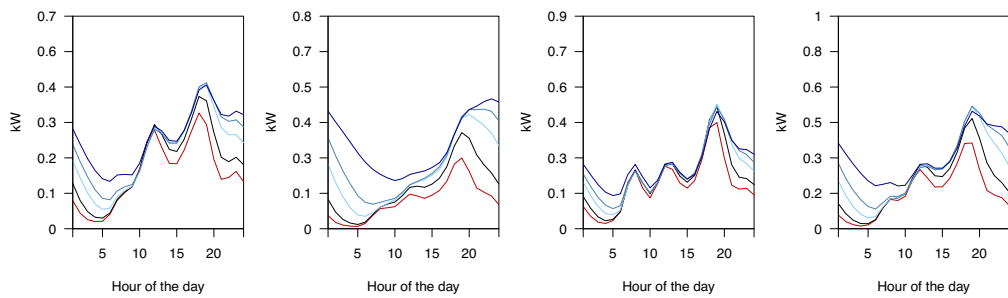
Segment 5: "Short-distance delivery vehicle" (SDDV, 4.4%) Segment 6: "Long-distance delivery vehicle" (LDDV, 5.4%) Segment 7: "Technical service vehicle" (TSV, 4.0%) Segment 8: "Company representative" (CR, 9.2%)

(b) Segment-wise

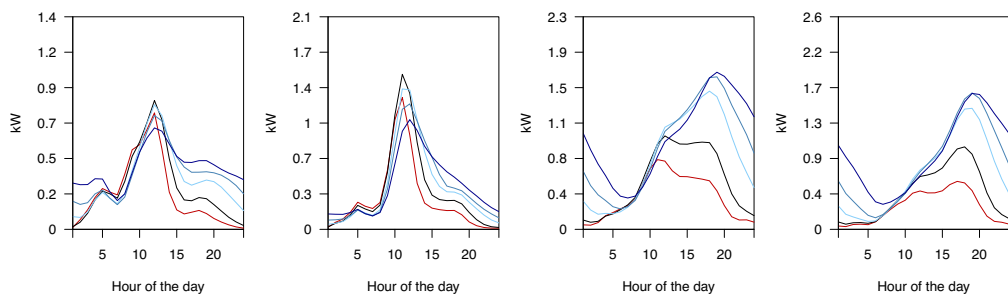
Figure 17. Grid impact of charging on the electric power network if charging is possible at the primary parking location



(a) Average across the entire fleet (100%)



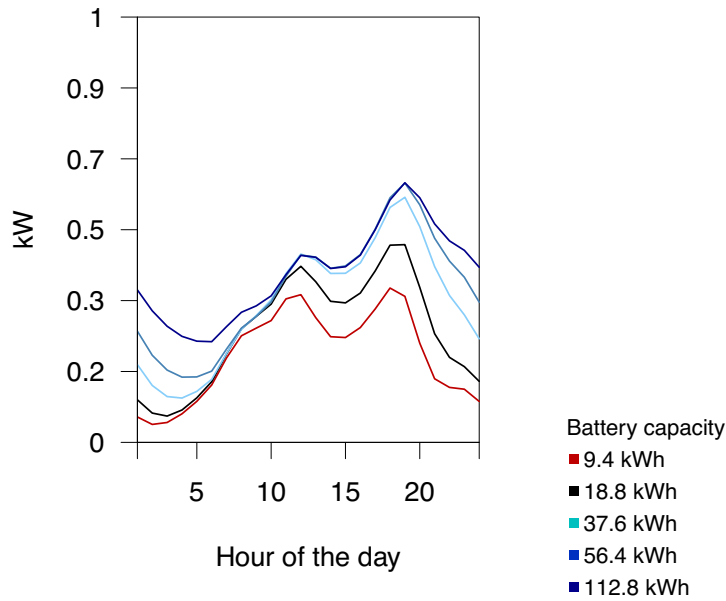
Segment 1: "Frequent local driver" (FLD, 16.4%) Segment 2: "Long-distance occasional driver" LDOD, 11.3%) Segment 3: "Steady commuter" (SC, 18.9%) Segment 4: "Unsteady commuter" (UC, 30.4%)



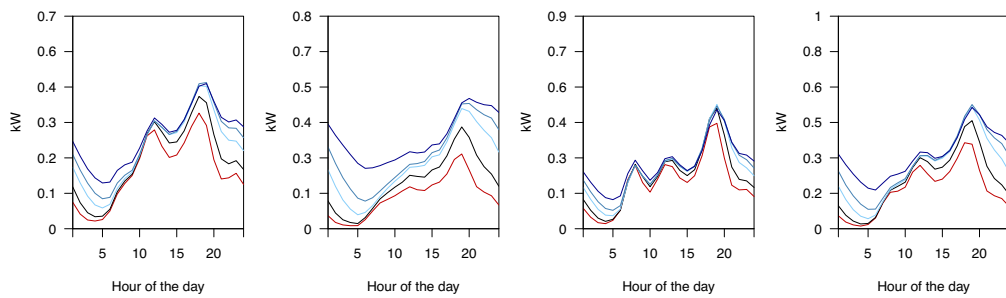
Segment 5: "Short-distance delivery vehicle" (SDDV, 4.4%) Segment 6: "Long-distance delivery vehicle" (LDDV, 5.4%) Segment 7: "Technical service vehicle" (TSV, 4.0%) Segment 8: "Company representative" (CR, 9.2%)

(b) Segment-wise

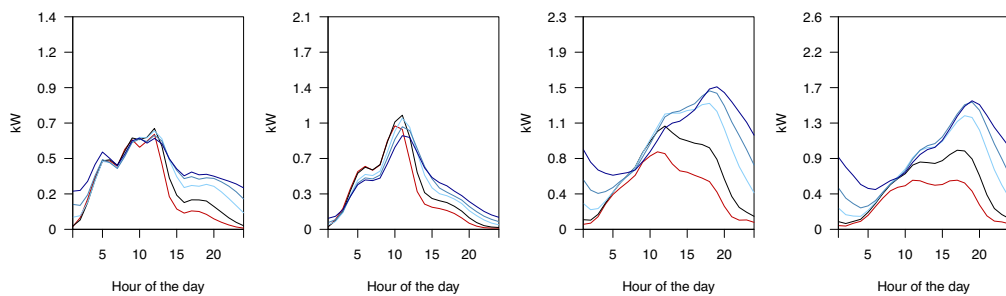
Figure 18. Grid impact of charging on the electric power network if charging is possible both at the primary and secondary parking location



(a) Average across the entire fleet (100%)



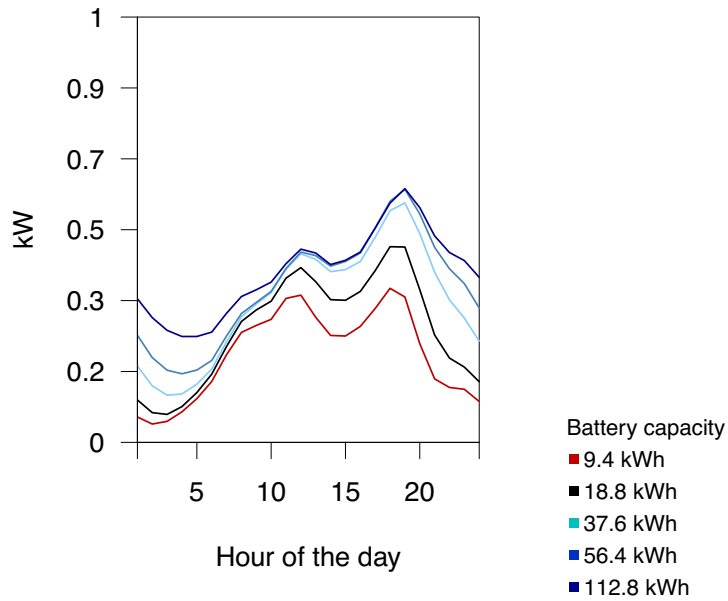
Segment 1: "Frequent local driver" (FLD, 16.4%) Segment 2: "Long-distance occasional driver" LDOD, 11.3%) Segment 3: "Steady commuter" (SC, 18.9%) Segment 4: "Unsteady commuter" (UC, 30.4%)



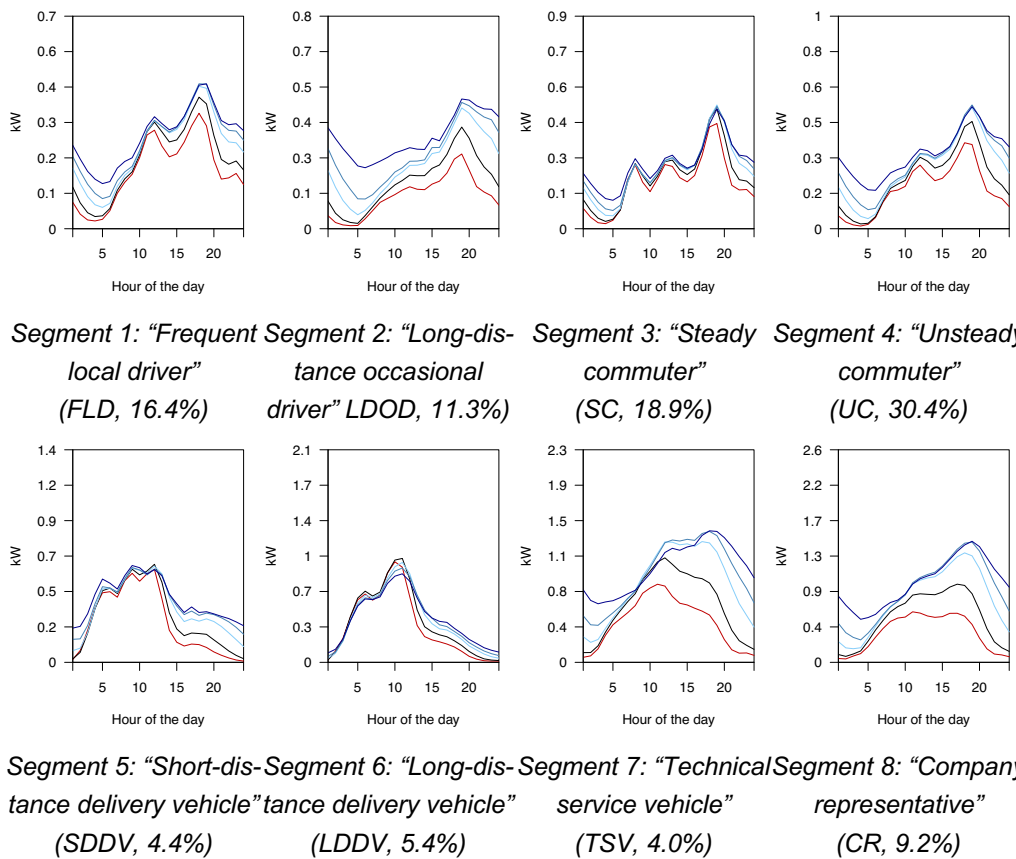
Segment 5: "Short-distance delivery vehicle" (SDDV, 4.4%) Segment 6: "Long-distance delivery vehicle" (LDDV, 5.4%) Segment 7: "Technical service vehicle" (TSV, 4.0%) Segment 8: "Company representative" (CR, 9.2%)

(b) Segment-wise

Figure 19. Grid impact of charging on the electric power network if charging is possible both at the primary and secondary parking location and at 10% of parking locations with 50 kW charging power

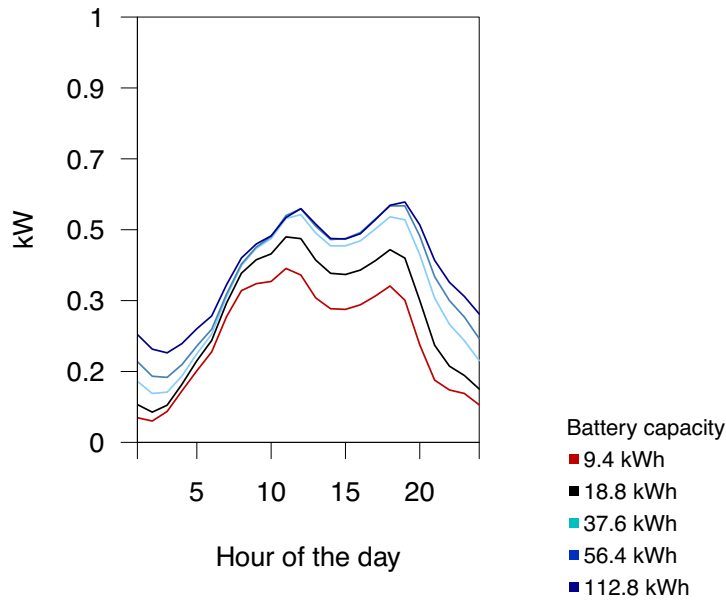


(a) Average across the entire fleet (100%)

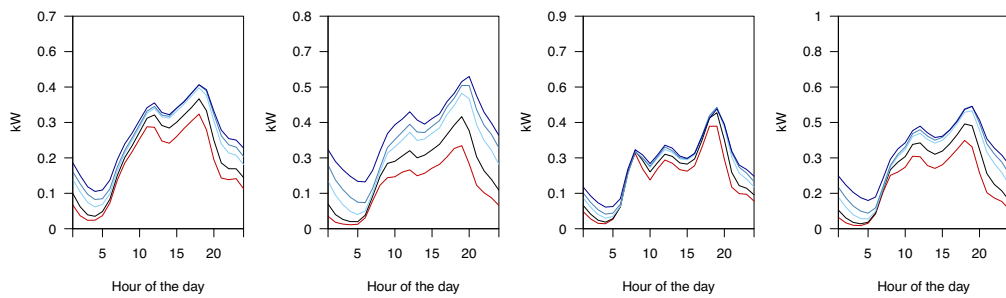


(b) Segment-wise

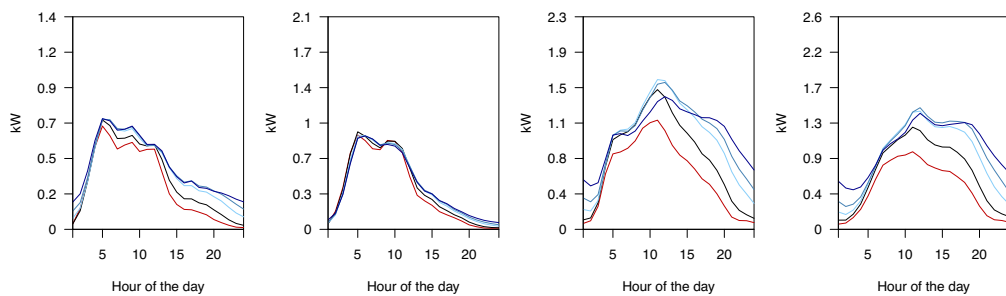
Figure 20. Grid impact of charging on the electric power network if charging is possible both at the primary and secondary parking location and at 10% of parking locations with 120 kW charging power



(a) Average across the entire fleet (100%)



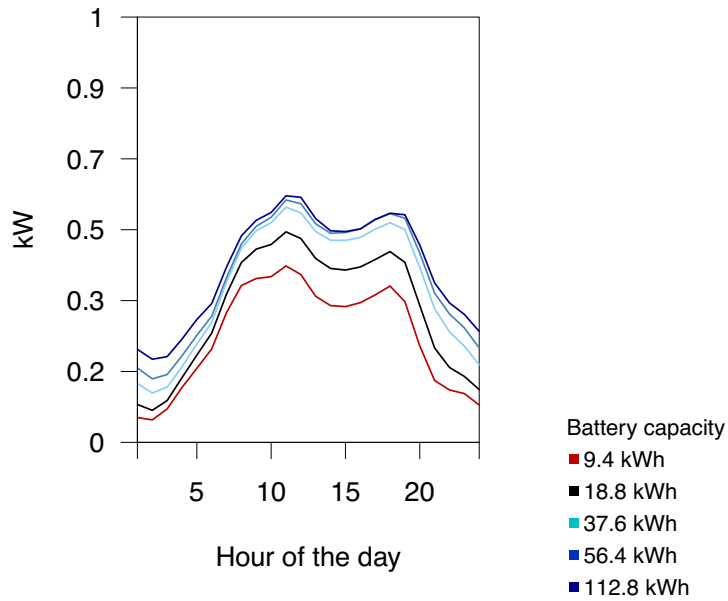
Segment 1: "Frequent local driver" (FLD, 16.4%) Segment 2: "Long-distance occasional driver" LDOD, 11.3%) Segment 3: "Steady commuter" (SC, 18.9%) Segment 4: "Unsteady commuter" (UC, 30.4%)



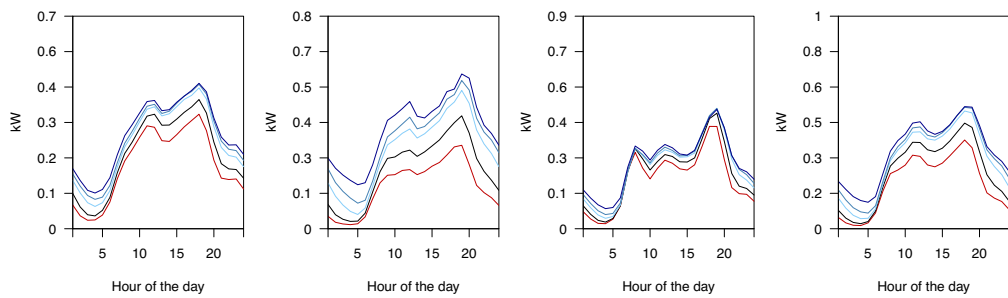
Segment 5: "Short-distance delivery vehicle" (SDDV, 4.4%) Segment 6: "Long-distance delivery vehicle" (LDDV, 5.4%) Segment 7: "Technical service vehicle" (TSV, 4.0%) Segment 8: "Company representative" (CR, 9.2%)

(b) Segment-wise

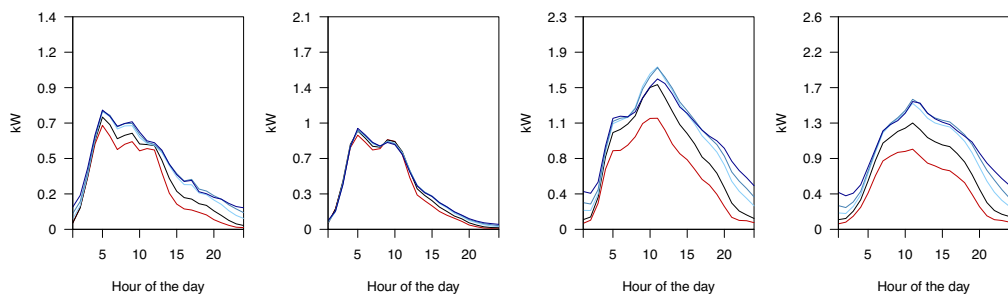
Figure 21. Grid impact of charging on the electric power network if charging is possible both at the primary and secondary parking location and at 40% of parking locations with 50 kW charging power



(a) Average across the entire fleet (100%)



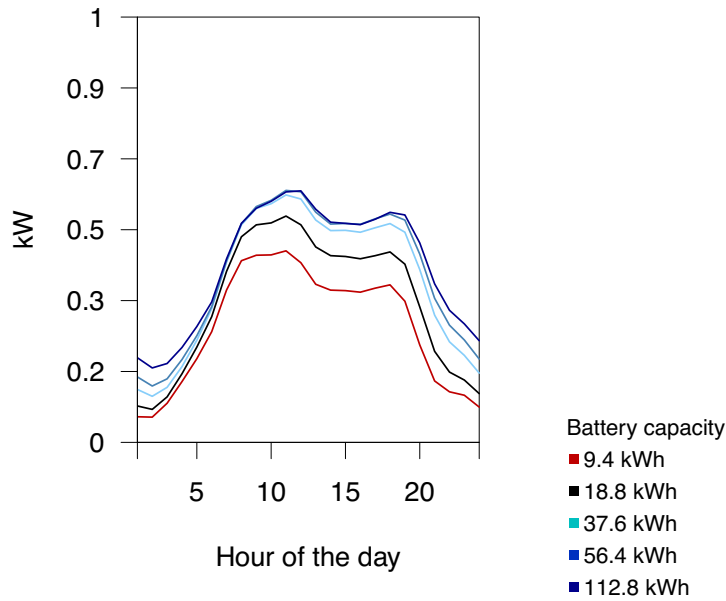
Segment 1: "Frequent local driver" (FLD, 16.4%) Segment 2: "Long-distance occasional driver" LDOD, 11.3%) Segment 3: "Steady commuter" (SC, 18.9%) Segment 4: "Unsteady commuter" (UC, 30.4%)



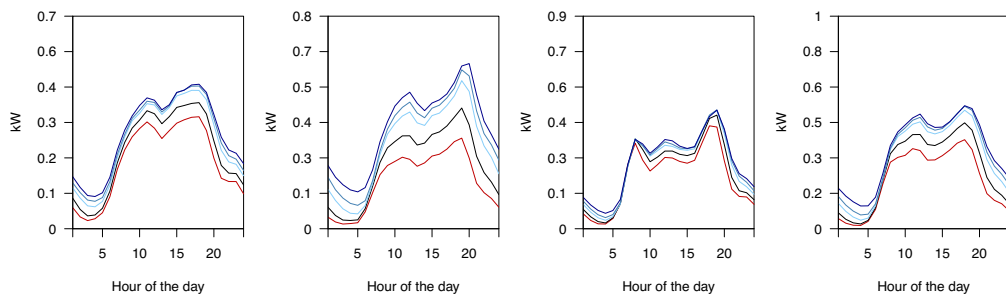
Segment 5: "Short-distance delivery vehicle" (SDDV, 4.4%) Segment 6: "Long-distance delivery vehicle" (LDDV, 5.4%) Segment 7: "Technical service vehicle" (TSV, 4.0%) Segment 8: "Company representative" (CR, 9.2%)

(b) Segment-wise

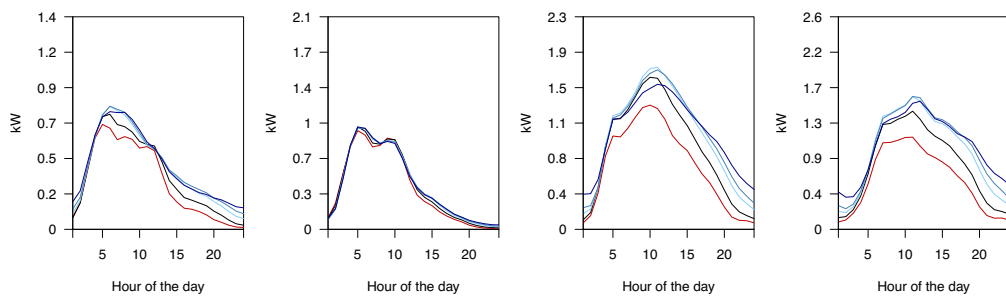
Figure 22. Grid impact of charging on the electric power network if charging is possible both at the primary and secondary parking location and at 40% of parking locations with 120 kW charging power



(a) Average across the entire fleet (100%)



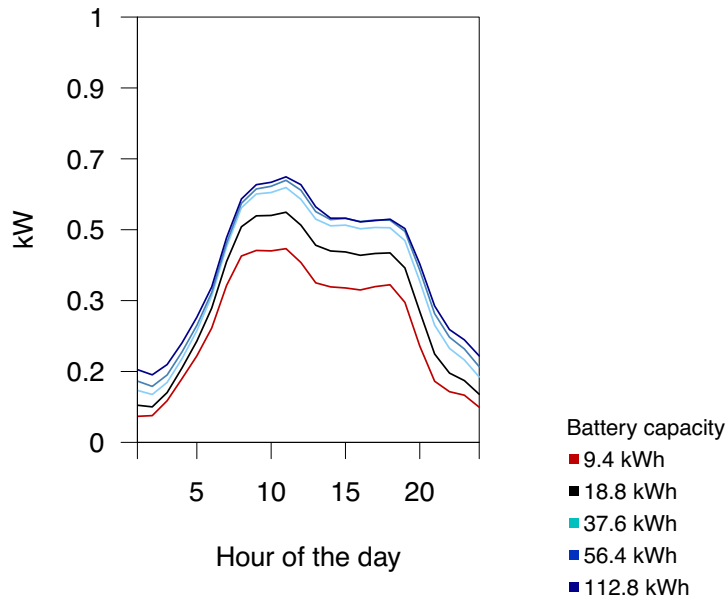
Segment 1: "Frequent local driver" (FLD, 16.4%) Segment 2: "Long-distance occasional driver" (LDOD, 11.3%) Segment 3: "Steady commuter" (SC, 18.9%) Segment 4: "Unsteady commuter" (UC, 30.4%)



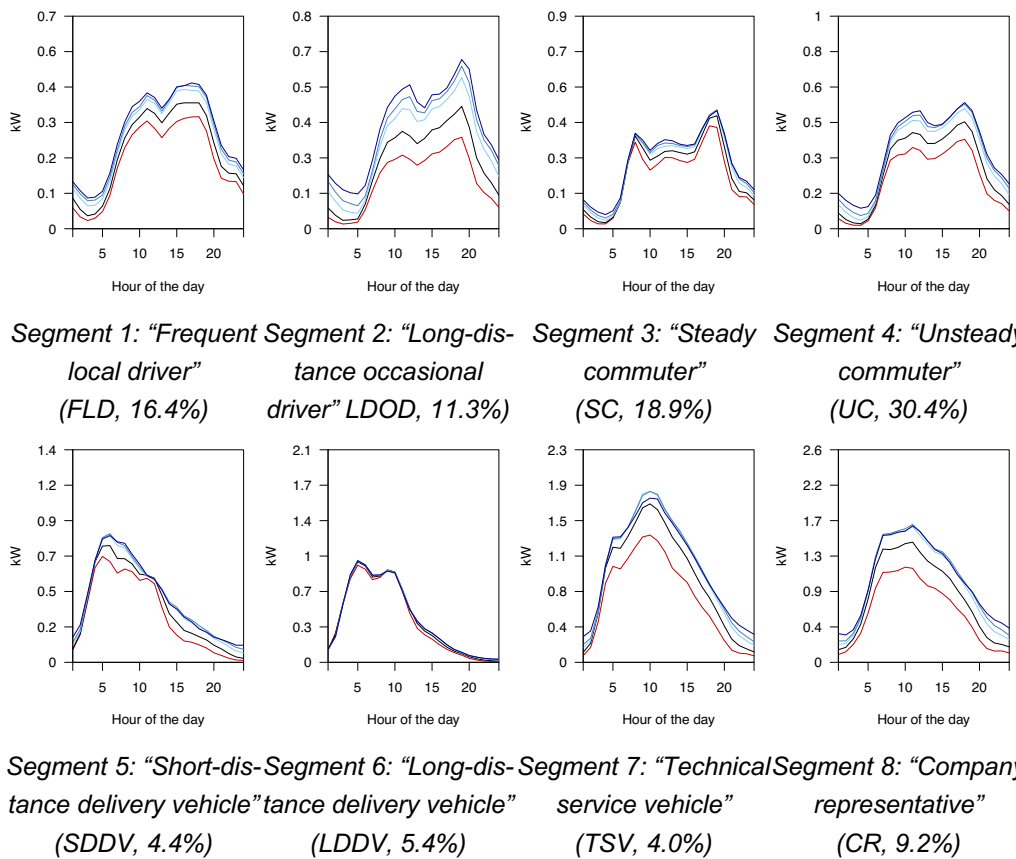
Segment 5: "Short-distance delivery vehicle" (SDDV, 4.4%) Segment 6: "Long-distance delivery vehicle" (LDDV, 5.4%) Segment 7: "Technical service vehicle" (TSV, 4.0%) Segment 8: "Company representative" (CR, 9.2%)

(b) Segment-wise

Figure 23. Grid impact of charging on the electric power network if charging is possible both at the primary and secondary parking location and at 70% of parking locations with 50 kW charging power

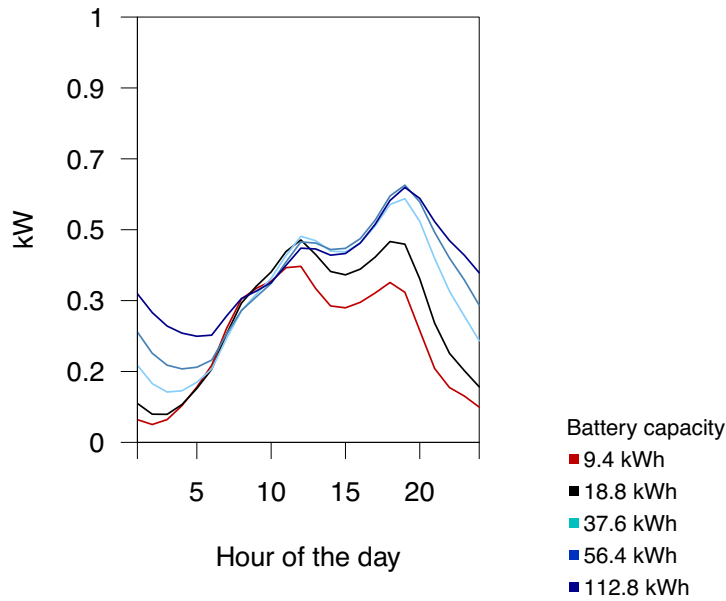


(a) Average across the entire fleet (100%)

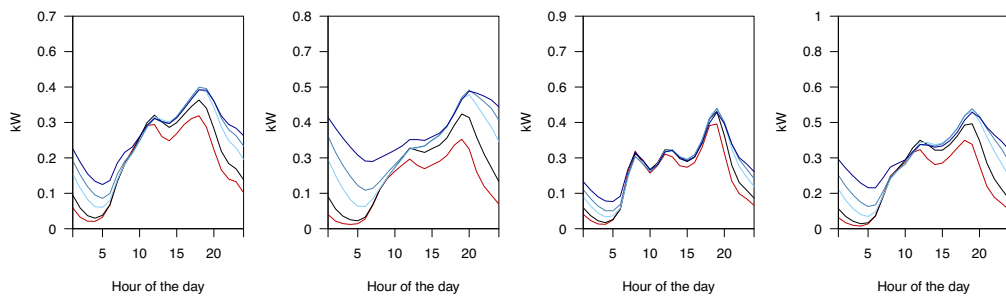


(b) Segment-wise

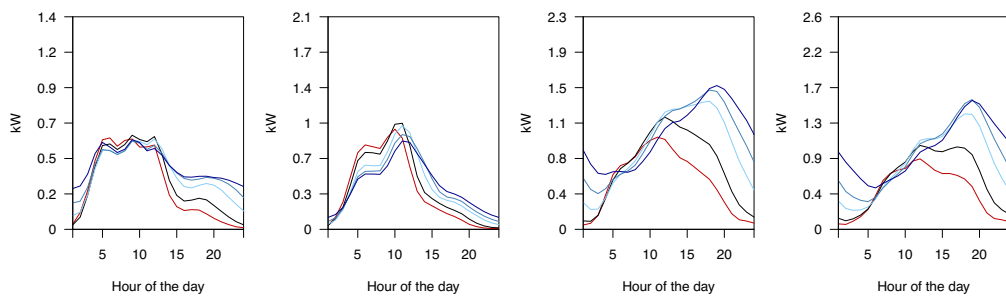
Figure 24. Grid impact of charging on the electric power network if charging is possible both at the primary and secondary parking location and at 70% of parking locations with 120 kW charging power



(a) Average across the entire fleet (100%)



Segment 1: "Frequent local driver" (FLD, 16.4%) Segment 2: "Long-distance occasional driver" LDOD, 11.3%) Segment 3: "Steady commuter" (SC, 18.9%) Segment 4: "Unsteady commuter" (UC, 30.4%)



Segment 5: "Short-distance delivery vehicle" (SDDV, 4.4%) Segment 6: "Long-distance delivery vehicle" (LDDV, 5.4%) Segment 7: "Technical service vehicle" (TSV, 4.0%) Segment 8: "Company representative" (CR, 9.2%)

(b) Segment-wise

Figure 25. Grid impact of charging on the electric power network if charging is possible both at the primary and secondary parking location and at 100% of parking locations with 3.7 kW charging power

Figure 17 and Figure 24 can be compared to show the segment specific implications of a charging infrastructure extension most prominently. Here, primary, or home charging is compared with a scenario where charging is possible at both private parking locations and publicly at 70% of parking locations with 120 kW charging power.

For segments 1, 2, 3, and 4 (FLD, LDOD, SC, and UC), which are also assumed to be typically privately held vehicles, demand continues to peak in the evening, but these demand peaks become less noteworthy because charging demand during the day considerably increases. For segments 5, 6, 7, and 8 (SDDV, LDDV, TSV, CR), which are considered to be vehicles with a business purpose, a greater charging infrastructure coverage leads to a shift of energy demand and peak demand to the left.

A comparison of Figure 24 and Figure 25, respectively of public charging at 70% of destinations with 120 kW charging power and of public charging at 100% of destinations with 3.7 kW charging power indicates that an increase in charging power shifts curves to the left, because more energy can be charged in less time and thus batteries are fully recharged earlier. This is most striking for segment 7 (TSV) and segment 8 (CR), where peak demand is shifted from the evening to late morning hours and noon. The combination of long individual trips and relatively short parking durations in these segments explains the extensive use and impact of fast public chargers.

3.3.4 Comparison of selected electric mobility scenarios

In the following, three interesting and very distinct electric mobility scenarios (and two sub-scenarios) are compared for eight different driver segments. First, the “modest” scenario assumes that a PHEV with a small 9.4 kWh battery is available and that charging is only possible at 3.7 kW home charging facilities. Two sub-scenarios assume either a large 112.8 kWh battery capacity or an excellent charging infrastructure (22.1 kW home and secondary charging, 120 kW charging at 70% of public parking locations). In the “ambitious” scenario, a 56.4 kWh PHEV is available, together with 7.4 kW charging at primary and secondary locations and 50 kW public charging at 10% of parking locations. Finally, the “excellent” scenario assumes that each vehicle has a 112.8 kWh battery capacity and that charging is possible with 22.1 kW at primary and secondary charging facilities and with 120 kW at 70% of parking locations. An overview is given:

Modest:

- 9.4 kWh battery capacity
- 3.7 kW home charging

Modest with excellent battery capacity:

- 112.8 kWh battery capacity
- 3.7 kW home charging

Modest with excellent infrastructure:

- 9.4 kWh battery capacity
- 22.1 kW home and secondary charging
- 120 kW public charging at 70% of parking locations

Overall, great shares of mileage (57%) can be electrified, even in an electric mobility scenario with a “modest” vehicle and infrastructure configuration. Drivers who cover long average roundtrip distances or whose average speed is high can electrify the least (LDOD: 33%, TSV: 36%, CR: 27%). If the mobility needs are less demanding, greater mileage shares can be covered electrically (FLD: 71%, SC: 72%, UC: 55%, SDDV: 79%, LDDV: 67%). Typically, the portion of destinations that can be reached electrically is higher than the portion of electrically covered mileage (73%). Almost all segments can reach more than 50% of destinations electrically (FLD: 89%, LDOD: 54%, SC: 86%, UC: 79%, SDDV: 86%, LDDV: 69%). Only drivers in two segments reach less than 50% (TSV: 44%, CR: 33%).

When considering the “modest” scenario and increasing the battery capacity, results show that all groups profit, such that the average portion of electrified mileage increases to 91%. Drivers with demanding mobility patterns profit the most from the increased battery capacity (LDOD: 80%, TSV: 88%, CR: 85%). Drivers who already covered great shares of mileage in the previous scenario could now electrify more than 90% of mileage (FLD: 94%, SC: 96%, UC: 91%, SDDV: 96%, LDDV: 98%).

If instead of the battery capacity, the infrastructure is improved in the “modest” scenario, results show that again, drivers generally profit. Still, the overall increase in electrified mileage is significantly lower (78% of mileage is electrified). Only in two segments more than 90% of mileage is electrified (SDDV: 93%, LDDV: 97%). A slow average driving speed and frequent stops during roundtrips could explain this result. For the other segments, the electrification potential is limited, which shows that an excessive charging infrastructure can't compensate for small battery capacities (FLD: 84%, LDOD: 61%, SC: 86%, UC: 75%, TSV: 77%, CR: 69%).

In the “ambitious”, yet realistic scenario, about 91% of mileage could be electrified. Consequently, most driver groups cover large mileage shares of more than 90% electrically (FLD: 93%, SC: 95%, SDDV: 97%, LDDV: 99%, TSV: 94%). Only drivers with demanding mobility requirements (e.g., long roundtrip distances, respectively high variations in roundtrip distance, or high speed) cover less (LDOD: 79%, UC: 89%, CR: 88%). Drivers in all segments could electrically cover about 90% of destinations or more.

With both an “excellent” charging infrastructure and a very large battery capacity, the average driver could cover about 99% of mileage electrically. In all groups, between 99% and 100% are covered (FLD: 99%, LDOD: 99%, SC: 100%, UC: 99%, SDDV: 100%, LDDV: 100%, TSV: 100%, CR: 100%). Drivers of all groups can reach almost every destination electrically.

A great share of electrified mileage does not necessarily imply a large number of electrified kilometers travelled. Drivers with typically high monthly mileage figures (SDDV, LDDV, TSV, CR) can electrify greater amounts of mileage, even if the relative share is low. Naturally, if monthly mileage is lower (as in segments FLD, LDOD, SC, and UC), also the relative share is low.

3.3.4.2 Comparison of the gasoline saving potential

In Table 20 the gasoline saving potential that is derived from the electrical energy demand is given for the “modest”, “ambitious”, and “excellent” scenario. It is assumed that the electric car has an efficiency of 90%, as inspired by (Diehlmann and Häcker, 2013; Karlsson and Kushnir, 2013; Mi, Masrur, and Gao, 2011) and that the internal combustion engine’s efficiency is about 30% (Diehlmann and Häcker, 2013). It is further assumed that gasoline contains 8.9 kWh/liter (Natural Resources Canada, 2018).

Table 20: Daily gasoline saving potential for selected electric mobility scenarios

Segment	1	2	3	4	5	6	7	8	ALL
Segment name	FLD	LDOD	SC	UC	SDDV	LDDV	TSV	CR	ALL
Segment size	149	103	172	276	40	49	36	84	909
% of fleet	16.4%	11.3%	18.9%	30.4%	4.4%	5.4%	4.0%	9.2%	100%
Daily mileage [km]	51	48	47	52	83	85	181	178	70
Modest scenario									
Electrified mileage [km]	36	16	34	29	65	57	65	49	40
Electrified mileage share	71%	33%	72%	55%	79%	67%	36%	27%	57%
Electricity demand [kWh]	3.90	1.97	4.06	3.40	4.87	5.67	6.39	5.12	3.91
Gasoline savings [liters]	1.31	0.66	1.37	1.15	1.64	1.91	2.15	1.72	1.32
Modest scenario with excellent battery capacity									
Electrified mileage [km]	48	39	45	48	80	83	159	152	64
Electrified mileage share	94%	80%	96%	91%	96%	98%	88%	85%	91%
Electricity demand [kWh]	6.56	6.60	6.30	7.38	8.79	9.78	20.72	19.59	8.80
Gasoline savings [liters]	2.21	2.23	2.12	2.49	2.96	3.30	6.99	6.60	2.97
Modest scenario with excellent infrastructure									
Electrified mileage [km]	43	29	41	39	77	82	138	122	55
Electrified mileage share	84%	61%	86%	75%	93%	97%	77%	69%	78%
Electricity demand [kWh]	5.14	4.33	5.23	5.33	7.53	9.58	16.77	15.07	6.85
Gasoline savings [liters]	1.73	1.46	1.76	1.80	2.54	3.23	5.65	5.08	2.31
Ambitious scenario									
Electrified mileage [km]	48	38	45	47	80	85	169	157	64
Electrified mileage share	93%	79%	95%	89%	97%	99%	94%	88%	91%
Electricity demand [kWh]	6.49	6.47	6.16	7.11	9.24	10.08	22.39	20.67	8.87
Gasoline savings [liters]	2.19	2.18	2.08	2.40	3.12	3.40	7.55	6.97	2.99
Excellent scenario									
Electrified mileage [km]	51	47	47	52	83	85	180	178	70
Electrified mileage share	99%	99%	100%	99%	100%	100%	100%	100%	99%
Electricity demand [kWh]	7.26	9.05	6.74	8.50	10.15	10.23	24.55	24.61	10.32
Gasoline savings [liters]	2.45	3.05	2.27	2.86	3.42	3.45	8.28	8.30	3.48

The gasoline saving potential is correlated with the amount of electrified mileage. Thus, particularly scenarios and segments with a high absolute mileage electrification potential are most promising candidates for gasoline saving. For example, in the “ambitious”

scenario the “technical service vehicle” (TSV) could save about 7.6 liters and the “company representative” (CR) could save about 7.0 liters of gasoline per day. In the “excellent” scenario the gasoline saving potential increases to about 8.3 liters of gasoline per day for both segments.

It is particularly interesting to note that the gasoline saving potential per 100 electrified km considerably increases with battery and infrastructure improvements. In the “modest” scenario, on average 3.3 liters of gasoline per 100 electrified km (57% of overall mileage) could be saved. In the “excellent” scenario, this value increases to 5 liters of gasoline per 100 electrified km (99% of overall mileage). The most likely explanation is that improvements allow drivers to cover more energy-demanding distances electrically.

3.4 Conclusion^{iv}

This study utilizes the high granularity and heterogeneity of a large sample of GPS driving data from conventional cars to assess the influence of battery capacity, charging infrastructure coverage, and charging power on the electrification of vehicle mileage. Results confirm – in line with the existing literature – that vehicles with small battery capacities and with a limited charging infrastructure are sufficient for a considerable portion of trips.

With 3.7 kW primary (e.g., home) charging, a 9.4 kWh PHEV can reach 73% of destinations fully electrically. Both charging infrastructure measures and larger PHEV batteries foster the electrification of transport. In this context, the systematic assessment of 180 distinct electric mobility scenarios allows us to evaluate the interdependence of charging infrastructure and vehicle battery capacity requirements with regard to their usefulness.

Current automotive market developments in terms of electric range (Slowik, Pavlenko, and Lutsey, 2016) and the anticipation that costs for infrastructure measures – including labor and equipment – remain high (National Academy of Sciences, 2015) particularly emphasize the significance of long-range electric vehicles. Furthermore, the acquisition of a vehicle with sufficient electric range lies within the individual driver’s domain which suggests an appropriate use of resources, while large scale charging infrastructure measures entail the risk of misallocation and low utilization of charging facilities.

In fact, an extensive charging infrastructure development is not essential for a vast majority of trips, if vehicles are equipped with reasonably large batteries. For example, if abovementioned vehicles could be charged with 3.7 kW at every parking location, the portion of electrically reachable destinations would be increased by 24% from 73% to 91%. However, the same portion of about 91% would be feasible if instead a 56.4 kWh PHEV could be charged at 3.7 kW at home only. With a large 112.8 kWh battery, this figure rises to 95% when home charging is the only charging option and to 97% if charging is also possible at the secondary parking location.

Still, even elementary electric mobility scenarios have a considerable impact on the electric grid. For example, abovementioned 9.4 kWh PHEV that is charged at the primary charging facility with 3.7 kW demands about 3.9 kWh per day to reach 73% of destinations electrically (i.e., electrify 57% of mileage). This strain placed on the electric grid is particularly high during peak times in the evening around 18 o'clock.

With larger PHEV batteries, the portion of electrically drivable mileage and with it the demand for energy increases. For example, if the 9.4 kWh battery was replaced by a 112.8 kWh battery, 95% of destinations could be reached electrically (i.e., electrify 91% of mileage), however, daily energy demand would rise to 8.8 kWh. With additional charging infrastructure expansions, such as a secondary private charging opportunity and 50 kW public chargers at 10% of parking locations, 9.6 kWh would be required each day to reach 98% of destinations (i.e., electrify 96% of mileage).

While results suggest that both battery capacity and charging infrastructure improvements increase the portion of electrically reachable destinations, the impact of charging power improvements is negligible. This is particularly important for the evaluation of home charging opportunity expansions. Due to long parking times (e.g., at night) the availability of a fast charging opportunity at home is hardly relevant. Still, public fast charging facilities may provide convenience and flexibility for the driver (Schroeder and Traber, 2012).

Furthermore, distinct mobility characteristics – including mileage, speed, and parking time – can be used to segment drivers into distinct groups. Such an approach shows that some segments are better suited for electric mobility than others and that variations in the actual driving needs of customer groups greatly influence the effectiveness of solutions and therefore should be given close attention.

For particular groups, such as “frequent local drivers” (FLD), “commuters” (SC and UC), or “short-distance delivery vehicles” (SDDV), limited battery capacities and basic charging opportunities are sufficient. For example, a 9.4 kWh battery capacity and a 3.7 kW home charging facility are sufficient to reach more than 79% of destinations electrically (89%, 86%, 79%, and 86%). Other groups, such as “company representatives” (CR) or “technical service vehicles” (TSV) reach only about 33% and 44% of destinations electrically. Here, a 56.4 kWh and a 37.6 kWh battery capacity would be required to make more than 75% of destinations electrically reachable (77% and 76%). With a 56.4 kWh battery, “long-distance occasional drivers” (LDOD) and “long-distance delivery vehicles” (LDDV) would increase their portion of electrically reachable destinations from 54% and 69% to 80% and 97%. “Frequent local drivers” (FLD), “commuters” (SC and UC), and “short-distance delivery vehicles” (SDDV) would reach 96%, 97%, 93%, and 96% of destinations electrically.

With a very large battery (112.8 kWh), results further improve. While drivers of most segments would reach almost all destinations electrically (FLD: 98%, SC: 99%, UC: 97%, SDDV: 98%, LDDV: 98%). Fast long-range “long-distance occasional drivers” (LDOD), “company representatives” (CR), and “technical service vehicles” (TSV) would reach about 90% of their destinations (88%, 87%, 90%).

If instead of a larger battery, a better charging infrastructure was available, such that 7.4 kW charging was possible both at home and at a secondary charging facility and 50 kW public charging was possible at 10% of parking locations, drivers of most segments would reach about 90% of destinations electrically (FLD: 94%, SC: 92%, UC: 88%, SDDV: 93%, LDDV: 90%). “Long-distance occasional drivers” (LDOD), “company representatives” (CR), and “technical service vehicles” (TSV) would reach only about 70%, 54%, and 64% of destinations electrically.

If both a larger battery (56.4 kWh) and a better charging infrastructure (7.4 kW home and secondary charging, 50 kW public charging at 10% of parking locations) were available, drivers in most segments would reach almost all of their destinations electrically (FLD: 99%, SC: 99%, UC: 97%, SDDV: 99%, LDDV: 100%, TSV: 95%). “Long-distance occasional drivers” (LDOD) and “company representatives” (CR) would both reach only about 90% and 91% of their destinations electrically.

If both a very large battery (112.8 kWh) and a better charging infrastructure (7.4 kW home and secondary charging, 50 kW public charging at 10% of parking locations) were available, reachability figures for drivers in almost all segments would increase to about 99-100% (FLD: 100%, SC: 100%, UC: 99%, SDDV: 100%, LDDV: 100%, TSV: 99%). “Long-distance occasional drivers” (LDOD) and “company representatives” (CR) could reach about 96% and 97% of destinations electrically.

In conclusion, it can be summarized that for a great majority of drivers the availability of PHEVs with large but realistic battery capacities can resolve concerns about the availability of an extensive charging infrastructure. Still, results might be somewhat biased by particular characteristics of the data. With long electric range vehicles in mind and regarding current research literature, future work should focus on an assessment of the need for a long-distance charging infrastructure and on regional variations of charging infrastructure and electricity demand.

ⁱⁱⁱ Major parts of this chapter (also including figures and tables) have been taken from an earlier version of the coauthored work (Wenig, Sodenkamp, and Staake, 2019) and were adapted where applicable.

^{iv} Major parts of this subchapter (also including figures and tables) have been taken from an earlier version of the coauthored work (Wenig, Sodenkamp, and Staake, 2019) and were adapted where applicable.

4 Potential for photovoltaic charging and load shifting at home

4.1 Introduction

The transition from combustion-based transportation to electric transportation has a considerable impact on the power grid, which is clearly shown when directly comparing the increased energy demand for vehicle charging with the electricity demand of domestic households (Wenig, Sodenkamp, and Staake, 2015). Still, while conventional combustion-based vehicles heavily depend on crude oil resources, one favorable aspect of electric mobility is that other energy sources, such as solar energy, can be used for transportation (Lund, 2007).

Against this backdrop, feasible measures to reduce the additional strain on the grid caused by PHEV charging include the utilization of household level photovoltaic systems to support both energy for the household itself and the charging of the vehicle and the application of managed charging.

In the following, related research work that employs GPS driving data analytics to have a closer look at the grid impact of both PHEVs and battery electric vehicles is reviewed. Here, particularly the utility of home charging, of managed charging, and of photovoltaic systems for vehicle charging is addressed.

(Betz, Walther, and Lienkamp, 2017) estimate the amount of energy demanded by commercial vehicles when the employee charges the electric car at home and (Shahidinejad, Filizadeh, and Bibeau, 2012) assess the grid impact of electric vehicles at the home charging location and provide the respective load profiles.

(De Gennaro, Paffumi, Scholz, et al., 2014, 2013; Paffumi, De Gennaro, Martini, et al., 2015) compare several charging strategies and assume that characteristics such as overnight charging or a certain minimum parking duration indicate home charging. They discuss the need for and the potential of managed charging – such as off-peak charging at night – to manage the grid impact of electric mobility.

(Ashtari, Bibeau, Shahidinejad, et al., 2012) compare the grid impact of electric vehicles with the typical load profile (without electric vehicles) in the respective region. This particularly includes home charging scenarios and shows that the charging of electric vehicle leads to increased peaks in the load profile. The impact of parameter variations, such as arrival and departure times, charging scenarios, or vehicle parameters on the load profile is discussed.

Similarly, (Dong, Lin, Liu, et al., 2014) compare the grid impact of electric vehicles with the typical load profile of the related region. Their assessment particularly includes a scenario in which charging at home is prioritized. The utilization of managed charging is briefly discussed.

(Betz and Lienkamp, 2016) demonstrate the use of a photovoltaic system for electric vehicle charging within a commercial company. They show that – combined with a storage system for surplus electrical energy – the self-consumption rate in such an organization can be considerably increased.

(Denholm, Kuss, and Margolis, 2013) compare the grid impact of PHEVs with a typical local energy demand profile. They state that while off-peak charging of PHEVs at night relieves the stress on the electric grid, daytime charging – i.e., opportunity charging while the vehicle is parked – is necessary to maximize the mileage electrification potential. Against this background, they assess the potential for photovoltaic charging, including charging delay to prioritize photovoltaic charging. They find that photovoltaic based charging opportunities can reduce the increased peak power grid impact caused by daytime PHEV charging.

Similarly, (Chaouachi, Bompard, Fulli, et al., 2016) assess the grid impact of electric vehicles in the context of the typical electricity demand profile of the considered area. They state that home charging typically begins in the late afternoon and thus overlaps to a large part with high overall electricity demand. At the same time, photovoltaic generation is only available at daytime. Thus, they suggest a shift of charging demand to daytime hours and quantify the increased utility of such photovoltaic systems.

(Wenig, Sodenkamp, and Staake, 2015) can be seen as a preparatory study that precedes this chapter. Here it was discussed to what extent energy from solar panels – at home and work place locations – during sunlight hours could be used to charge the battery of an electric vehicle.

These studies assess the grid impact from PHEV charging and they discuss the use of managed charging and of photovoltaic systems. While they may also be viable for the assessment of the grid impact from PHEV charging at home locations, previous results particularly stress the importance of home charging for mileage electrification (c.f. (Sodenkamp, Wenig, Thiesse, et al., 2019; Wenig, Sodenkamp, and Staake, 2019, 2015), and chapters 2 and 3, respectively), such that in the course of this chapter, an in-depth focus on the residential domain is set and a closer examination of the private household case is carried out.

In (Wenig, Sodenkamp, and Staake, 2015) also the noteworthy potential for photovoltaic charging at a secondary charging facility was shown. Still, The perception of home charging as a most convenient method (Wenig, Sodenkamp, and Staake, 2015) and the importance of the residential sector for photovoltaic generation (SolarPower Europe, 2017; U.S. Energy Information Administration, 2017) further motivate the focus on the home charging scenario.

Linking the electricity demand of a single car to the electric load profile of a potentially larger organization is out of the scope of this chapter, because here strong assumptions which are difficult to justify (e.g., regarding the energy demand profile and size of a

typical enterprise or the availability and capacity of a photovoltaic system) would be necessary.

As a consequence, and to contribute to the related work, this chapter aims at quantifying the grid impact of PHEVs in the private household domain by comparing the charging demand of vehicles with the load profile of a typical private household. Particularly, the availability of a home-based photovoltaic system is considered in order to assess its impact on the energy demand profile.

Results from previous work also indicate that with unmanaged charging, vehicles are typically charged in the evening (or at noon), which results in power demand peaks if charging takes place immediately, using the available charging power (c.f. (Sodenkamp, Wenig, Thiesse, et al., 2019; Wenig, Sodenkamp, and Staake, 2019, 2015) and chapters 2 and 3, respectively). However, home parking times are often much longer than charging times. Thus, peak power demand could be managed by shifting charging demand from peak hours to less critical time periods (Palensky and Dietrich, 2011; Prügler, 2013; Shimizu, Ono, Hirohashi, et al., 2016), or by reducing the charging power (Shimizu, Ono, Hirohashi, et al., 2016).

In the following, the integration of PHEV charging demand and household electricity demand time series is suggested. The PHEV charging demand is derived from the GPS driving data-based simulation, while the household electricity demand is based on a typical standard household load profile (Schellong, 2016), as published by (Stadtwerke Unna; GIPS, 2018; Stadtwerke Unna, 2018). Statements on the energy demand of home-charged PHEVs can be provided at the individual household's level for the entire time period represented in the mobility data and 24-hour load profiles can be derived. From here, two research tasks emerge.

First, the potential for residential photovoltaic charging under realistic conditions can be estimated and compared with the assumed electricity demand profile of related private households of PHEV drivers. Location- and time-specific solar irradiation data (MINES ParisTech and Transvalor S.A., 2017) is utilized to estimate the energy generation potential of a residential photovoltaic system (Hofierka and Kaňuk, 2009; Hopf, Kormann, Sodenkamp, et al., 2017). On this basis it can be assessed, to what extent a residential photovoltaic system could be used for PHEV charging and how this would change a household's power demand curve.

Second, also the application of a managed charging (i.e., load shifting) strategy for home-charging PHEVs takes place and the potential of load shifting for peak grid demand reduction is assessed. A simple load shifting strategy is suggested that exploits the entire parking time window during a home charging event and thus allows PHEV charging with reduced power for a longer period of time. Consequently, during peak hours, the power demand impact is reduced while at the end of the parking event the same amount of energy has been charged.

4.2 Methodology

4.2.1 *Integration of household load profiles*

From 909 data sets used in (Wenig, Sodenkamp, and Staake, 2019) and in chapter 3, 700 data sets that are supposed to relate to privately held vehicles form the data basis for this chapter. More specifically, the four segments (1) “frequent local driver” (FLD, $n=149$), (2) “long-distance occasional driver” (LDOD, $n=103$), (3) “steady commuter” (SC, $n=172$), and (4) “unsteady commuter” (UC, $n=276$) are included for the assessment of households. A manual inspection of satellite imagery supports the selection of these groups. The majority of respective primary charging locations (median coordinates) are typically residential.

For this study, the Coordinated Universal Time in Central Europe (UTC+1) is assumed (Central Intelligence Agency, 2018a, 2018b) to merge the GPS data-based time series and both solar irradiation data and a synthetic household load profile. Such a choice appears to be reasonable as data from an Italian data provider and from Italian motorists was used (Ippisch, 2010). Only on rare occurrences, vehicles drive outside of the described time zone, possibly because of vacation, business trips, etc. Thus, for the sake of comparability of results, UTC+1 is used in the overall context of this work.

A standard load profile for generic private households can be used as a data basis for household electricity demand assessment (Schellong, 2016; Stadtwerke Unna; GIPS, 2018; Stadtwerke Unna, 2018). The data provides information for work days, Saturdays, Sundays, summer, winter, and intermediate seasons. Furthermore, the data can be adjusted to the varying yearly electricity consumption of an average household in the respective region (Schellong, 2016; World Energy Council, Enerdata, and ADEME, 2016). The process of generating a household load profile is based on (Schellong, 2016).

Additional regional or seasonal adjustments of the standard load profiles, caused for example by temperature (Schellong, 2016), are out of the scope of this chapter. Particularly the popularity of air conditioning equipment in warmer Mediterranean regions (De Almeida, Fonseca, Schlomann, et al., 2011) is not considered in this study.

According to (Schellong, 2016), holidays equate Sundays when applying the standard household load profile. Therefore, the households’ load curves for Sundays are used during national holidays (Ambasciata d’Italia Londra, 2018). Furthermore, instead of the seasonal time periods from (Schellong, 2016), meteorological seasons (Trenberth, 1983) are used for reasons of comprehensibility and comparability of results. Apart from this, the standard load profile is adjusted to the typical yearly energy demand of households.

GPS data of Italian drivers from 2007 to 2009 is combined with a German standard load profile from 2002. No representative standard load profile for Italy or the European area was found. (Eckstein, Buddeke, and Merten, 2015) support the observation that currently no appropriate alternative to the German standard load profile is available and

also indicate that load profiles for different parts of Europe are roughly comparable. Therefore, the proposed utilization of the standard load profile is justified.

In summary, for each vehicle – respectively for each car owner – a synthetic household electricity demand time series is generated and merged with the home charging demand data derived from the PHEV simulation.

4.2.2 *Integration of residential photovoltaic systems*

The home location of a car (i.e., primary cluster with monthly variation) is assumed to be the location of the household. Consequently, time and location sensitive global horizontal irradiation (GHI) data from CAMS radiation service (MINES ParisTech and Transvalor S.A., 2017) can be obtained for these locations. The basic functionality of merging GPS driving data with irradiation data was demonstrated in (Wenig, Sodenkamp, and Staake, 2015).

15 latitudinal locations (daily limit of solar data service at the time of implementation) between the most northern and the most southern home locations of all vehicles are assumed in order to grab GHI data. The observation of annual average GHI on a world map (as for example provided in (World Bank Group, 2018)) indicates that such an approach sufficiently considers variations in irradiation for different latitudinal locations. For the longitudinal location, the mean longitude of entries is used.

Irradiation data will refer to the closest primary parking location of the vehicle. Because of the monthly clustering approach, a vehicle (respectively a driver) can have several primary – or home base – locations. However, the assumed household remains the same. When the vehicle is not parked at home, the location of the household is assumed to be the average of latitudinal and longitudinal coordinates.

GHI data from CAMS radiation service is grabbed automatically (MINES ParisTech and Transvalor S.A., 2017) at these locations and adjusted to the UTC+1 time zone. GHI data is merged with household data and parking event data to provide an integrated time series with one-hour granularity.

A photovoltaic system can be integrated into the household. Based on (Hofierka and Kaňuk, 2009; Hopf, Kormann, Sodenkamp, et al., 2017) the hourly generated energy G_{pV} of the photovoltaic system is estimated as follows: $G_{pV} = A_{pV} \cdot \delta_{pV} \cdot GHI$.

Here, the surface area of the photovoltaic cells A_{pV} is assumed to be 10 m², as inspired by (Hofierka and Kaňuk, 2009) and the efficiency of the photovoltaic system δ_{pV} is assumed to be 14% (17% module efficiency and 80% performance ratio (Fraunhofer ISE, 2017)). GHI is derived from the time series provided by (MINES ParisTech and Transvalor S.A., 2017).

4.2.3 Integration of a load shifting strategy

The electricity demand of the PHEV can be managed by means of a load shifting strategy. Particularly charging at night appears to be promising. In the algorithmic implementation, the energy demanded for charging the car is shifted such that the entire time window of the parking event can be exploited for charging. The approach could potentially lower the electric vehicle charging peak demand (for example in the evening) without changing the state of charge of the vehicle's battery at the end of the parking event when the next trip begins.

In the following, the basic idea of the load shifting strategy is briefly explained. Note however, that in the algorithmic implementation the hourly-based charging behavior of a lithium-ion battery is assumed, such that a state of charge greater than 80% leads to a longer charging time (c.f. (Sodenkamp, Wenig, Thiesse, et al., 2019; Wenig, Sodenkamp, and Staake, 2019, 2015) and chapters 2 and 3). The unmanaged charging approach assumes that the car can be charged as fast as possible by taking advantage of the full available charging power P without using the entire available parking time for charging.

If the parking duration d is long, such that $P \cdot d < B - soc_0$ with B being the battery capacity and soc_0 being the state of charge when the vehicle arrives at the charging location, only a part of the duration d is used for charging. However, the entire parking time – for example during long night parking time windows – could be utilized, such that the vehicle could be fully charged just in time when a driver wants to depart after the parking event.

Here, $P_s = \frac{B - soc_0}{d}$, such that the charging strategy takes advantage of the entire parking duration and charging power $P_s \leq P$ with P_s being the charging power when a load shifting strategy is applied. This has the potential to reduce peak power demand, as will be shown in subsequent sections, while the amount of charged energy remains unchanged.

4.3 Results

4.3.1 Comparison of parking and charging times

First, parking times and charging times are compared using the average profile of 700 simulated PHEVs. A PHEV with a 112.8 kWh battery is assumed. This is motivated by the considerably high mileage electrification potential of large PHEVs with large batteries in home charging scenarios, as demonstrated in chapter 3 and in (Wenig, Sodenkamp, and Staake, 2019). Furthermore, 7.4 kW home charging facilities are considered. Parking time is assessed at hourly granularity.

The analysis of average parking times indicates that at this home location the vehicle is typically parked during nighttime hours. In the previous chapter it was shown that there

is a charging demand peak in the evening, while the remaining parking time at night is not used for charging. From this, a considerable potential for load shifting with the objective of peak demand reduction in the evening can be identified. A smaller charging demand peak around noon indicates a potential for photovoltaic charging during day-time hours.

4.3.2 Grid Impact on the Household Level and Photovoltaic System Integration

In the following, the implementation of the suggested simulation model is presented for a representative electric mobility scenario. It again assumes a 7.4 kW home charging opportunity, a 10 m² residential photovoltaic system, and a 112.8 kWh battery capacity of the PHEV. Again, the average of 700 synthetic households, together with 700 simulated PHEVs and 700 simulated photovoltaic systems is given. In addition to the assessment of a residential photovoltaic system, both a managed and an unmanaged charging approach are compared.

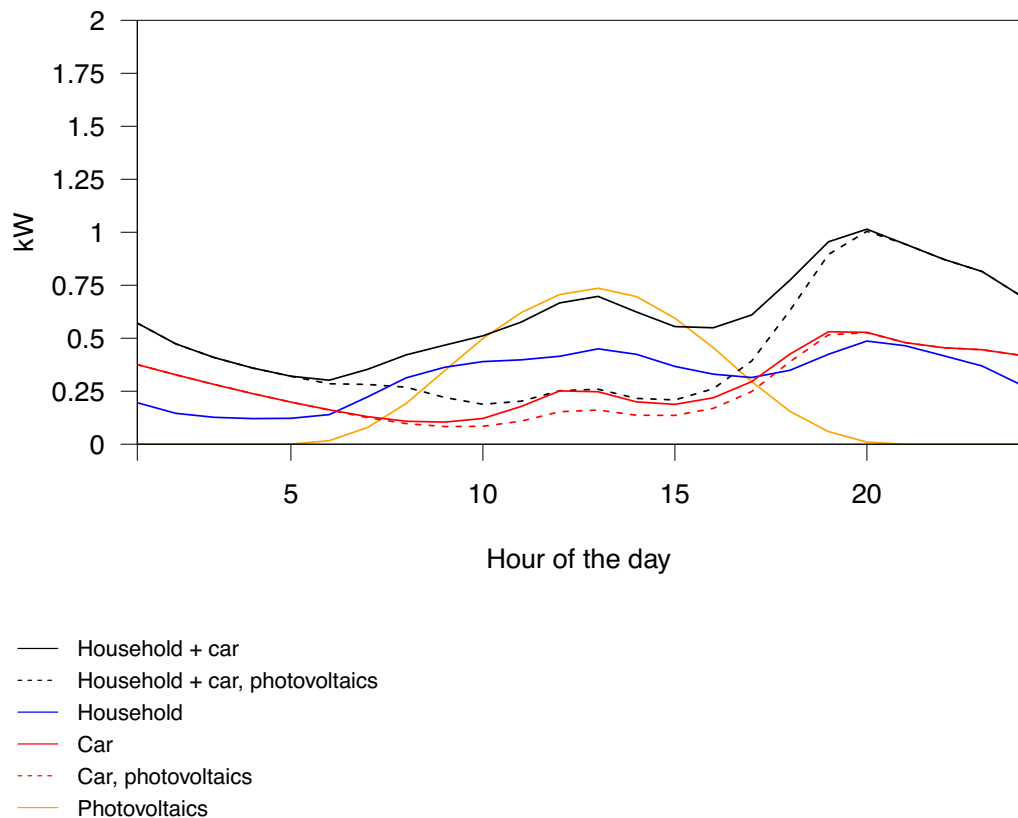


Figure 26: 24-hour load profiles for the average household with PHEV use and photovoltaics

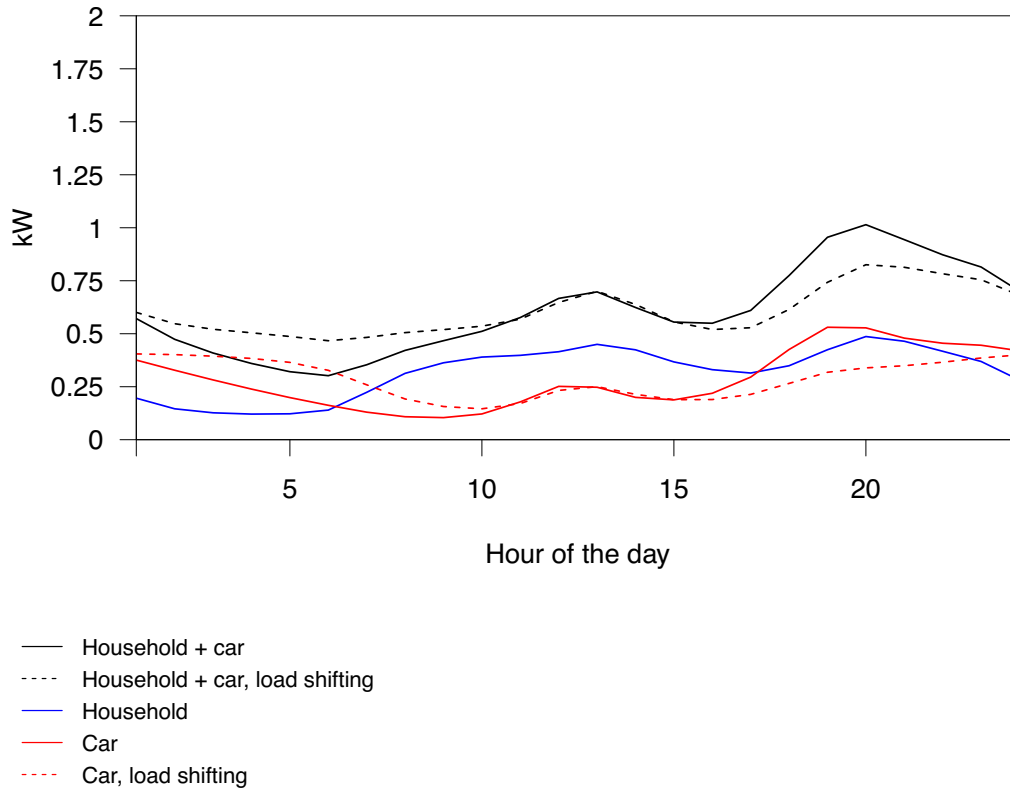


Figure 27: 24-hour load profiles for the average household with PHEV use and load shifting

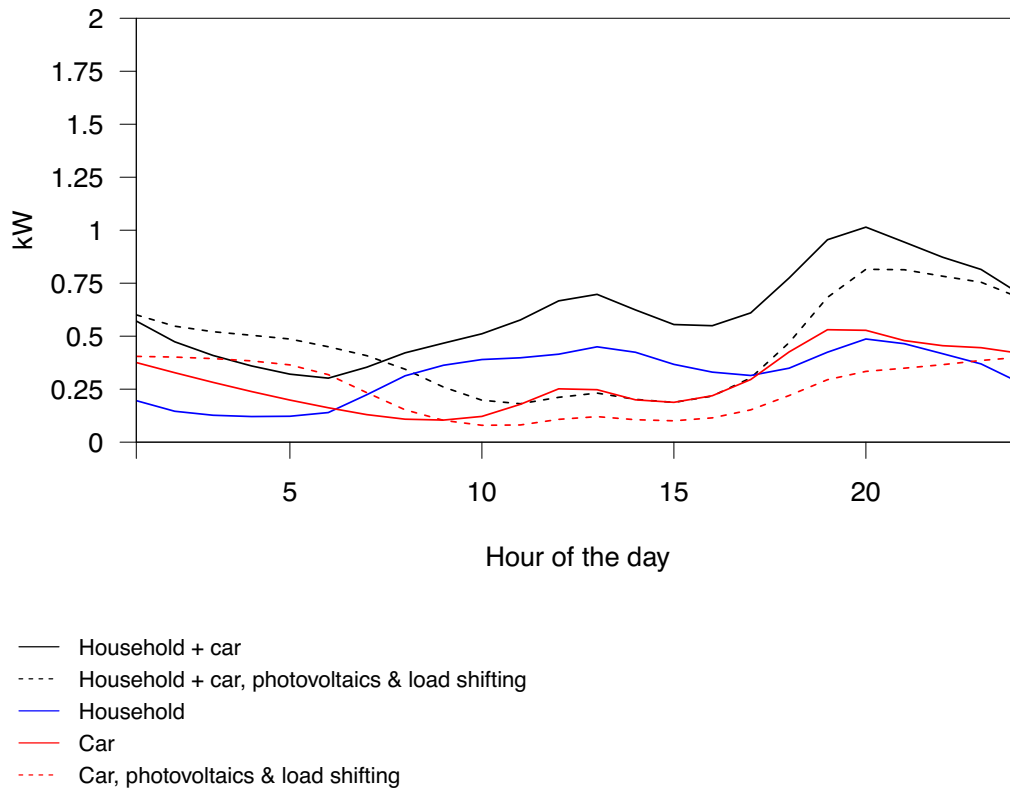


Figure 28: 24-hour load profiles for the average household with PHEV use and both photovoltaics and load shifting

Figure 26 and Figure 27 draft the average 24-hour load profile of a household (blue line). The red line shows the charging demand profile of the PHEV. The energy demand of both the household and the PHEV is depicted in black. The dashed lines indicate the effect of using electricity from a photovoltaic system for the household and for PHEV charging (Figure 26) and of a load shifting approach for vehicle charging (Figure 27). The yellow line in Figure 26 depicts the electricity that can be generated by the photovoltaic system.

The utilization of a photovoltaic system reduces the daytime energy demand; particularly during peak demand hours around noon. With a load shifting approach, energy demand in the evening is shifted to night and morning hours.

In Figure 28 the impact of both the use of a photovoltaic system and the application of load shifting is shown. The figure clearly shows that this combination leads to decreased electricity demand peaks both at noon and in the evening.

4.3.3 Comparison of Driver Segments

Results are based on presumably private car holders. From this, differences between groups of drivers can be further analyzed, such that the PHEV charging load, the household load profile, the impact of the utilization of a residential photovoltaic system, and the impact of a load shifting strategy can be compared for each of the considered segments.

In (Wenig, Sodenkamp, and Staake, 2019) and in chapter 3, four driver segments that are assumed to be related to private car holders were identified. Key results for the grid impact assessment at household level differ for each segment, as depicted in Table 21.

Table 21: Grid impact assessment for each segment (112.8 kWh PHEV, 7.4 kW home charging, 10 m² photovoltaic system)

Segment	1	2	3	4	ALL
Segment name	FLD	LDOD	SC	UC	ALL
Segment size	149	103	172	276	700
% of fleet	21.3%	14.7%	24.6%	39.4%	100%
Daily photovoltaic energy output [kWh]	5.5	5.5	5.5	5.5	5.5
Daily electricity grid demand [kWh]					
Household	7.6	7.6	7.6	7.6	7.6
PHEV charging	6.7	6.8	6.3	7.5	6.9
<i>" using photovoltaics</i>	<i>5.9</i>	<i>6.4</i>	<i>5.8</i>	<i>6.9</i>	<i>6.3</i>
<i>" using photovoltaics & load shifting</i>	<i>5.5</i>	<i>6.0</i>	<i>5.4</i>	<i>6.6</i>	<i>6.0</i>
Household and PHEV charging	14.3	14.4	14.0	15.1	14.5
<i>" using photovoltaics</i>	<i>10.7</i>	<i>11.0</i>	<i>10.5</i>	<i>11.6</i>	<i>11.0</i>
<i>" using photovoltaics & load shifting</i>	<i>10.5</i>	<i>10.8</i>	<i>10.3</i>	<i>11.4</i>	<i>10.9</i>

The average household in this simulation requires 7.6 kWh of electricity per day and additional 6.9 kWh for charging the PHEV. The residential photovoltaic system can generate 5.5 kWh per day on average. If energy from the photovoltaic system is used to cover the household energy demand and the charging demand of the PHEV, a demand of about 11 kWh remains on average per day and has to be drawn from the power grid.

It is interesting to note that with load shifting, slightly more energy from the photovoltaic system can be used for charging. Apparently, with the resulting decrease in peak charging power and with longer charging time windows during daytime hours, more solar energy that is not consumed by the household can be used to charge the vehicle.

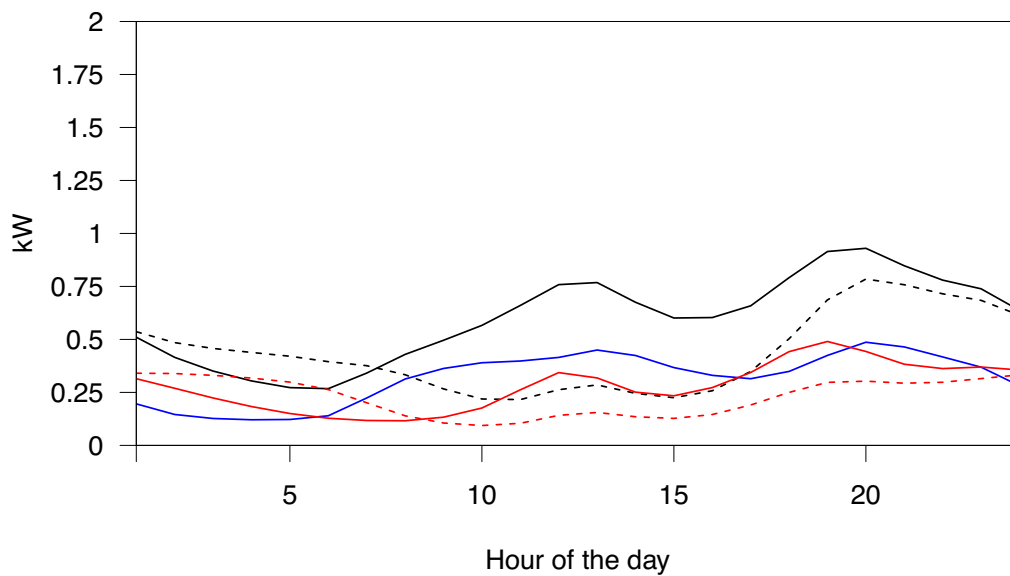


Figure 29: 24-hour load profiles for the average household with PHEV use and both photovoltaics and load shifting (FLD)

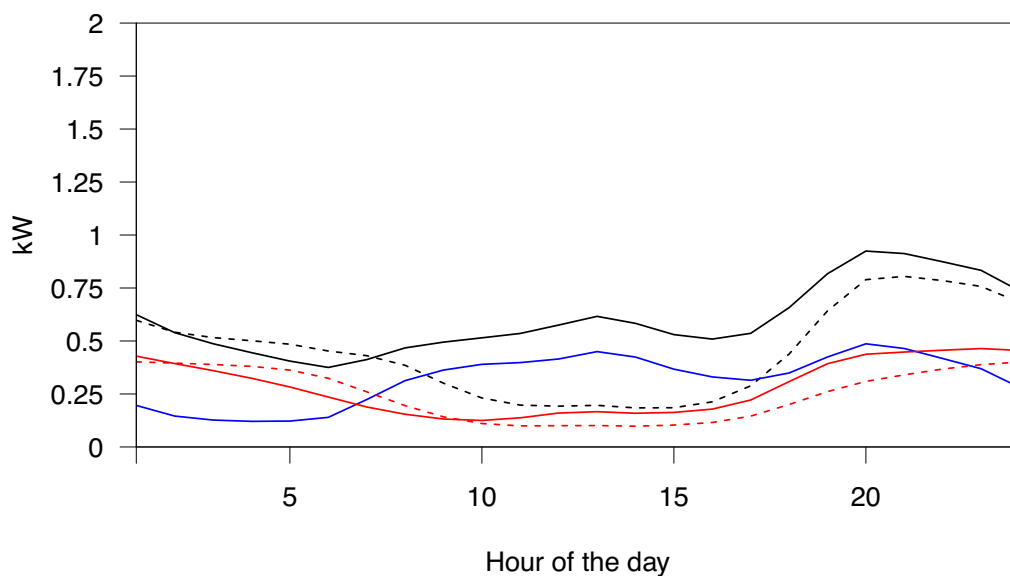


Figure 30: 24-hour load profiles for the average household with PHEV use and both photovoltaics and load shifting (LDOD)

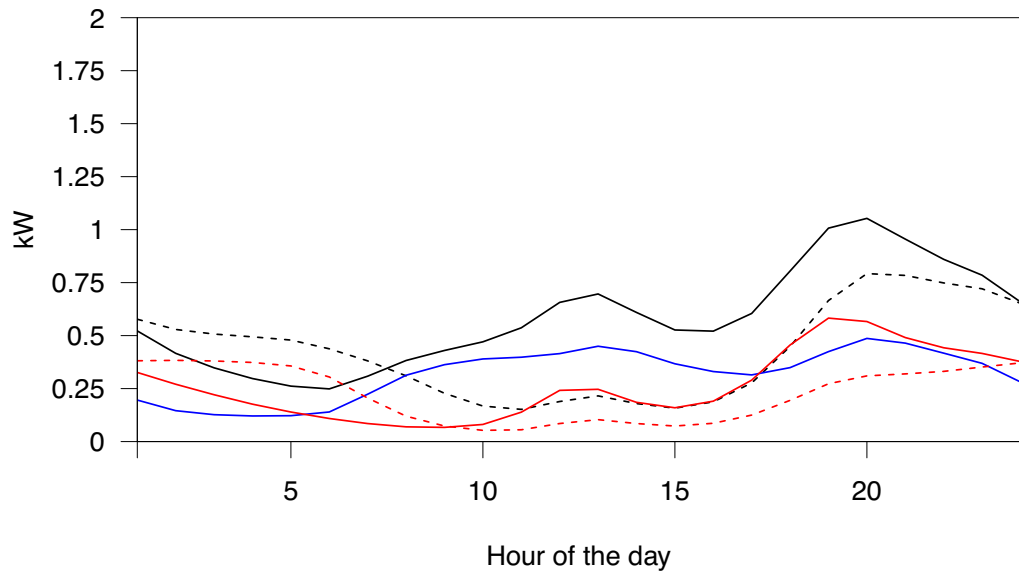


Figure 31: 24-hour load profiles for the average household with PHEV use and both photovoltaics and load shifting (SC)

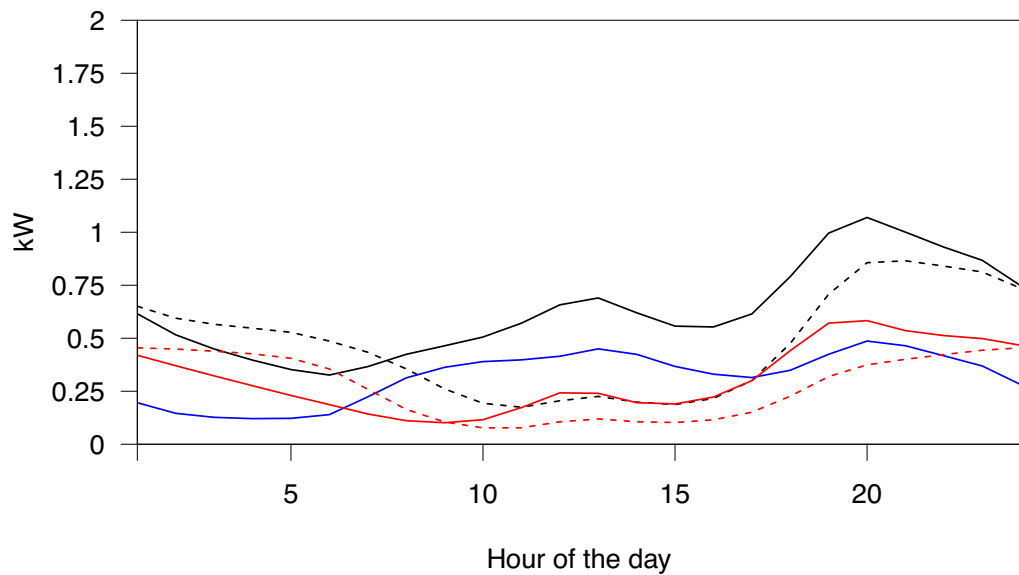


Figure 32: 24-hour load profiles for the average household with PHEV use and both photovoltaics and load shifting (UC)

Supplementary to Figure 28, in Figure 29 to Figure 32, the varying 24-hour load profiles for the average PHEV (solid red line) and the average household with PHEV use (solid black line) are depicted for each segment. Profiles are roughly comparable with peak charging demand occurring at noon and in the evening. Still, these peaks are less pronounced for the “long-distance occasional driver” (LDOD) segment. For all of the segments, peaks at noon and in the evening can be reduced by means of photovoltaic charging and load shifting, as a comparison of the solid and the dotted red and black lines shows.

4.3.4 *The impact of home charging power*

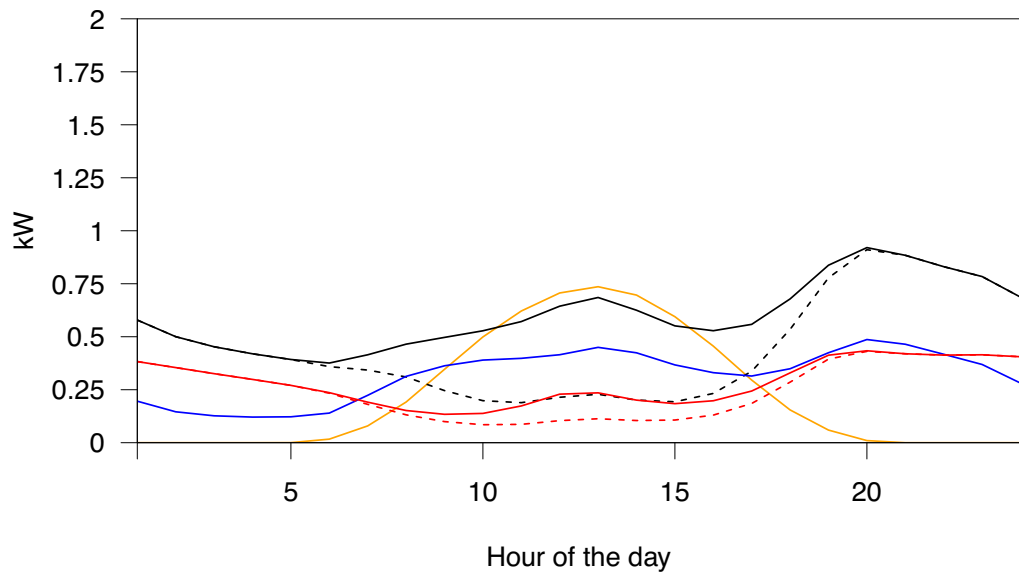
In the following Figure 33 to Figure 35, results for the low 3.7 kW and high 22.1 kW home charging power scenarios from (Wenig, Sodenkamp, and Staake, 2019) and chapter 3 are contrasted. This comparison includes the impact of photovoltaic charging (Figure 33) and of a load shifting strategy (Figure 34) for the average over all residential households for each pair of graphical representations. In (Figure 35), the impact of a combination of photovoltaic charging and load shifting is depicted.

A comparison of Figure 33 a) and Figure 33 b), shows that power demand peaks at noon and in the evening are significantly greater if charging power is higher. However, electricity from a photovoltaic system (yellow line) can be used more effectively during sunlight hours, particularly at noon, if the overall charging power is lower, as can be observed when comparing the grid power demand of a car with (dotted red line) and without the use of photovoltaic charging (solid red line) in Figure 33 a) and in Figure 33 b).

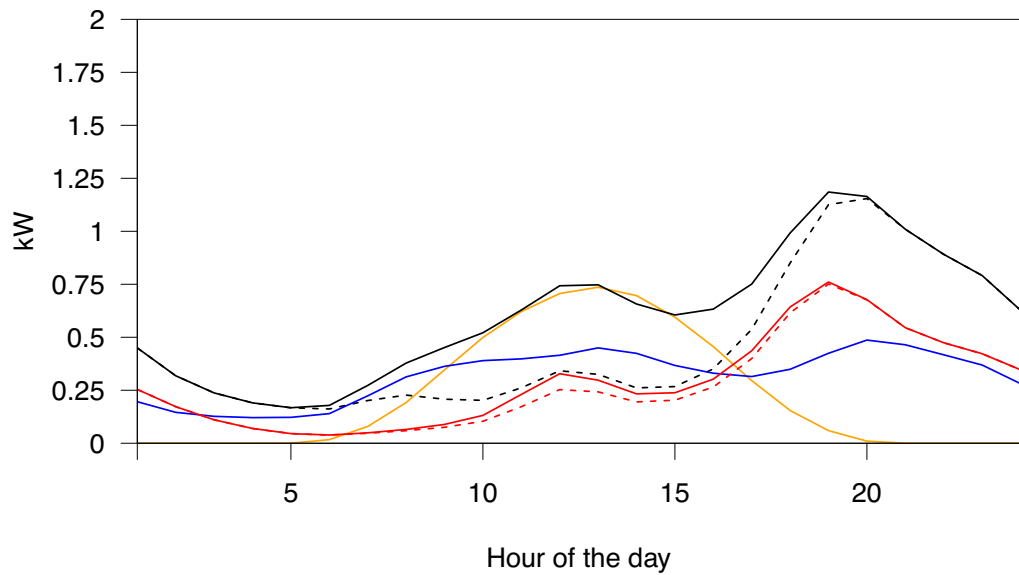
In Figure 34 the effect of load shifting on the 24-hour-load profile for the average driver is visualized when a) 3.7 kW or b) 22.1 kW charging power is available. For the 3.7 kW case the effect is limited, while for the 22.1 kW case, a load shifting strategy has a noteworthy effect on peak grid impact alleviation; apparently because often the higher available charging power is not needed to fully charge the battery just in time before the start of the next trip. This becomes clear when comparing the solid red line (without load shifting) and the dotted red line (with load shifting) in Figure 34 a) and in Figure 34 b).

Figure 35 visualizes the 24-hour load profiles for a combination of both a photovoltaic system and a load shifting strategy. Again, a) 3.7 kW and b) 22.1 kW are compared. Particularly in the 22.1 kW case, such a combination helps further alleviating demand peaks, both at noon and in the evening.

Notably, here the combination of a load shifting strategy and photovoltaic charging can help further reducing the peak charging power demand at noon, as becomes clear when comparing Figure 33 b) with Figure 35 b). The load shifting approach leads to longer charging time windows with reduced charging power if the parking duration is sufficiently high. This also results in a prolonged use of the photovoltaic energy output for PHEV charging.



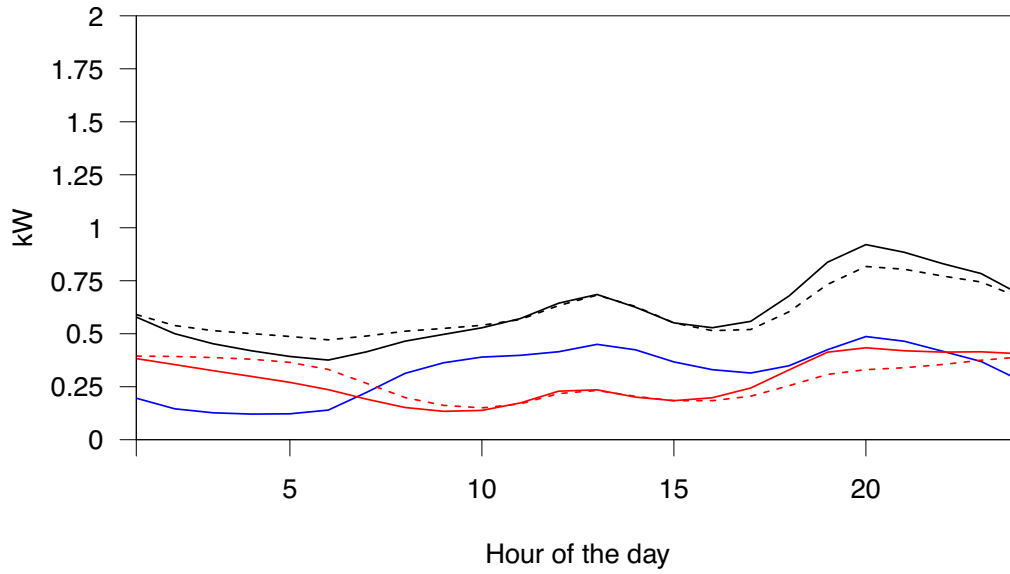
a) 3.7 kW charging power



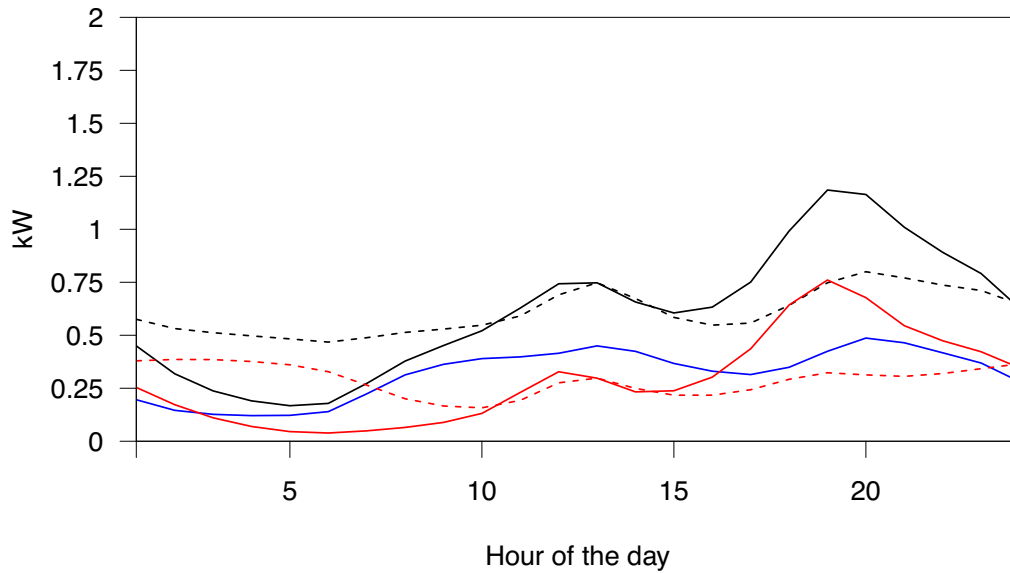
b) 22.1 kW charging power

- Household + car
- - - Household + car, photovoltaics
- Household
- Car
- - - Car, photovoltaics
- Photovoltaics

Figure 33: 24-hour load profiles for the average household with PHEV use and photovoltaics when a) 3.7 kW and b) 22.1 kW charging power is available.



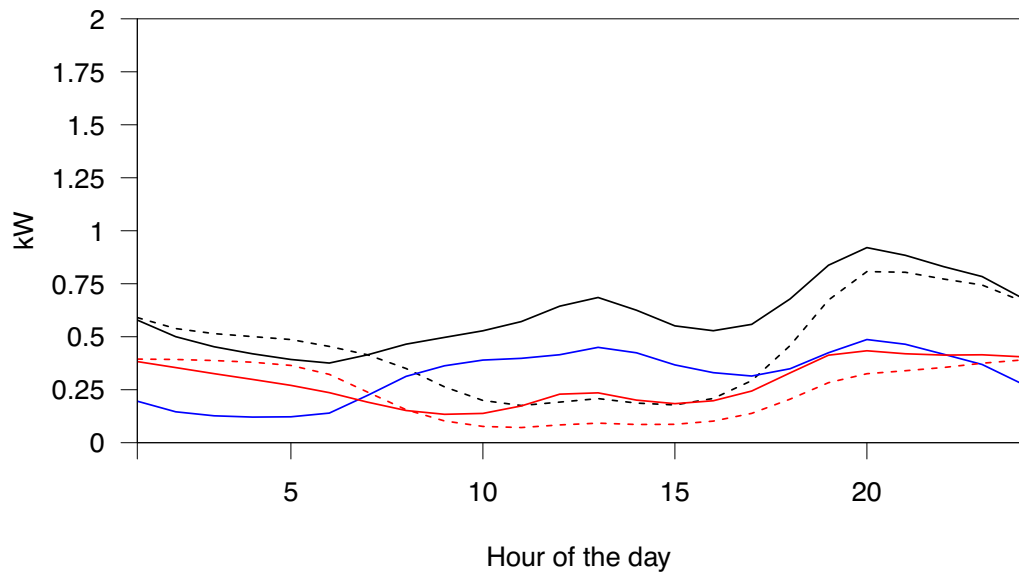
a) 3.7 kW charging power



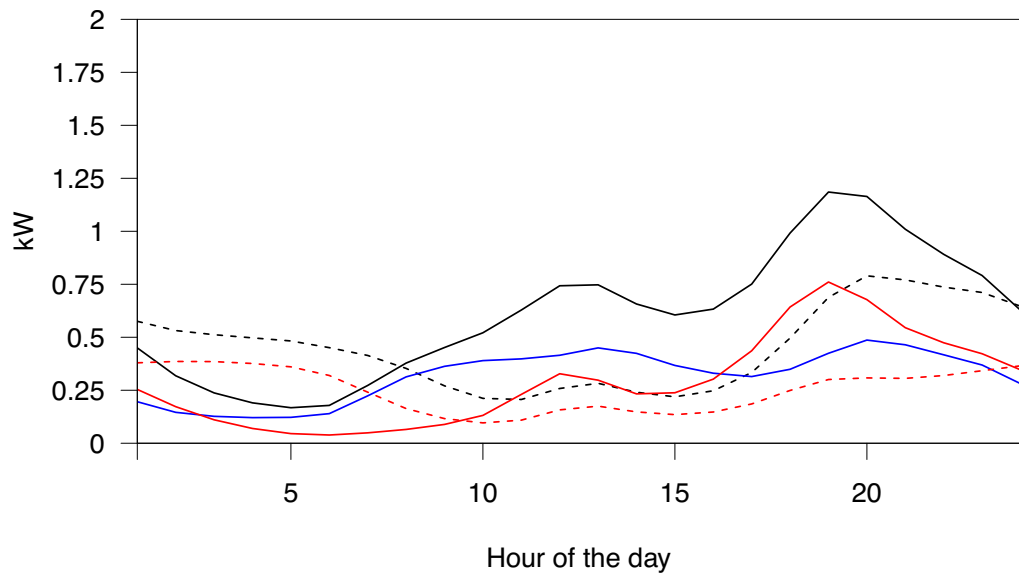
b) 22.1 kW charging power

- Household + car
- - - Household + car, load shifting
- Household
- Car
- - - Car, load shifting

Figure 34: 24-hour load profiles for the average household with PHEV use and load shifting when a) 3.7 kW or b) 22.1 kW charging power is available.



a) 3.7 kW charging power



b) 22.1 kW charging power

- Household + car
- - - Household + car, photovoltaics & load shifting
- Household
- Car
- - - Car, photovoltaics & load shifting

Figure 35: 24-hour load profiles for the average household with PHEV use and both photovoltaics and load shifting when a) 3.7 kW or b) 22.1 kW charging power is available.

In Table 22, these results are provided in aggregated form for the average of an entire day and in addition, key figures are given for each segment. These key figures support the observation that a combination of photovoltaic charging and a load shifting strategy is particularly valuable in the 22.1 kW charging scenario.

If 3.7 kW home charging is possible, photovoltaic charging can reduce the grid energy demand from 6.8 kWh to 6.0 kWh per day (88%). With a load shifting strategy this value further decreases to 5.7 kWh (85%).

If 22.1 kW home charging is possible, photovoltaic charging reduces the energy demand from the grid from 7.0 kWh to 6.5 kWh (94%). However, if both photovoltaic charging is possible and a load shifting strategy is applied, this value decreases further to 6.1 kWh (87%).

About two third of energy generated by the photovoltaic system can be used to provide energy for the household and to charge the PHEV with solar energy in both the 3.7 kW and 22.1 kW home charging power case. The remaining one third could not be used locally.

Table 22: Grid impact assessment for each segment, comparing a home charging power of a) 3.7 kW and b) 22.1 kW

Segment	1	2	3	4	ALL
Segment name	FLD	LDOD	SC	UC	ALL
Segment size	149	103	172	276	700
% of fleet	21.3%	14.7%	24.6%	39.4%	100%
Daily photovoltaic energy output [kWh]	5.5	5.5	5.5	5.5	5.5
Daily electricity grid demand [kWh]					
Household	7.6	7.6	7.6	7.6	7.6
a) 3.7 kW home charging power					
PHEV charging	6.6	6.5	6.3	7.3	6.8
" using photovoltaics	5.5	5.9	5.5	6.5	6.0
" using photovoltaics & load shifting	5.3	5.6	5.3	6.3	5.7
Household and PHEV charging	14.2	14.1	13.9	14.9	14.4
" using photovoltaics	10.5	10.6	10.4	11.3	10.8
" using photovoltaics & load shifting	10.3	10.5	10.2	11.2	10.7
b) 22.1 kW home charging power					
PHEV charging	6.7	6.9	6.3	7.5	7.0
" using photovoltaics	6.1	6.7	5.9	7.1	6.5
" using photovoltaics & load shifting	5.6	6.2	5.4	6.7	6.1
Household and PHEV charging	14.4	14.5	14.0	15.1	14.6
" using photovoltaics	10.8	11.2	10.5	11.7	11.2
" using photovoltaics & load shifting	10.6	10.9	10.3	11.5	10.9

4.3.5 The effect of a larger photovoltaic system

The effect of a larger photovoltaic system is assessed as well. While in the previous scenarios, a 10 m² photovoltaic system was considered, in this section, the area of the photovoltaic system is assumed to be 42.56 m², which is inspired by the average living area of a person in Europe (European Commission, 2011). Typical living areas of households may be larger, but when considering for example the roof slope or multiple

floors, this assumption appears to be reasonable. Results are provided for the 7.4 kW home charging case, using a 112.8 kWh PHEV.

Table 23: Grid impact assessment for each segment, using 42.56 m² photovoltaic systems

Segment	1	2	3	4	ALL
Segment name	FLD	LDOD	SC	UC	ALL
Segment size	149	103	172	276	700
% of fleet	21.3%	14.7%	24.6%	39.4%	100%
Daily photovoltaic energy output [kWh]	23.2	23.3	23.2	23.3	23.3
Daily electricity grid demand [kWh]					
Household	7.6	7.6	7.6	7.6	7.6
PHEV charging	6.7	6.8	6.3	7.5	6.9
" using photovoltaics	4.7	5.8	4.9	6.0	5.4
" using photovoltaics & load shifting	4.6	5.2	4.7	5.8	5.2
Household and PHEV charging	14.3	14.4	14.0	15.1	14.5
" using photovoltaics	8.5	9.4	8.6	9.7	9.2
" using photovoltaics & load shifting	8.4	9.0	8.5	9.6	9.0

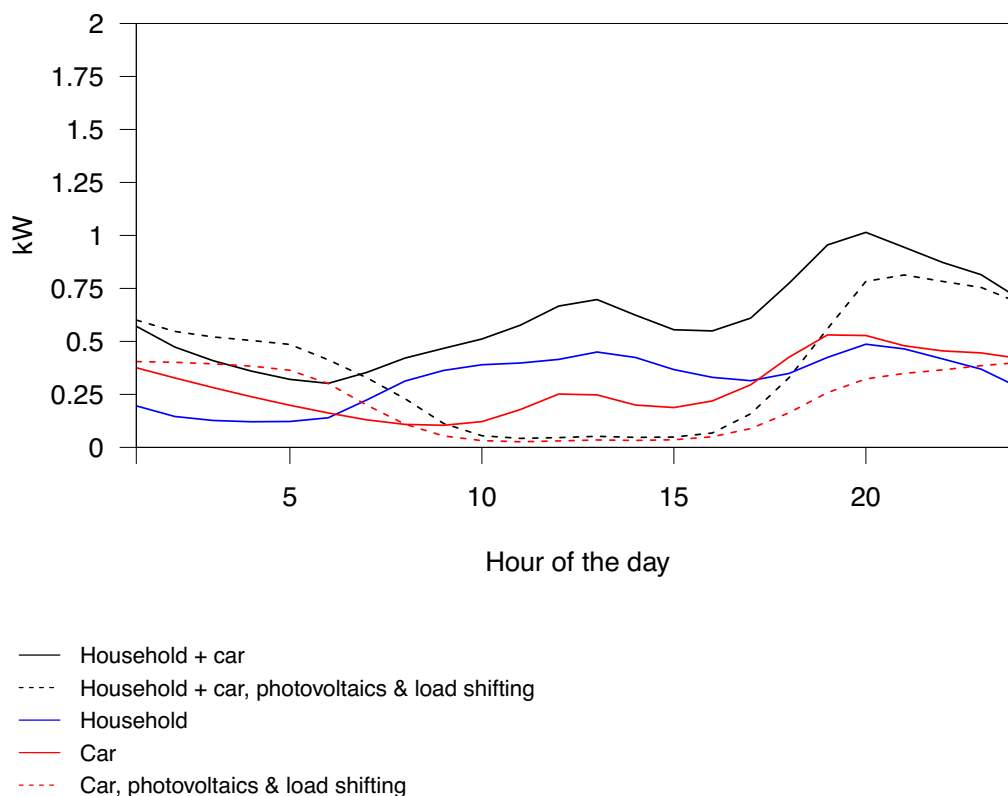


Figure 36: 24-hour load profiles for the average household with a 42.56 m² photovoltaic system, PHEV use and load shifting

In Table 23, key figures for the average driver and for each segment are provided. It is assumed that a 42.56 m² photovoltaic system is available. When comparing Table 23 (42.56 m²) and Table 21 (10 m²), results show that even more solar energy can be used

to provide the electricity both for the household and for PHEV charging. Still, the overall daily photovoltaic energy output is only used to a lesser part for self-consumption.

Figure 36 provides the 24-hour load profile for an average household with PHEV use and load shifting, when instead of a 10 m² photovoltaic system, a 42.56 m² area is available. Figure 36 can be compared with Figure 28 (10 m² photovoltaic system) to show that on average, such a sufficiently large photovoltaic system can provide almost the entire demanded electricity around noon.

4.3.6 The effect of a smaller vehicle battery capacity

In this subsection, the effect of a smaller 18.8 kWh vehicle battery capacity is assessed. This capacity value was chosen to enable an appropriate comparison of observations from the previous chapter 3 and (Wenig, Sodenkamp, and Staake, 2019). Results are given for the 7.4 kW home charging case, assuming a 10 m² area of the photovoltaic system.

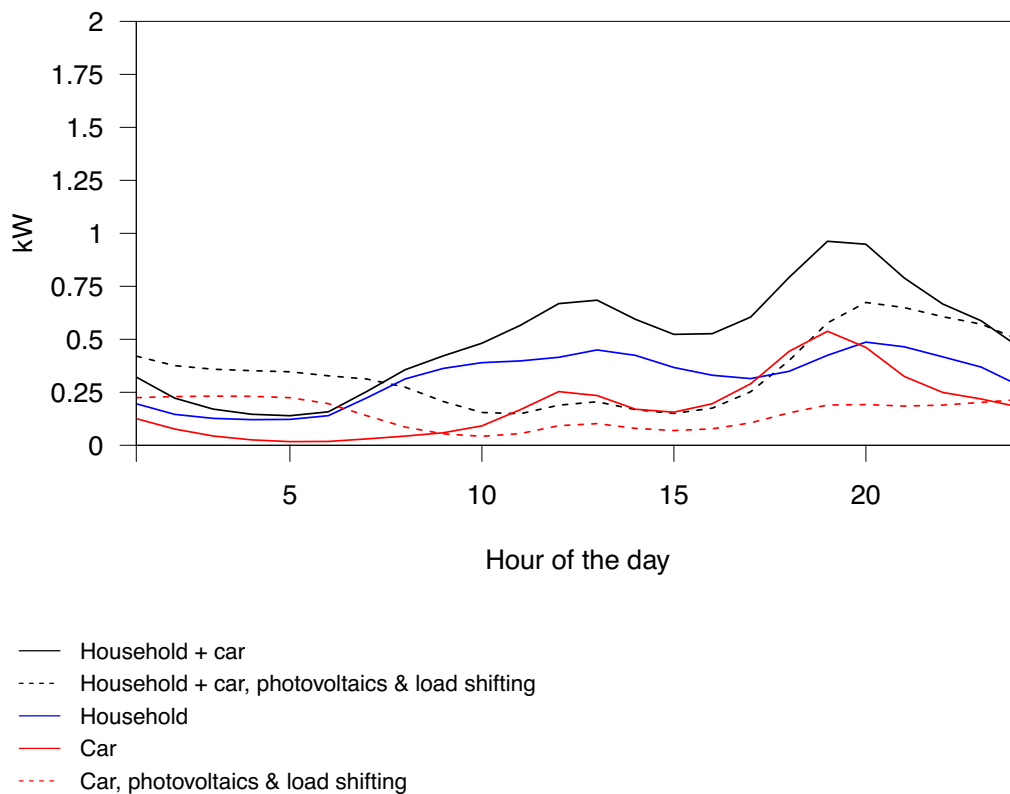


Figure 37: 24-hour load profiles for the average household with 18.8 kWh PHEV use and both photovoltaics and load shifting

Figure 37 depicts the 24-hour load profiles for the average household when instead of a battery capacity of 112.8 kWh (c.f. Figure 28), a smaller 18.8 kWh battery is used. Again, the impact of both a residential photovoltaic system and of a load shifting strategy is assessed. Results show that energy demand peaks at noon and in the evening are reduced.

Table 24 provides key figures for the average driver and for individual segments. The comparison of Table 24 (112.8 kWh) and Table 21 (18.8 kWh), shows that despite a lower energy demand, the amount of energy that could be used from the photovoltaic system is roughly the same.

Table 24: Key results for each segment when an 18.8 kWh PHEV is available

Segment	1	2	3	4	ALL
Segment name	FLD	LDOD	SC	UC	ALL
Segment size	149	103	172	276	700
% of fleet	21.3%	14.7%	24.6%	39.4%	100%
Daily photovoltaic energy output [kWh]	5.5	5.5	5.5	5.5	5.5
Daily electricity grid demand [kWh]					
Household	7.6	7.6	7.6	7.6	7.6
PHEV charging	4.7	3.0	4.9	4.5	4.4
" using photovoltaics	4.0	2.8	4.4	4.0	3.9
" using photovoltaics & load shifting	3.6	2.4	4.0	3.7	3.6
Household and PHEV charging	12.3	10.6	12.5	12.1	12.0
" using photovoltaics	8.8	7.3	9.0	8.7	8.6
" using photovoltaics & load shifting	8.6	7.1	8.9	8.5	8.4

4.4 Conclusion

The comparison of the home charging demand profile of a typical PHEV and the load profile of a private household shows that they roughly resemble each other. Charging events of PHEVs frequently occur at noon or in the evening and therefore overlap with peak electricity demand times of typical private households, such that both the overall electricity demand of these households and peak electricity demand at noon and in the evening considerably increase.

Consequently, the utility of a residential photovoltaic system for electricity demand peak mitigation was assessed in a data-based simulation approach. Results show that residential photovoltaic systems could be utilized to relieve the stress on the electric grid and to reduce the amount of demanded energy. Particularly during time windows around noon with both high solar irradiation and a peak in electricity demand, solar energy could be used to reduce the peak load.

Such a utilization of solar energy for PHEV charging increases the energy self-sufficiency of the household and the utility of the household's photovoltaic system. Furthermore, a part of the energy required for passenger transportation can be provided by a renewable source. Still, only a portion of the energy that is generated by the residential photovoltaic system can be used by the household itself or for PHEV charging because the usage is limited to daylight hours. Electricity demand peaks in the evening remain unchanged.

Here, results indicate that the application of a load shifting strategy could help reducing these pronounced power demand peaks in the evening. To do so, long overnight parking time windows are exploited for charging, such that charging power and as a consequence, peak power demand in the evening can be significantly decreased. By utilizing such a managed charging approach, the electricity demand is distributed more evenly over the whole parking period without affecting the state of charge of the battery at the end of the parking period, when the PHEV is used again.

Finally, the comparison of distinct private driver segments shows that electricity demand profiles of different groups share some similarities. Notably, power demand peaks occur at noon and in the evening, even though the average peak demand level may vary. This indicates that suggested measures to influence the PHEV charging demand profile – using solar energy and applying a load shifting strategy – could be applied by a greater variety of PHEV driver groups.

The results that were presented in this chapter and the underlying methodology can help to assess the potential use of solar energy and of load shifting for vehicle charging. The observations indicate that electric mobility has a considerable impact on the energy demand profile of individual households and that both residential photovoltaic systems and managed home charging can relax the peak electricity demand of PHEVs.

To further increase the utility of photovoltaic systems for PHEV charging, future work could assess stationary batteries that temporarily store surplus solar energy during time windows with high photovoltaic energy generation (e.g., at noon) for later use during hours with little or no solar energy output (i.e., at night) (Betz and Lienkamp, 2016; Truong, Naumann, Karl, et al., 2016). Furthermore, managed charging strategies that prioritize the use of solar energy (Chaouachi, Bompard, Fulli, et al., 2016) could be created and assessed.

5 Discussion

5.1 Research problem and aim of this thesis

This work is concerned with the assessment of mobility scenarios to help making better decisions concerning the implications of electric driving. The thesis builds upon a simulation based approach that employs GPS driving data to assess electric mobility scenarios and to derive insights on the potential for mileage electrification of combustion-based vehicles and the resulting electricity grid impact (Wenig, 2014a, 2014b; Wenig, Sodenkamp, and Staake, 2015). To further develop and extend this preliminary work, four specific research problems are approached.

First, the application of a cluster analysis procedure is applied in chapter 2 and in (Sodenkamp, Wenig, Thiesse, et al., 2019), respectively, to identify and compare typical vehicle usage patterns. To do so, variables that appropriately reflect the energy consumption and charging behavior of an electric car (such as driven distance and speed or the home parking duration) are utilized to segment drivers according to their mobility needs. Distinct driver segments emerge and are evaluated with regard to their readiness for electric car adoption.

Second, an evaluation of both vehicle battery size and private and public charging infrastructure requirements for electric mobility takes place. The topic is presented in chapter 3 and in (Wenig, Sodenkamp, and Staake, 2019), respectively.

Influencing factors – battery capacity, charging power, charging infrastructure coverage – are systematically evaluated. The presented methodology allows for the assessment of the substitutability between extended battery capacities (and therefore electric range) and charging infrastructure measures.

Third, in chapter 4, home charging demand time series are derived from the previous application of the simulation approach and compared with typical private household electricity demand patterns and with the expected photovoltaic energy generation potential of a residential photovoltaic system.

Consequently, the utility and effect of distributed (i.e., solar) energy sources for PHEV charging can be included in the simulation. From this, the potential for peak grid impact reduction – particularly during time windows around noon with strong solar irradiation – is estimated.

Fourth, and in addition to the procedure in chapter 4, an assessment of managed charging (i.e., load shifting) for peak grid demand reduction takes place. A simple load shifting strategy takes advantage of parking durations that exceed regular charging times, such that the charging power usage and consequently the peak electricity demand – particularly in the evening – are reduced and shifted to later hours.

In the following, these four research issues are addressed in more detail. Major results and observations are recapitulated, and consequent implications are discussed from the policy, customer, energy supplier, automotive industry, research, and environmental perspective.

5.2 Major findings and implications

5.2.1 Driver segmentation

In chapter 2 and in (Sodenkamp, Wenig, Thiesse, et al., 2019), real-world GPS-based mobility data from a large sample of conventional car drivers was assessed and by means of a partitioning-based cluster analysis approach, individual driver segments were identified on the foundation of their distinct vehicle usage patterns. Thus, group specific knowledge on drivers is utilized for a segment-wise evaluation of electric vehicle utility and impact.

This particularly includes the quantification of mileage that could be electrified and the charging impact on the power network for each group. It can be discovered that the mileage electrification potential for different segments varies drastically, indicating that mobility solutions such as vehicle range and the availability of secondary (e.g., workplace) charging facilities should be tailored to realistic customer needs.

For example, drivers with demanding mobility requirements especially profit from larger batteries and long roundtrip distance drivers gain from an additional charging opportunity. This is particularly important to note because drivers with high overall mileage can electrify the highest absolute number of kilometers, even though this does not necessarily imply a high relative share.

The impact on the power grid was quantified and compared, such that it could be evaluated which driver groups put particular stress on grid. Variations of the grid impact of different groups and peaks in the late morning and afternoon are identified. Notably, vehicles that are assumed to be used for business activities consume more energy than average and their peak power demand is usually highest during weekdays and lowest on weekends. This emphasizes the necessity for a segment-specific electric mobility assessment and provides results beyond one-size-fits-all solutions.

In Figure 38, the daily energy demand for the average driver and for seven segments, as identified in chapter 2 and in (Sodenkamp, Wenig, Thiesse, et al., 2019) is given: (1) “frequent local driver” (FLD), (2) “commuter (short)” (CS), (3) “commuter (long)” (CL), (4) “delivery (short)” (DS), (5) “service provider” (SP), (6) “delivery (long)” (DL), and (7) “company representative” (CR). In the depicted case, an 18.8 kWh battery and 7.4 kW charging facilities at the primary and secondary parking location are available. The different results for each segment become clearly visible.

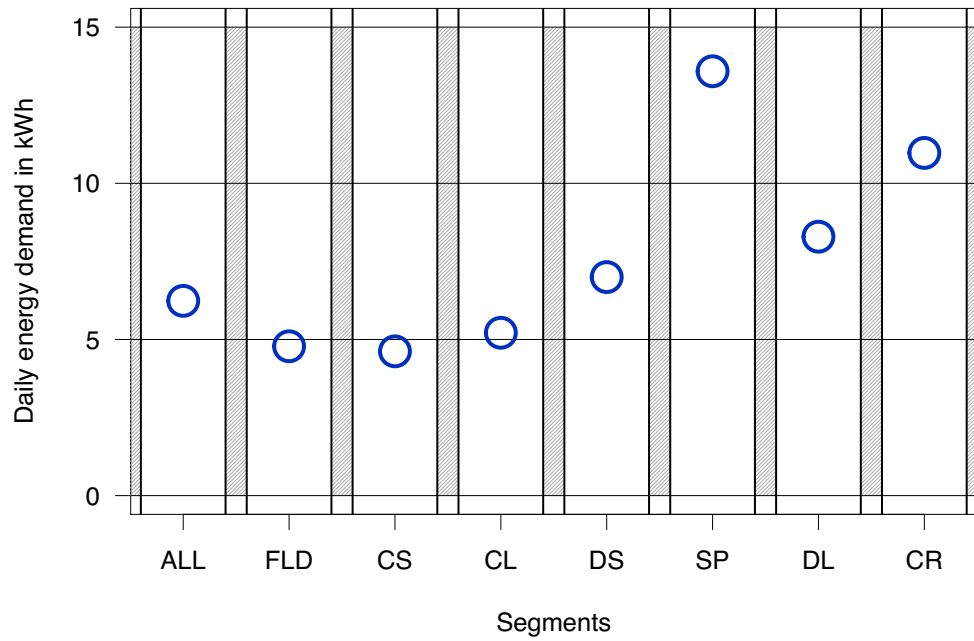


Figure 38: Average daily energy demand for PHEV charging when an 18.8 kWh battery capacity and 7.4 kW charging power at a primary and a secondary parking location are available

For the same scenario, in Figure 39, the share of mileage that could be driven electrically is depicted for the average driver and for each of the identified driver groups. Again, the visualization highlights that results for the seven identified driver segments are significantly different.

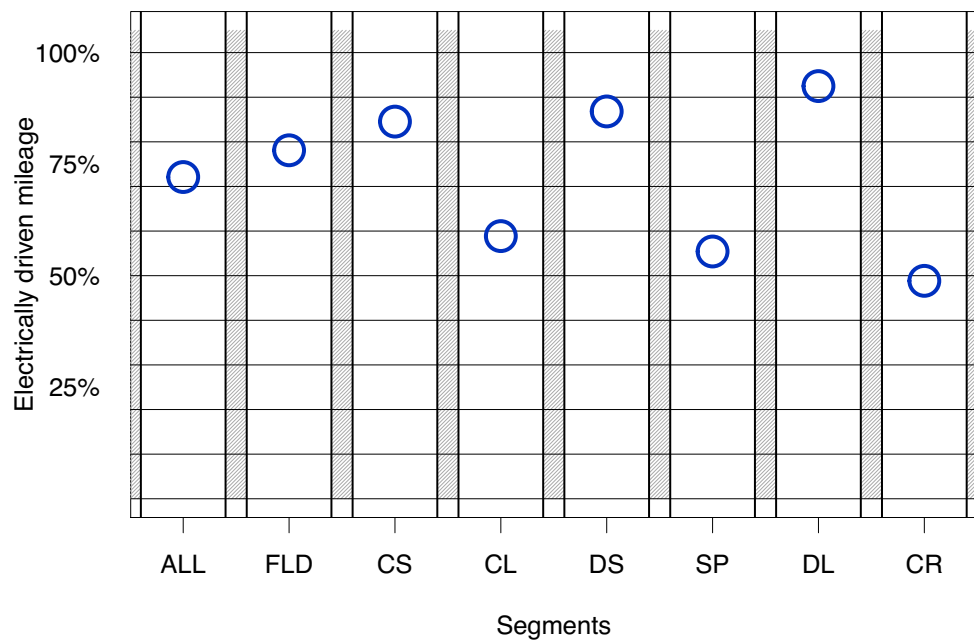


Figure 39: Share of mileage that can be electrified when an 18.8 kWh battery capacity and 7.4 kW charging power at a primary and a secondary parking location are available

For example, while a short-distance commuter (CS) would require about 4.6 kWh per day to electrify about 85% of mileage, a typical “company representative” (CR) would demand about 11 kWh per day to electrify only about 49% of mileage. These differences can be explained by the distinct driving behavior of each group. Here, on average the “company representative” (CR) drives faster and covers longer distances than the short-distance commuter (CS).

A segmentation of drivers according to their driving behavior shows that the assumption of one average driving pattern does not sufficiently consider the varying mobility demand of individuals. Instead, distinct groups of individual drivers with a similar mobility demand should be assessed to provide a more realistic evaluation of electric mobility. The comparison of driver segments identifies groups with a high potential for mileage electrification and thus can help to better quantify the potential for increased future electric vehicle market shares.

5.2.1.1 Policy perspective

A segmentation based electric mobility assessment approach could help to set attainable policies and plans that are based on realistic predictions and assumptions concerning what driver groups could readily switch to a PHEV (Anable, Skippon, Schuitema, et al., 2011). On this basis, governmental incentives could be better targeted by addressing the actual mobility requirements of distinct driver groups (Anable, 2005; Anable, Skippon, Schuitema, et al., 2011).

For example, by driving a PHEV with a small size 6.3 kWh battery, a “commuter (short)” (CS) that charges only at home could electrify about 66% (82% with 18.8 kWh) of mileage. This accounts for about 879 to 1,087 km per month. Also “delivery (short)” (DS) vehicles with many short-haul routes could electrify about 64% (86% with 18.8 kWh) of mileage or 1,797 to 2,417 km per month. Thus, with comparatively little effort – and thus with comparatively inexpensive support measures – major mobility needs could be met electrically.

On the other hand, for example, a “company representative” (CR) could electrify only about 17% (43% with 18.8 kWh) of mileage. Although this corresponds to about 1,008 to 2,472 km per month that could be electrified in absolute terms, to reach larger relative shares of electrified mileage, vehicles with a greater electric range (or more charging facilities) would be necessary. For example, with a 56.4 kWh battery, corresponding figures rise to 78% and 4,469 km. Consequently, for a large-scale hybridization and electrification of such a corporate vehicle fleet, more expensive incentive measures appear to be necessary.

5.2.1.2 Customer perspective

Car customers are encouraged to consider similarities with certain driver groups to evaluate with a higher reliability whether a certain PHEV satisfies their mobility needs or not.

As was shown, given a certain electric range and charging opportunity, the mileage electrification potential varies between different driver groups.

A group specific comparison of the electric mobility potential and impact also offers a better reference point for possible future PHEV customers. Drivers can relate to the mobility patterns of a distinct segment, which thus serves as solid basis for making purchase decisions regarding vehicle features.

Individuals can plan with and manage possible limitations or characteristics of electric mobility particularities, such as a limited electric range or a charging infrastructure that is different from the familiar gas station network. For example, it is unproblematic to electrify short-distance roundtrips with a limited electric range vehicle. In that regard, driver segments with short median roundtrip distances (“frequent local driver” (FLD), 11.43 km; “commuter (short)” (CS), 24.50 km; “delivery (short)” (DS), 0.73 km) could electrify 59%, 66%, and 64% of their mileage, using only a 6.3 kWh battery capacity and a home charging facility.

To also cover long-distance travel demands electrically, specific mobility needs of groups can be considered. Besides acquiring longer electric range vehicles and the application of hybrid technologies (for example, with a 56.4 kWh battery, the “frequent local driver” (FLD) could cover 87%, the “commuter (short)” (CS) 91%, and the “delivery (short)” (DS) vehicle 94% of mileage electrically), alternative means of transport – such as car rental services (Bühler, Cocron, Neumann, et al., 2014; Greaves, Backman, and Ellison, 2014) or public transportation (Greaves, Backman, and Ellison, 2014) – could address varying range needs.

5.2.1.3 Energy supplier perspective

It was shown that the mileage electrification potential of individual drivers of a larger fleet varies. Therefore, a segment specific assessment of electrifiable mileage allows for more realistic predictions and consequently, for a more realistic estimation of the expected additional power grid impact of a certain group.

It has to be considered that the additional stress that is put to the power grid is very different for distinct driver groups. For example, a “service provider” would require 22.2 kWh per day to electrify 81% of mileage. Quite in contrast to this, a “commuter (short)” (CS), would require only 5.2 kWh per day to electrify 91% of mileage. Against this backdrop, electricity suppliers can consider the composition of a geographic region’s car fleet and can consequently derive measures to ensure a dependable future power supply.

Apart from this, providers could utilize knowledge on distinct drivers’ electricity demand profiles to provide group-specific electricity tariffs. For example, night tariffs could be offered to “frequent local drivers” (FLD) or to commuters (CS and CL) to encourage them to shift load from peak hours in the evening to night hours. Moreover, providers

could promote the installation of charging facilities, for example at workplaces, to support charging of PHEVs during the day.

5.2.1.4 Automotive industry perspective

The automatic acquisition of mobility data during trips and its customer-oriented use is a still relatively novel approach in the automotive context (Paefgen, Staake, and Thiesse, 2013). With the utilization of driving data for electric mobility assessment and with the consequent prediction of the mileage electrification potential of driver groups, knowledge on the electric range and battery requirements of customers can be derived. This allows manufacturers to provide valuable group-specific information of their products to customers and to better diversify their portfolio according to their customer groups.

Moreover, manufacturers can utilize information on segment specific vehicle requirements to create advertising that corresponds to the customers' needs (Hodson and Newman, 2009). For example, short electric range vehicles with 6.3 kWh batteries could be advertised to "commuters (short)" (CS) to electrify about 66% of their mileage (assuming home charging). More expensive long electric range vehicles (International Economic Development Council, 2013) with 56.4 kWh batteries could be offered to potentially less cost-sensitive "company representatives" (CR), which allows them to electrify 78% of mileage (again assuming home charging).

5.2.1.5 Research perspective

The comparison of distinct driver groups derived from a segmentation approach can provide added value for electric mobility assessment (Anable, 2005; Anable, Skippon, Schuitema, et al., 2011). In this work, the use of a clustering algorithm (Hartigan and Wong, 1979) is suggested to derive distinct groups of drivers based on their mobility patterns and to assess them in terms of their readiness for PHEV adoption.

To do so, the work applies a model that processes GPS-based mobility data and that derives statements on the expected electric driving potential and power grid impact of PHEVs (Wenig, Sodenkamp, and Staake, 2015) and evaluates and compares results for distinct groups of drivers. A general observation of results indicates that there are indeed significant differences between clusters, both in terms of mileage electrification potential and power grid impact, such that for future research, an increased focus on differences between distinct groups of drivers can be recommended.

5.2.1.6 Environmental perspective

Differences in the mileage electrification potential of drivers also imply distinct impacts of PHEVs from an environmental perspective. While groups such as the "commuter (short)" (CS) could electrify 66% of their mileage using a 6.3 kWh battery (and assuming home charging), groups with more demanding mobility patterns, such as the "company

representative” (CR) would require much larger batteries to electrify similarly large shares of mileage (here: 78% using a 56.4 kWh battery). However, the use of a larger battery does not only imply higher monetary costs (International Economic Development Council, 2013), but also an increased demand in scarce raw materials for battery production (International Energy Agency, 2018).

On the other hand, with larger batteries, the range requirements of long-distance drivers can be better met. For example, when assuming a charging opportunity at the primary parking locations (i.e., the home base) and the availability of 56.4 kWh battery, a “commuter (short)” (CS) could electrify only about 1,211 km per month. “Company representatives” (CR) however could electrify 4,469 km per month and “service providers” (SP) could electrify 5,260 km per month. As a consequence, greater amounts of fossil fuel could be saved, and thus local car exhaust emission could be substantially reduced.

5.2.2 Battery versus infrastructure assessment

Chapter 3 and (Wenig, Sodenkamp, and Staake, 2019) emphasize the comparison of battery and charging infrastructure configurations for PHEV driving scenarios to find characteristics that enable a large share of electrified mileage. The provided method allows for a systematic and large-scale electric mobility assessment based on real-world data. From this, trade-offs between battery capacity and charging infrastructure expansions can be evaluated. Subsequently, driver segments that could readily utilize PHEVs in the regarded scenario can be identified.

The systematic comparison of electric mobility scenarios includes short to long electric range vehicles and infrastructure coverages from home to ubiquitous charging, with charging power variations. Even with limited electric range vehicles and if only home charging was possible, a great portion of mileage could be electrified by the average driver.

An increase in charging power also increases peak power demand, however the availability of more charging facilities (such as a secondary private charging location or a public charging infrastructure) can reduce the demand peak. Charging infrastructure expansions have particular value for vehicles with limited electric range. In contrast, the importance of an extensive charging infrastructure is reduced if large batteries that provide long electric range are utilized. So, vehicles with a large – yet realistic – electric range can alleviate constraints imposed by the non-availability of widespread public charging opportunities for a large majority of drivers.

Results show – in compliance with cost-benefit considerations – that realistically large battery capacities outperform even large-scale infrastructure expansions. Such a battery increase is particularly valuable for drivers with demanding driving behavior (e.g., long roundtrips and fast driving). With increasing amounts of electrified mileage also gasoline savings increase. Interestingly, with both battery capacity and infrastructure improvements, the gasoline saving potential per electrified kilometer further increases,

presumably because more energy intensive, i.e., fast and long-distance trips can be electrified.

In Figure 40 to Figure 42, 24-hour load profiles for charging in three selected electric mobility scenarios from chapter 3 are compared. Figure 40 shows the load profile in a “modest” scenario, where a 9.4 kWh battery could be charged at the primary parking location with 3.7 kW. Demand peaks in the evening. A smaller peak can be seen around noon. In this scenario about 57% of mileage could be electrified.

Figure 41 provides the load profile for an “ambitious” electric mobility scenario. Here, a 56.4 kWh battery could be charged both at a primary and at a secondary parking location with 7.4 kW and at 10% of parking locations with 50 kW. About 91% of mileage could be electrified, but the energy demand is considerably increased and the energy demand peak in the evening becomes more prominent.

Finally, in the scenario underlying Figure 42, the battery of the vehicle has a capacity of 112.8 kWh. Charging is possible at the primary and secondary location with 22.1 kW or in public at 70% of parking locations with 120 kW. In this “excellent” electric mobility scenario, about 99% of mileage could be electrified. However, once again the overall energy demand is increased. This time more energy is consumed during the day and particularly the demand peak at noon is significantly higher.

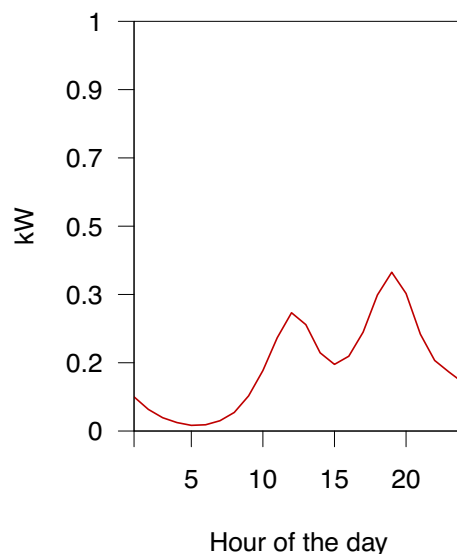


Figure 40: “Modest” electric mobility scenario: Grid impact of charging on the electric power network if charging is possible at the primary parking location with 3.7 kW charging power and if a 9.4 kWh battery capacity is available

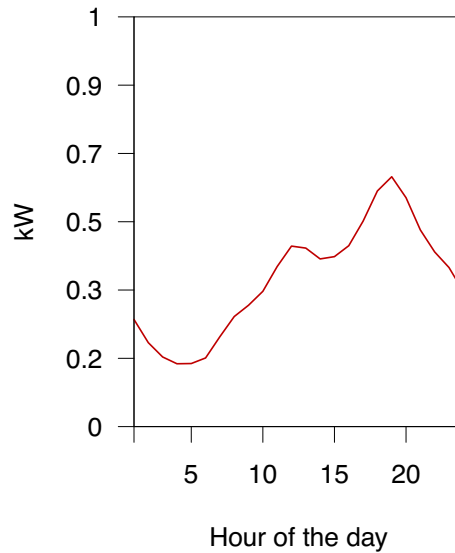


Figure 41: “Ambitious” electric mobility scenario: Grid impact of charging on the electric power network if charging is possible both at the primary and secondary parking location with 7.4 kW and at 10% of parking locations with 50 kW charging power and if a 56.4 kWh battery capacity is available

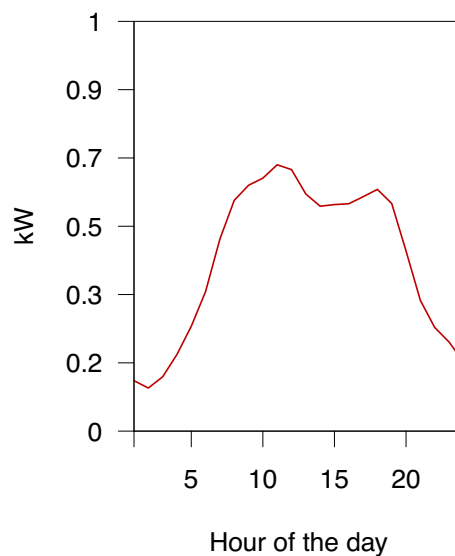


Figure 42: “Excellent” electric mobility scenario: Grid impact of charging on the electric power network if charging is possible both at the primary and secondary parking location with 22.1 kW and at 70% of parking locations with 120 kW charging power and if a 112.8 kWh battery capacity is available

Overall, results indicate that under the assumption of an extensive electrification of transport, the electricity that is demanded for vehicle charging has a considerable effect on the power grid. Besides battery size, charging power, and infrastructure coverage, also the charging behavior of individuals has been found to be a relevant influencing factor for the assessment of electricity demand. Variations in both individual mobility needs and electric mobility scenario parameters have to be taken into account to gain insights into the energy demand and grid impact of electric mobility and to provide a sufficient planning basis for energy suppliers.

The results imply that the technical requirements for a complete electrification of mileage are high and that a reasonable assessment of the utility of the electric range of vehicles should consider both electric range parameters and the available charging infrastructure – including both the location of the charging facilities and the available charging power.

Due to an already established and dense fuel station infrastructure (Fuels Europe, 2017), so far these issues played a lesser role for combustion-based vehicles and now have to be put into focus as key components of electric transportation to satisfy driver needs (Anderson, Lehne, and Hardinghaus, 2018; Rezvani, Jansson, and Bodin, 2015). Nevertheless, it has been shown that with sufficiently long electric range cars, charging infrastructure requirements decrease.

Only a smaller share of mileage can be driven electrically if the battery capacity of the vehicle is limited. Moreover, range anxiety further increases the electric range that is actually demanded and desired by drivers (Neubauer and Wood, 2014). Thus, in such cases, range extenders (National Academy of Sciences, 2015) could be utilized to compensate for a limited electric range of the vehicle.

5.2.2.1 Policy perspective

Policy targets concerning the electrification of transport have to consider the limitations of both vehicles and the charging infrastructure (National Academy of Sciences, 2015). The approach that is suggested in this work includes the systematic assessment of battery capacity and charging infrastructure parameters. From this, strategies could be developed that can help reaching electric mobility goals.

For example, an average PHEV driver with an 18.8 kWh battery could electrify about 69% of mileage, if charging was possible at home (assuming a 7.4 kW charging facility). By doubling the battery capacity to 37.6 kWh, 79% of mileage could be electrified.

A similar share of 77% could be achieved by adding a secondary charging opportunity and a public 50 kW charging infrastructure that enables the driver to charge at 10% of parking locations. Consequently, policy measures should regard the effect of both PHEV battery capacities and of infrastructure measures to foster an increase in electrified mileage of a vehicle fleet.

Moreover, by comparing the outcome of different electric mobility scenarios, more realistic goals could be derived that aim at providing cost-efficient and effective measures to foster electric driving. For example, if the abovementioned 37.6 kWh battery capacity was increased by a factor of 3, leading to a 112.8 kWh battery capacity, instead of 79% of mileage, 93% could be electrified.

To reach a similar share of mileage of 94% using a 37.6 kWh battery, a secondary charging facility and an extensive 50 kW public charging infrastructure that enables

charging at 70% of parking locations would be necessary. Most probably, due to high costs, such an infrastructure would be unfeasible under realistic conditions (National Academy of Sciences, 2015).

From these results, reasonable incentive measures could be derived. For example, policy measures to increase the electric car market share could particularly include both financial incentives for electric driving and charging infrastructure measures (International Energy Agency, 2018). Here, the provided methodology could help assessing the usefulness of such measures before implementing them.

5.2.2.2 Customer perspective

From a customer perspective, the battery capacity of a PHEV appears to be highly relevant for mileage electrification. Provided a 7.4 kW home charging opportunity, the average driver of a limited electric range vehicle with a 9.4 kWh battery could electrify about 57% of mileage. If instead a 112.8 kWh battery was available, the share of electrified mileage would go up to about 93%.

However, the high prices of long electric range vehicles appear to be problematic (International Economic Development Council, 2013). Nevertheless, the prices of batteries – which are considered key cost drivers of electric cars – decreased significantly over the past years (Nykvist and Nilsson, 2015). Nykvist and Nilsson (2015) found that battery prices declined by about 14% annually from 2007 to 2014 and Kapoor and MacDuffie (2017) showed that average battery prices further decreased since 2014, resulting in an annual decline of about 16% from 2007 to 2017. Such an assumed annual decline by 14% to 16% implies a price drop of about 80% after 10 years, as depicted in Figure 43.

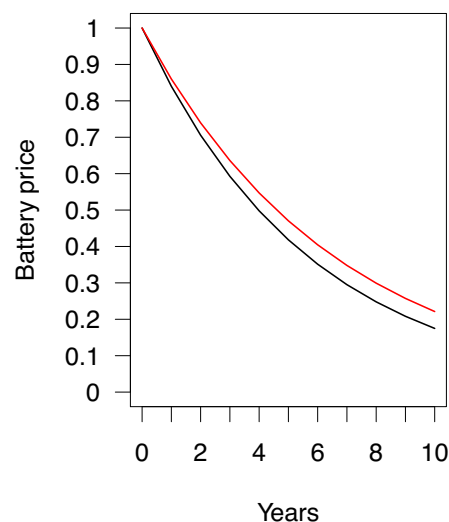


Figure 43: Battery price trend, assuming a 14% (red line, based on (Nykvist and Nilsson, 2015)) or 16% (black line, based on (Kapoor and MacDuffie, 2018)) annual price drop

When deciding which electric car characteristics are both affordable and meet the individual mobility demand, potential PHEV customers should take into account both the battery capacity of the car and the availability of a charging infrastructure. As was shown above, comparing a 9.4 kWh and a 112.8 kWh battery capacity, the average driver could electrify 57% and 93% of mileage – or reach 74% and 96% of destinations fully electrically – if only a 7.4 kW home charging facility was installed. The share of electrified mileage increases to 63% and 95%, if a secondary charging opportunity exists. With an additional 50 kW public charging infrastructure, accessible from 10% of parking locations, this value further rises to only about 67% and 97%.

5.2.2.3 Energy supplier perspective

A variety of both private and public parking lots, for example at home or at work, but also at the roadside or at commercial buildings are suitable locations to set up charging points (International Energy Agency, 2018; San Román, Momber, Abbad, et al., 2011), which facilitates the development of a public charging infrastructure. In that regard, the globally increasing number of public charging opportunities supports the continuation of the trend towards greatly increased electric vehicle market shares (International Energy Agency, 2018). Regarding the thus increasing charging demand and consequently the related electricity requirements, energy suppliers can be considered to be among the main stakeholders of the electric car industry (International Energy Agency, 2018).

In that regard, power suppliers have to adjust to this increasing electricity demand. For example, a typical driver that uses a PHEV with an 18.8 kWh battery and charges at home requires about 5.4 kWh per day to charge the vehicle. With a 112.8 kWh battery, this value increases to about 9.2 kWh per day.

In these home charging scenarios, charging power demand peaks at 0.6 kW and 0.7 kW in the evening. Interestingly, while the availability of a secondary charging facility and a 50 kW public charging infrastructure at 10% of parking locations increases the overall electricity demand to 6.5 kWh and to 9.8 kWh, charging demand peaks decrease to 0.5 kW and 0.6 kW. Consequently, suppliers could support infrastructure measures that provide additional charging opportunities during the daytime to mitigate peak electricity demand caused by PHEV charging in the evening.

5.2.2.4 Automotive industry perspective

Presented results and the underlying methodology can help car manufacturers to make realistic estimates concerning the potential for electric driving. Here, results particularly emphasize the importance of making affordable PHEVs with sufficiently long electric range available.

For example, even with a (rather improbable) charging infrastructure that allows drivers to charge with 3.7 kW during every parking event, about 74% of mileage could be electrified if the available PHEV had a battery capacity of 9.4 kWh. However, with a 112.8 kWh battery capacity, 91% of mileage could be covered electrically, even if charging with 3.7 kW was possible only at the primary parking location. With an additional secondary charging opportunity, the value increases to 94%.

Nevertheless, to extensively increase the share of electrically driven mileage and consequently to make all electric driving thinkable for an average driver, a combination of both long electric range and an extensive infrastructure of fast charging opportunities appears to be necessary. For example, an average driver that owns a 112.8 kWh PHEV requires 22.1 kW charging opportunities at the primary and secondary parking location and a 50 kW public charging infrastructure that allows charging at 40% of parking locations to electrify about 99% of mileage.

Consequently, next to the electric range of the vehicle, car makers should also consider the locally available charging infrastructure when marketing PHEVs. Besides providing long electric range vehicles, automotive manufactures can carry out measures to provide access to a sufficient charging infrastructure for their customers (International Energy Agency, 2018).

5.2.2.5 Research perspective

The presented methodology can be utilized with the GPS mobility data of a fleet that represents a given area and possibly different groups of drivers. Based on such data, it helps shedding a light on the impact of variations in electric range and in charging infrastructure characteristics. By systematically comparing the results of different scenarios, potentially subjective assumptions on the availability of battery capacities and charging opportunities can be avoided.

Results, both in terms of electrified mileage and power grid impact, clearly differ for distinct scenarios. For example, the share of electrifiable mileage ranges from 57% (PHEV with a 9.4 kWh battery capacity and 3.7 kW home charging) to 99% (PHEV with a 112.8 kWh battery capacity, 22.1 kW home and secondary charging, 50 kW charging at 70% of parking locations). In the first scenario, a daily electricity demand increase of 3.9 kWh with a peak in the evening can be observed. The second scenario shows an additional electricity demand of 10.3 kWh per day, peaking shortly before noon. Consequently, the research results suggest that parameter choices (here: charging power, charging infrastructure coverage, and battery capacity) have a significant impact on the outcome of electric mobility studies and should thus be particularly well-considered.

5.2.2.6 Environmental perspective

Exhaust pollution, caused by gasoline (and diesel) combustion is a major concern both from an environmental and from a public health perspective (Hickey, Boscarato, and

Kaspar, 2014). In this context, electric mobility can greatly contribute to fuel saving, as was shown in chapter 3 and thus help reducing the environmental and health impact of passenger transportation. This is particularly the case if electricity for vehicle charging can be generated from renewable sources (Carvalho, 2016; Liserre, Sauter, and Hung, 2010). After all, both environmental and health issues motivate governmental electric mobility incentives and may lead to a continuation thereof (International Energy Agency, 2018).

Besides predicting the potential for mileage electrification, the provided methodology estimates the additional electricity demand that is required for vehicle charging. For example, given the availability of a 9.4 kWh PHEV and a 3.7 kW home charging opportunity, the average driver would demand about 3.9 kWh of electric energy per day. With a 56.4 kWh battery capacity, 22.1 kW charging opportunities at home and secondary parking locations, and a 50 kW public charging infrastructure available at 10% of parking locations, this value rises to 8.9 kWh per day.

Based on the prediction of mileage electrification potential and energy demand for charging, the gasoline (or possibly diesel) saving potential can be estimated. Here, the abovementioned 3.9 kWh of energy used per day for electric driving correspond to 1.4 liters of gasoline per car and day. 8.9 kWh correspond to 3.0 liters per car and day.

5.2.3 Integration of vehicle charging into residential households

Home charging allows for the electrification of a major share of mileage, given a sufficiently large battery capacity. However, the energy demand for vehicle charging is high. Thus, chapter 4 puts a particular focus on the power grid impact of home charging in the residential domain. Both residential photovoltaic charging and a load shifting strategy are identified as possible means for grid impact alleviation and their potential is assessed.

A comparison of home charging demand and the typical 24-hour load profile of private households shows that in both cases typical energy demand peaks occur at noon and in the evening. However, vehicles of assumed private car owners are regularly parked during night hours for an extended period of time which leads to a great load shifting potential in the evening.

Instead of charging with maximum power and as quickly as possible, peak power demand could be decreased during peak hours in the evening. Consequently, the energy that is required for charging could be consumed more evenly between the evening and morning hours without adversely affecting the mileage electrification potential. Such a load shifting strategy is most beneficial for peak demand reduction in the evening if the available charging power is high and it is useful for peak demand reduction both for charging small and large vehicle batteries.

While vehicles are regularly parked at night, also parking at noon is common, such that a potential for photovoltaic charging can be identified. Photovoltaic charging can remove

stress from the grid during daytime hours and especially during peak demand hours at noon.

This is particularly true if charging power is limited because a common photovoltaic system is not necessarily sufficient to provide a high peak power. Load shifting allows more energy from the photovoltaic system to be used during daytime hours, presumably because of the lower power demand and longer charging times.

Depending on the electricity generation capacity (i.e., size) of the photovoltaic system, greater parts of the electricity peak demand and of the overall daytime electricity demand can be covered. Interestingly, larger batteries do not considerably increase the overall self-consumption because many charging events typically take place at night.

Figure 44 provides the 24-hour load profile for the average private household with a 112.8 kWh PHEV that is charged with 7.4 kW (black line). The red line represents the load profile if a 10 m² photovoltaic system is available. Here, peak power demand at noon is considerably decreased. The blue line shows a scenario where load shifting is possible for vehicle charging. It indicates that a load shifting procedure clearly reduces the energy demand peak in the evening.

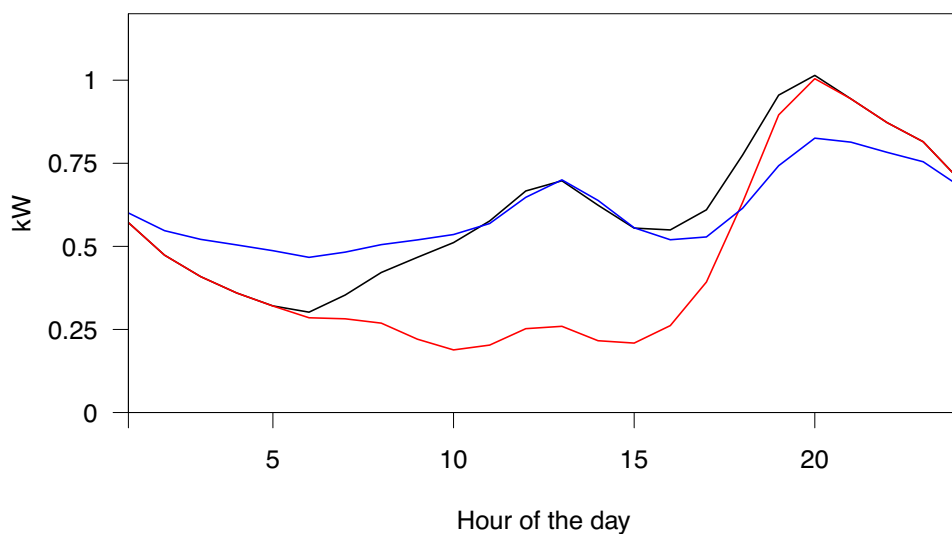


Figure 44: 24-hour load profile for the average private household with PHEV charging (112.8 kWh battery capacity, 7.4 kW charging power; black line) and when either a photovoltaic system (10 m²; red line) is available or load shifting is possible (blue line)

Figure 45 shows the charging demand profile of the average PHEV (black line). Again, the photovoltaic system considerably reduces the grid energy demand of the PHEV during daytime hours (red line), such that peak power demand for vehicle charging at noon is decreased. Still, as discussed in chapter 4, the usage of the photovoltaic system for vehicle charging in this scenario is limited, which can be explained by a limited charging demand during daytime hours. The blue line represents the reduced peak charging power demand in the evening when load shifting is possible.

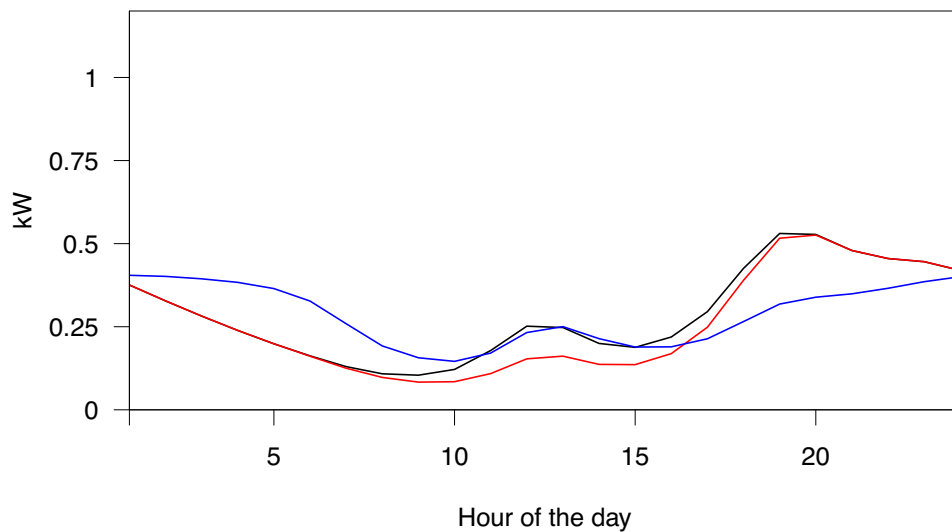


Figure 45: 24-hour load profile for the average PHEV that is charged at the primary location (112.8 kWh battery capacity, 7.4 kW charging power; black line) and when either a photovoltaic system (10 m²; red line) is available or load shifting is possible (blue line)

5.2.3.1 Policy perspective

The possibility to use energy that was generated by a residential photovoltaic system to charge a PHEV contributes to the household's self-supply of energy. For example, charging the 112.8 kWh PHEV with solar energy at home increases the electricity self-consumption rate of the household by about 8%. Consequently, incentives that foster the purchase of residential photovoltaic systems by PHEV owners and vice versa could be taken into consideration by policy decision makers that aim at increasing the share of renewable energy consumption (European Commission, 2018; International Renewable Energy Agency, 2017).

Furthermore, the use of electricity from a residential photovoltaic system for PHEV charging can reduce an electricity peak demand from PHEV charging at noon by about 36%. To reduce the larger PHEV charging demand peak in the evening, a load shifting strategy could be applied to decrease peak power demand by about 24% and to shift it to later hours. In this context, policy makers could set up suitable frameworks that encourage both load shifting from the demand-side and the integration of renewable energy (International Renewable Energy Agency, 2017).

5.2.3.2 Customer perspective

Results of this work also indicate that the availability of a residential photovoltaic system could influence the evaluation of a PHEV that is charged at home from a customer's perspective. It was shown that the use of solar energy for PHEV charging decreases

peak power demand of the PHEV at noon (about 36%) and increases the self-consumption rate of the household (about 8%). Together with price trends that indicate that photovoltaic module prices dropped by about 10% per year since 1980 (Farmer and Lafond, 2016) (c.f. Figure 46), these results indicate that the integration of residential photovoltaic power generation could be a promising approach for PHEV drivers.

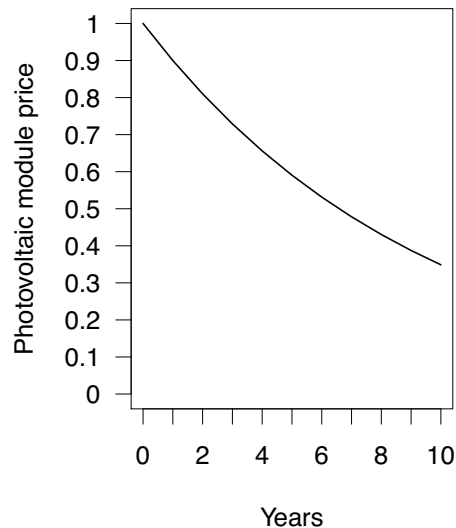


Figure 46: Photovoltaic module price trend, assuming a 10% annual price drop, based on (Farmer and Lafond, 2016)

Furthermore, load shifting could reduce the peak charging demand in the evening (24%) and shift the electricity demand to night hours without changing the state of charge of the PHEV at the beginning of the next trip after the parking event. Thus, from the PHEV customer's perspective, electricity tariffs that offer lower electricity prices at night become attractive (Prügler, 2013).

5.2.3.3 Energy supplier perspective

Energy suppliers could offer such tariffs and thus allow their customers to exploit lower energy prices during off-peak hours at night (Prügler, 2013). The reduction of power demand peaks could thus help to reduce the demand for potentially expensive reserve capacities (Prügler, 2013).

Here, both means of peak power demand reduction, photovoltaic charging (36% at noon) and load shifting (24% in the evening) could be fostered to manage the increased electricity demand from PHEV charging at home. Consequently, measures that support residential photovoltaic generation or load management could mitigate the negative side effects of peak home charging demand.

5.2.3.4 Automotive industry perspective

Given regular daytime parking hours at home, owners of both, residential photovoltaic systems and PHEVs could improve the photovoltaic systems' monetary benefits by increasing the self-consumption of generated energy (Lang, Ammann, and Girod, 2016). Consequently, from the automotive manufacturers' perspective, the availability of home charging opportunities that support photovoltaic charging (and possibly the use of a load shifting strategy) could increase the value of PHEVs for residential photovoltaic system owners.

Moreover, car manufacturers could emphasize that PHEV driving provides the opportunity to use locally generated renewable energy for transportation. This observation could have a positive impact on the product evaluation of environmentally aware customer groups (Anable, Skippon, Schuitema, et al., 2011).

5.2.3.5 Research perspective

To the author's knowledge and with reference to the literature review from chapter 4, the available research literature on GPS data-based electric mobility scenarios assessment only rarely includes the impact of photovoltaic charging and of load shifting in the domestic domain. Consequently, a novel method to observe the potential for both, photovoltaic charging and load shifting in the context of a private household that uses a PHEV, is provided.

The research work thus constitutes an innovative integration of behavioral (i.e., mobility) time series data, and of both household load profiles and location and time specific irradiation data. Results show that the potential grid impact of PHEVs has to be regarded in the context of realistic scenarios, such as the already existing grid impact of private households, both with and without residential photovoltaic systems and applied load shifting strategies to derive reliable and applicable conclusions.

5.2.3.6 Environmental perspective

The globally increasing photovoltaic power generation (Farmer and Lafond, 2016) (c.f. Figure 47) makes an electric transportation scenario that is at least partially powered by solar energy conceivable. Recent publications state that the global photovoltaic energy generation capacity increased by more than 40% annually from 1983 to 2013 (Farmer and Lafond, 2016), respectively from 2000 to 2017 (Jäger-Waldau, 2017). Naturally, such past developments do not necessarily indicate a future growth. However, they give reason for the expectation of a further upward trend.

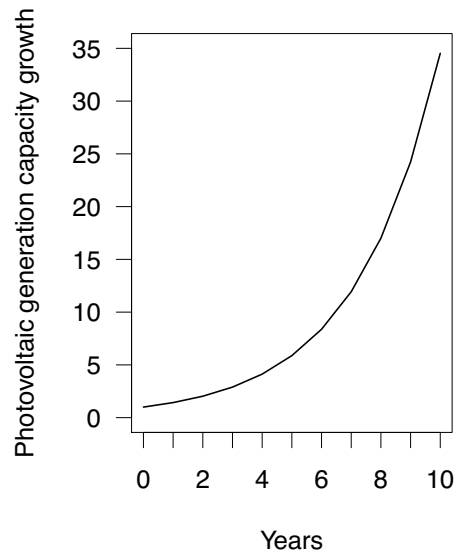


Figure 47: Global photovoltaic generation capacity growth, assuming an annual 42.5% increase, based on (Farmer and Lafond, 2016)

With regard to residential photovoltaic electricity generation, results show that charging PHEVs with solar energy can increase the energy self-consumption rate of the household (about 8%). Consequently, more energy that is required for transportation could be generated locally from renewable sources.

5.3 Limitations and recommendations for future research

The informative value of results presented in this work is limited by the quality and bias of underlying data. The methodology that was used in this work could be adapted and used with alternative data sets that represent different regions and different vehicle fleets. Following this, a comparison of the driving behavior and electric mobility potential could include far-reaching statements on the impact of country- and area-specific particularities.

Furthermore, a higher level of granularity of mobility time series would enable the consideration of measured acceleration data or respective values derived from speed measurements. Instead, in (Wenig, Sodenkamp, and Staake, 2015) and in the course of this work, the suggested estimation of additional energy required for acceleration was derived from driving cycles.

Such a higher granularity of data would also make the integration of measured or deduced altitude feasible. Still, the influence of altitude is assumed to be limited when regarding a longer period of time, such as in the presented results, because the total tractive effort required to move a car increases during an uphill ride, but in turn decreases when driving downhill (Larminie and Lowry, 2003).

To improve the comparability of results, it was assumed that distinct driver segments use the same vehicle model. In future work, the impact of car characteristics that go

beyond the capacity of batteries, including the weight and external dimensions of the vehicle, could be assessed and varied for distinct groups.

Also, the scenarios that were emphasized could be extended to address further questions that lie beyond the scope of this work. For example, a focus could be put on the identification of the specific charging infrastructure requirements for long distance trips and for interregional mobility. In addition, the utility of alternative and on-demand means of mobility – such as public transportation – to complement limited electric range vehicles (International Energy Agency, 2018) could be studied in a data-driven approach for groups with infrequent long-distance roundtrips.

With respect to the assessment of electrifiable mileage and the power impact of vehicle charging, a particular focus of future work could also lie on the effect of seasonal differences and on the regional variety of weather conditions. Here, possible topics include the reduced electric range of PHEVs in cold climate (Assum, Kolbenstvedt, and Figenbaum, 2014), but also the impact of auxiliaries such as air conditioning or heating (Greaves, Backman, and Ellison, 2014).

Results of this work also show that with an increased electricity demand at domestic households, caused by vehicle charging, the self-consumption of energy generated by possibly available residential photovoltaic systems could be increased. Moreover, photovoltaic charging could significantly reduce power demand peaks at noon. Still, parking time windows with high solar irradiation are limited. A possible solution would be the use of residential batteries that could temporarily store electricity from the photovoltaic system during periods of high solar irradiation and provide the stored energy when electricity demand exceeds photovoltaic generation (for example at night) (Betz and Lienkamp, 2016; Truong, Naumann, Karl, et al., 2016) or the application of a managed charging strategy that prioritizes photovoltaic charging (Chaouachi, Bompard, Fulli, et al., 2016).

Both further economic (Bubeck, Tomaschek, and Fahl, 2016; Wu, Inderbitzin, and Bening, 2015) and environmental (Hawkins, Singh, Majeau-Bettez, et al., 2013) cost-benefit calculations in the context of electric mobility and concerns regarding the assessment of an increased demand in scarce resources for electricity storage (Ziemann, Grunwald, Schebek, et al., 2013) are out of the scope of this work. Still, future work could address these issues and provide predictions on the expected costs and benefits of different electric mobility scenarios in greater detail.

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