Techno-economic optimization and environmental evaluation of electric vehicles in commercial fleets

Zur Erlangung des akademischen Grades eines

Doktors der Ingenieurwissenschaften
(Dr.-Ing.)

von der KIT-Fakultät für Wirtschaftswissenschaften
des Karlsruher Instituts für Technologie (KIT)

genehmigte

Dissertation

von

Maximilian Schücking

Tag der mündlichen Prüfung: 17. Juli 2020
Referent: Prof. Dr. Wolf Fichtner
Korreferent: Prof. Dr. Orestis Terzidis

Für meine Familie

Danksagung

Diese Arbeit entstand während meiner Tätigkeit erst als wissenschaftlicher Mitarbeiter bei Competence E (heute Batterietechnikum) am Karlsruher Institut für Technologie (KIT) und dann als Gründer der e-Motion Line GmbH. Ich danke hier insbesondere Herrn Dr. Andreas Gutsch und Herrn Dr. Olaf Wollersheim für die persönliche Förderung und die vielfältige Unterstützung bei der Ausgründung und dem Aufbau der e-Motion Line. Zudem gilt mein spezieller Dank meinen Mitgründern und guten Freunden Herrn Max Nastold und Herrn Philip Wahl für ihr Verständnis trotz der sehr intensiven Zeit beim Aufbau der e-Motion Line mir die erforderliche Freiheit für die Promotion gegeben zu haben.

Für die Möglichkeit zur Promotion als externer Doktorand am Lehrstuhl für Energiewirtschaft des Instituts für Industriebetriebslehre und Industrielle Produktion (IIP), für das die Jahre hindurch entgegengebrachte Vertrauen und das konstruktive Feedback von Anfang bis zum Abschluss meiner Arbeit gilt mein ganz besonderer Dank Herrn Prof. Dr. Fichtner. Für die Übernahme des Korreferats danke ich sehr Herrn. Prof. Dr. Terzidis sowie Herrn Prof. Dr. Kay Mitusch für die Übernahme der Rolle des Prüfers und Frau Prof. Dr. Melanie Volkamer für den Prüfungsvorsitz bei meiner mündlichen Prüfung.

Des Weiteren möchte ich ganz besonders Herrn PD Dr. Patrick Jochem danken. Ohne seine vielfältige und engagierte Unterstützung wäre diese Arbeit nicht entstanden. Als Gruppenleiter der Arbeitsgruppe Transport und Energie hat er mich als externen Doktoranden aufgenommen und stand mir trotz seiner neuen Rolle am Institut für Technische Thermodynamik des Deutschen Zentrums für Luft- und Raumfahrt (DLR) bis zum Abschluss jederzeit mit Rat und Tat zur Seite. Auch meinen Kolleginnen und Kollegen der Arbeitsgruppe möchte ich in diesem Kontext sehr für den intensiven Austausch und die kollegiale Zusammenarbeit danken, insbesondere Herrn Thomas Dengiz, Herrn Dr. Axel Ensslen, Herrn Dr. Jonathan Gomez, Herrn Dr. Thomas Kaschub, Frau Sabrina Ried, Herrn Johannes Schäuble, Frau Dr. Katrin Seddig, Herrn Zongfei Wang und Herrn Christian Will.

Ebenso danke ich herzlich allen Co-Autoren der wissenschaftlichen Paper dieser Dissertation, speziell den bisher an anderer Stelle noch nicht genannten Herrn Dr. Michael Held, Herrn Henning Steffens und, Herrn Dr. Kevin Stella für die sehr konstruktive und erfolgreiche Zusammenarbeit.

Nicht zuletzt danke ich für das Korrekturlesen der unterschiedlichen Abschnitte meinem Vater Herrn Dr. Christoph Schücking sowie meinem Schwager Herrn Dr. Paul Schönberger.

Mein größter Dank gilt meiner Frau für ihre motivierende Unterstützung, den täglichen Rückhalt und das Verständnis für die geopferten Wochenenden.

Stuttgart, im August 2020

Maximilian Schücking

Kurzzusammenfassung

Die Einführung von batterieelektrischen Fahrzeugen (E-Pkw) gilt als eine wichtige Maßnahme zur Emissionsverringerung im Straßenverkehr. Gewerbliche Flotten in Deutschland bilden hierfür einen vielversprechenden Markt. Um dieses Potential zu realisieren, ist sowohl eine techno-ökonomische Optimierung als auch eine ökologische Bewertung über den Lebenszyklus erforderlich. Das Ziel der Dissertation ist es, hierfür ein methodisches Rahmenwerk zu liefern.

Die kumulative Dissertation besteht aus fünf Artikeln, die sich den einzelnen Bestandteilen des Rahmenwerks widmen und großteils auf Technologie- und Nutzungsdaten aus eigenen Messungen aufbauen. Der erste Artikel, Schücking et al. (2016) [Paper I], ist eine technische Analyse. Sie untersucht den realen Energieverbrauch von E-Pkws im Vergleich zu konventionellen Fahrzeugen und identifiziert optimale Betriebspunkte. Die Ergebnisse heben den Einfluss verschiedener Faktoren auf den Energieverbrauch als wichtige Komponente detaillierter techno-ökonomischer und ökologischer Betrachtungen hervor. Der zweite und der dritte Artikel haben einen techno-ökonomischen Fokus. Sie beschäftigen sich mit der Frage, wie E-Pkws einen schnelleren wirtschaftlichen Break-even im Vergleich zu konventionellen Fahrzeugen erreichen können. Der zweite Artikel, Schücking et al. (2017) [Paper II], stellt Ladestrategien vor, welche eine höhere Auslastung der E-Pkw ermöglichen und damit zu geringen Gesamtkosten im Vergleich zu konventionellen Pkw führen können. Unsicherheiten in Fahrprofilen und Energieverbrauch begrenzen die Anwendbarkeit dieser Strategien. Der dritte Artikel, Schücking & Jochem (2020) [Paper III], knüpft hieran an. Er schlägt ein zweistufiges stochastisches Optimierungsmodell zur Minimierung der Investition und Betriebskosten eines E-Pkw unter Berücksichtigung dieser Unsicherheiten vor. Neben der stochastischen Betrachtung ist auch die Abwägung zwischen Batteriekapazität und Ladeleistung in der Investitionsentscheidung ein neuer Beitrag zur Forschung. Im Kontext der stochastischen Optimierung werden ein Hidden Markov Modell zur Generierung komplexer Fahrprofile und eine neue Szenario-Reduktionsheuristik als methodische Weiterentwicklungen angewandt. Artikel vier und fünf liefern eine ökologische Bewertung. Die empirischen Daten sowie der Fokus auf den deutsch-französischen Grenzverkehr zeichnen beide Artikel aus. Der vierte Artikel, Ensslen et al. (2017) [Paper IV], konzentriert sich auf die E-Pkw Nutzungsphase. Er verdeutlicht den Einfluss unterschiedlicher Strommixe und Ladezeitpunkte auf die CO_2-Emissionen und Reduktionspotentiale. Der fünfte Artikel, Held & Schücking (2019) [Paper V], betrachtet verschiedene ökologische Wirkungskategorien (wie z.B. Klimawandel, Versauerung Eutrophierung) über den gesamten Lebenszyklus mittels eines modularen Screening-Modells. Die Ergebnisse unterstreichen den Einfluss der Batterie und der Nutzungsphase auf die ökologische Gesamtbilanz. Dem übergreifenden Forschungsziel folgend, zeigen die Ergebnisse der einzelnen Artikel in ihrer Kombination, dass die Optimierung des wirtschaftlichen Nutzens auch die ökologischen Vorteile erhöhen kann. Die ex-ante Ermittlung der optimalen Batteriekapazität sowie ein hoher Betriebsgrad erhöhen nicht nur die Wettbewerbsfähigkeit von E-Pkw, sondern beschleunigen unter bestimmten Voraussetzungen auch den ökologischen Break-even in einem Großteil der betrachteten Wirkungskategorien. Die Eigenschaften, die gewerbliche Anwendungen aus wirtschaftlicher Sicht zu einem vielversprechenden Einführungsmarkt für E-Pkws machen, können damit auch die angestrebten ökologischen Vorteile unterstützen.

Abstract

The introduction of battery electric vehicles (BEVs) is considered an important measure to reduce emissions from road transport. The commercial vehicle market in Germany forms a promising introductory market. However, the widespread substitution of internal combustion engine vehicles (ICEVs) by BEVs is still hindered by technical restrictions and higher investment. Under the goal of a rapid BEV introduction ramp-up to support emission reduction targets, the techno-economic optimization of BEV investment and operations becomes strongly intertwined with the environmental evaluation. The aim of this thesis is to provide a methodological framework, which helps to identify essential conditions, prerequisites, and measures required for a joint economic and environmentally beneficial deployment of BEVs in commercial applications.

This thesis consists of five papers, which introduce individual components of the framework and are largely based on technology and usage data from own measurements. The first paper, Schücking et al. (2016) [Paper I], is a technical analysis. It examines the real energy consumption of BEVs compared to internal combustion engine vehicles (ICEVs) and identifies optimal operating points. The results highlight the influence of various factors on energy consumption, which is a key input for a detailed techno-economic optimization and environmental evaluation. The second and third paper have a techno-economic focus. They deal with the question of how BEVs can achieve a faster economic break-even compared to ICEVs. The second paper, Schücking et al. (2017) [Paper II], presents charging strategies that allow a higher utilization of the BEVs and thus can lead to lower total costs compared to ICEVs. Uncertainties in mobility patterns and energy consumption limit the applicability of these strategies. The third paper, Schücking & Jochem (2020) [Paper III], follows up on this. Taking these uncertainties into account, the paper proposes a two-stage stochastic optimization model to jointly minimize the investment and operating costs of a BEV. In addition to the stochastic approach, the inclusion of the trade-off between battery and charging capacity in the investment decision is a new contribution to the research. In the context of stochastic optimization, a hidden Markov model for the generation of complex driving profiles and a new scenario reduction heuristic are applied as methodological enhancements. The fourth and fifth paper provide the environmental evaluation. The empirical utilization data as well as the emphasis on Franco-German border traffic characterize both papers. The fourth paper, Ensslen et al. (2017) [Paper IV], focuses on the utilization phase. It highlights the influence of different electricity mixes and charging times on carbon dioxide (CO_2) emissions and reduction potentials. The fifth paper, Held & Schücking (2019) [Paper V], assesses several environmental impact categories (e.g. global warming potential, acidification potential, and eutrophication potential) over the entire life cycle using a simplified modular screening model. The results underline the strong influence of the battery and the utilization phase on the overall environmental impact. In line with the overarching research objective, the results of the individual papers combined indicate that the optimization of the economic benefit can also increase the environmental benefits. The ex-ante determination of the optimal battery and charging capacity as well as a high degree of operation not only increase the competitiveness of BEVs, but under certain conditions can also accelerate breaking-even in several environmental impact categories. The characteristics that make commercial applications from an economic point of view a promising introduction market for BEVs can thus also support the achievement of the desired ecological benefits.

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List of figures (Part A)

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List of abbreviations (Part A)

AC	Alternating current
AP	Acidification potential
ASM	Asynchronous machine
BEV	Battery electric vehicle
CCS	Combined charging system
CO	Carbon monoxide
CO_2	Carbon dioxide
DC	Direct current
EM	Electric motor
EOL	End-of-life
EP	Eutrophication potential
EVSE	Electric vehicle supply equipment
FCEV	Fuel-cell electric vehicle
FDP	Fossil depletion potential
FEP	Freshwater eutrophication potential
GHG	Greenhouse gas
GTW	Grid-to-wheel
GWP	Global warming potential
HEV	Hybrid electric vehicles
HMM	Hidden Markov model
HTP	Human toxicity potential
ICE	Internal combustion engine
ICEV	Internal combustion engine vehicles
ILCD	International life cycle data system
KiD	Vehicles in Germany/Kraftfahrzeuge in Deutschland
KPI	Key performance indicators
LCA	Life cycle assessment
LCC	Life cycle costing
LCI	Life cycle inventory
LCIA	Life cycle impact assessment
LCSA	Life cycle sustainability assessment
Li-ion	Lithium-ion
MDP	Metal depletion potential
MEP	Marine eutrophication potential
MiD	Mobility in Germany/Mobilität in Deutschland
MOP	German mobility panel/ Deutsches Mobilitätspanel
NEDC	New European driving cycle
NO_x	Nitrogen oxides
ODP	Ozone depletion potential
PED	Primary energy demand
PHEV	Plug-in hybrid electric vehicle
PM	Particulate matter
PSM	Permanently excited synchronous machine
PTW	Plant-to-wheel
REEV	Range-extended electric vehicles
RES	Renewable energy source
SAA	Sample average approximation

SLCA	Social life cycle assessment
SO_2	Sulfur dioxide
SOC	State of charge
TCO	Total cost of ownership
TETP	Terrestrial eutrophication potential
TTW	Tank-to-wheel
VOC	Volatile organic compounds
WTW	Well-to-wheel

Part A - Overview article

1. Introduction

Transport causes almost a quarter of all greenhouse gas (GHG) emissions in Europe, and it is the main root of local air pollution in cities (European Commission, 2016). The international efforts to reduce GHG emissions and limit the Global Warming Potential (GWP) have led to the Accord de Paris where it was agreed to hold *"(…) the increase in the global average temperature to well below 2 °C above pre-industrial levels and to pursue efforts to limit the temperature increase to 1.5 °C (…)"* (United Nations, 2015). However, on several measures required to reach that goal, such as guidelines for a common carbon market, the members of the international community have so far not reached an agreement (UNFCCC, 2019). Next to the GWP, the negative impact of local air pollution has become an important topic in public and political discussions. Although slight improvements are noted in Germany, the high levels of nitrogen oxides and particles in city centers lead to continuous warnings from the European Commission and can ultimately lead to legal proceedings and fines (Umweltbundesamt, 2018). In other parts of the world, such as China and India, local air pollution from transportation is far worse, contributing to the heavy smog that causes widespread health problems (Forbes, 2017; The New York Times, 2020).

Enabled by the recent progress in battery technology, the electrification of road transport is seen as a promising way to decrease local as well as global emissions (Creutzig et al., 2015; IEA, 2019; Jochem, Doll, & Fichtner, 2016). A combination of mobility and energy transition with an increasing share of renewable energies is key (Jochem, Babrowski, & Fichtner, 2015; Sohnen, Fan, Ogden, & Yang, 2015; Wietschel et al., 2019). Hence, the European Commission has put the policy areas of clean energy and sustainable mobility at the core of the European Green Deal (European Commission, 2020). Amongst other targets, the investment plan seeks a 90% reduction of transport emissions by 2050 (European Commission, 2019). In line with this goal, the German federal and state governments also try to accelerate the replacement of internal combustion engine vehicles (ICEVs) by battery electric vehicles (BEVs) through regulatory changes, short-term tax incentives, and direct premiums (Bundesregierung, 2016). With 83.175 registered BEVs in Germany at the end of 2019, it has been clear for some time that the initial target of one million BEVs by 2020 will not be reached (KBA, 2019b; Zeit Online, 2018). Therefore, the federal initiatives have been expanded further as part of the Klimaschutzprogramm 2030, e.g. with the increase of the direct premiums for BEVs from 4,000 € to 6,000 € (BMWi, 2020). Moreover, local driving bans on Diesel vehicles are being executed to improve local air quality in city centers (Bundesverwaltungsgericht, 2018; Stadt Stuttgart, 2019). Governments of other countries go as far as announcing future bans on new registrations of ICEVs, e.g., Norway by 2025 or France by 2040 (The Guardian, 2017).

With increasing battery capacities, higher charging power, and falling prices the technical substitution potential, as well as the economic profitability of BEVs, is improving. Despite the advances in lower operational costs and the ongoing political support BEVs still have significant disadvantages compared to ICEVs that confine their current adoption by commercial and private users (Ensslen, Ringler, Jochem, Keles, & Fichtner, 2014). The main technical and economic hurdles for a widespread introduction are the limited range, the longer recharging time, and the purchase price (Globisch & Dütschke, 2013; Hacker et al., 2011; Sierzchula, 2014).

Commercial transport is increasingly considered to be the more promising introduction market for BEVs (The Economist, 2018). In comparison to privately owned vehicles, commercial ones have a faster turnover rate (Nesbitt & Sperling, 2001). For commercial use cases, the technical restrictions are less problematic because mobility patterns show lower variance and are more predictable. ICEVs can also be used in mixed fleets for trips above the maximum range (Ketelaer, Kaschub, Jochem, & Fichtner, 2014). Studies show that the technical specifications of the first mass-market BEV models were already sufficient to cover most of the mobility demand of various commercial use cases (Gnann, Plötz, Kühn, & Wietschel, 2015; Hacker, von Waldenfels, & Mottschall, 2015; Ketelaer et al., 2014; Plötz, Gnann, Kuehn, & Wietschel, 2013). Due to the growing battery capacities over recent years the technical substitution potential is constantly increasing (Lutsey, Grant, Wappelhorst, & Zhou, 2018). The maximum range of BEVs is predicted to rise to 800 km in the next ten years (Thielmann et al., 2020). Additionally, the higher annual mileage of commercial vehicles allows taking more advantage of the lower operating costs facilitating an earlier break-even relative to an ICEV (Gnann, Plötz, Kühn, et al., 2015; Ketelaer et al., 2014; Plötz et al., 2013). Even though commercial vehicles only make up 10.8% of the total registered vehicles in Germany with 63.6% of all annual new registrations they are a crucial introductory market (KBA, 2019b, 2019a). To accelerate the introduction of commercial BEVs in Germany, the coalition agreement of the current federal government includes an extraordinary depreciation allowance for commercial BEVs in addition to the existing short-term tax incentives and direct premiums (Bundesregierung, 2018). This extraordinary depreciation allowance has been increased and expanded until 2030 (Handelsblatt, 2019). The technical and future economic advantages of BEVs, the public incentive schemes, and the risk of a local or total ban of ICEVs raise the need for organizations to evaluate the techno-economic potential and environmental impact of BEVs.

Even though research has assessed the techno-economic optimization and environmental impact of BEVs extensively, the publications usually focus on one or the other field of research. With the objective of a rapid BEV introduction ramp-up to support traffic emission reduction targets, both fields of research become strongly intertwined. To the best of the author's knowledge, no publication offers a holistic framework of methodical approaches to evaluate, simulate, and optimize the case-specific utilization as well as the whole life cycle of commercial BEVs from an economic and an environmental perspective.

Moreover, in the individual fields of research, techno-economic optimization and environmental impact of BEVs, there are still gaps. A large amount of literature with an economic focus has been dedicated to forecasting the (commercial) market penetration of BEVs using or combining econometric, discrete choice, agent-based simulation, system dynamics or integrated assessment models (Jochem, Gómez Vilchez, Ensslen, Schäuble, & Fichtner, 2018). Many of these rely on the total cost of ownership (TCO) approach in some form. Only a limited number of studies takes a more incremental TCO approach by optimizing the investment and operation of BEVs in specific commercial use cases (Davis & Figliozzi, 2013; Feng & Figliozzi, 2013; Hiermann, Puchinger, Ropke, & Hartl, 2016; Kuppusamy, Magazine, & Rao, 2017; Sassi, Cherif, & Oulamara, 2015). Even fewer are based on real BEV utilization data (Lebeau et al., 2015), even though they can have a significant influence on the technical and therefore economic substitution requirements. Furthermore, these approaches neglect the specific effect of uncertainties in the input data from utilization or the potential benefits of optimizing the trade-off between battery and charging capacity in the investment decision. Concerning the environmental impacts, several studies have assessed the direct emissions in operation or provide a full life cycle assessment (LCA) (Helmers & Weiss, 2017; Nordelöf, Messagie, Tillman, Ljunggren Söderman, & Van Mierlo, 2014). The use of case-specific BEV utilization data can notably improve the results since they are highly sensitive to different utilization parameters. However, only a few include the data of specific commercial use cases (Held et al., 2016; Muneer et al., 2015). For both the assessment of the direct carbon dioxide (CO_2) emissions and saving potentials, as well as the LCAs case-specific studies based on long-term utilization data, are missing from the literature (Egede et al. 2015).

Two objectives for this thesis can be derived from the research gaps described above: firstly, it aims to fill the identified gaps in the individual fields of research, techno-economic optimization and environmental impact of BEVs, based on detailed empirical data and to combine existing methods into new methodical advancements to do so. Secondly, the thesis's additional goal is to bring the two fields of research together. Considering the dependencies in the results of the two fields of research allows drawing general conclusions for the essential conditions, prerequisites, and measures required for a joint economic and environmentally beneficial deployment of BEVs in commercial applications.

Table 1 provides an overview of the five papers, which constitute the new research presented in this thesis including the specifically addressed research questions, applied methodology, and assessed use cases. The papers presented in this thesis are distinguished into three subject areas. Subject area 1 has a technical focus and consists of Schücking et al. (2016) [Paper I]. It offers a detailed technical analysis of the BEVs' energy consumption in long-term deployment and uses the empirical data to calibrate a vehicle dynamics model. Subject area 2 has a techno-economic focus containing two papers that follow the aim of increasing the BEVs' competitiveness. Schücking et al. (2017) [Paper II] focuses on the operations and presents empirical evidence and conceptual suggestions of how in use cases with a high degree of predictability the BEVs' utilization and therefore their competitiveness can be increased through charging strategies. Schücking & Jochem (2020) [Paper III] takes a broader approach by introducing a two-stage stochastic program that optimizes the investment decision and the operational costs considering uncertainties in energy consumption and the detailed technical constraints set by a BEV. Subject area 3 delivers the analysis of the direct CO_2 emissions and life cycle environmental impacts for BEVs in commercial applications. Ensslen et al. (2017) [Paper IV] focuses on utilization and calculates time-dependent CO_2 emission reduction potentials based on empirical BEV charging profiles. Held & Schücking (2019) [Paper V] evaluates the whole life cycle from an environmental perspective and provides an LCA covering the stable impact categories based on a simplified screening approach. In total, all papers present an interdisciplinary approach to evaluate, simulate, and optimize the case-specific utilization of commercial BEVs from an economic and environmental perspective by offering a holistic framework of methodical approaches (Figure 7). The energy consumption of the BEVs and the commercial mobility profiles are the center of the framework. They set the basis as essential technical requirements for the following detailed economic and environmental assessment. The research in this thesis is to a large extent based on newly recorded empirical utilization data (mobility profiles and energy consumption), which is evaluated and used to calibrate the applied technical, techno-economic, and environmental models.

Table 1: Overview of the five research papers presented in this thesis

	Subject area 1 **Technical**	**Subject area 2** **Techno-economic**	**Subject area 3** **Environmental**
Paper	***Schücking et al. (2016)*** ***Paper I*** *Influencing factors on specific energy consumption of EV in extensive operations*	***Schücking et al. (2017)*** ***Paper II*** *Charging strategies for economic operations of electric vehicles in commercial applications*	***Ensslen et al. (2017)*** ***Paper IV*** *Empirical carbon dioxide emissions of electric vehicles in a French-German commuter fleet test*
Research questions	1. What is the real energy consumption of BEVs in long-term deployment? 2. What are the key influence factors on the specific energy consumption? 3. Where is the point of highest comparable efficiency?	1. How can charging strategies that enable a high annual mileage under the present restrictions be implemented, assessed, and optimized?	1. How much energy was consumed by the BEVs depended on different measurement points? 2. What are the time-depended PTW CO_2 emissions caused by the BEVs? 3. How high are the CO_2 emission reduction potentials?
Method	- Recording & analysis of empirical data - Vehicle dynamics model to simulate energy consumption	- Recording & analysis of empirical data - Definition of key performance indicators (KPI)	- Recording & analysis of empirical data - Simulation of time-dependent charging emissions
Use-case	- Commuting of shift workers - Business trips on fixed routes	- Commuting of shift workers - Business trips on fixed routes	- Commuting of shift workers
Paper		***Schücking & Jochem (2020)*** ***Paper III*** *Two-Stage Stochastic Program Optimizing the Total Cost of Ownership of Electric Vehicles in Commercial Fleets*	***Held & Schücking (2019)*** ***Paper V*** *Utilization effects on battery electric vehicle life-cycle assessment: A case-driven analysis of two commercial mobility applications*
Research questions		1. How does uncertainty actual energy consumption effect the optimal BEV investment choice and operational costs? 2. What is the effect on the TCO of considering the trade-off between battery and charging capacity in the investment decision?	1. How high are the life cycle environmental impacts of BEVs in long-term deployment? 2. What are the effects of different energy mixes and cross-border traffic? 3. At what mileages do BEVs break-even compared to ICEVs for different impact factors?
Method		- Total cost of ownership (TCO) - Stochastic programming - Hidden Markov model - Scenario reduction	- Recording & analysis of empirical data - Life cycle assessment (LCA) for different impact categories
Use-case		- Home nursing service	- Commuting of shift workers - Business trips on fixed routes

The thesis is divided into three parts. Part A offers an introduction to BEVs and commercial transport. Based on previous research, it proposes a framework for identifying promising commercial use cases. Furthermore, it provides an overview of the current state of research and illustrates the gaps in the literature in terms of content and methodology. Also, Part A gives an overview of how the five research papers add new methodical approaches and empirical insights attempting to fill the identified gaps. It concludes by pointing out interconnections between the results of the papers, stating the limitations, and providing links and outlook for future research. Part B consists of the five papers constituting the research of this thesis. Part C acts as a further appendix to the research papers. It provides additional details concerning data, data processing, and modeling, as well as parts of the program source code.

2. Commercial electric mobility

Ups and downs characterize the history of BEVs over the last 150 years. It started with an early success story followed by a sharp decline and many years of only minor importance. The first experimental BEV was built in 1834, more than 50 years before the first ICEV (Chan, 2013). As the first commercial applications, electric taxis were introduced in New York City in 1897 and Germany in 1904 (Chan, 2013). At the turn of the 19th to the 20th century, 38% of all automobiles in the US were powered by electricity and only 22% by gasoline with the rest powered by steam (Guarnieri, 2012). The advantages over other drivetrain technologies were the same as today: no gear shift, no exhaust, and easy to start as well as recharge. With the discovery of vast crude oil reserves and the development of the electrical starter, ICEVs became cheaper and more convenient to operate. As a result, BEVs gradually disappeared after 1920 (Guarnieri, 2012). Sporadic initiatives to reintroduce the technology failed over the years. Only the invention of high power and high energy battery technologies in combination with increasing environmental awareness and the decline in crude oil reserves started the comeback of BEVs to the mass market in 2010 around 100 years after their first peak.

2.1 Battery electric vehicles and charging infrastructure

This thesis defines BEVs as four-wheel passenger cars (European Directive 2007/46/EG class M1) or light-duty vehicles (European Directive 2007/46/EG class M1) for which the traction battery is the only form of energy supply. Hence, it excludes all two-wheelers, utility vehicles, and other forms of BEVs as well as vehicles with other (additional) forms of energy storage. Therefore, hybrid electric vehicles (HEVs), plug-in hybrid electric vehicles (PHEVs), range-extended electric vehicles (REEVs), and fuel-cell electric vehicles (FCEVs) are not subject of this thesis.

The BEV's components can be distinguished into three basic categories: powertrain, energy storage, and glider (Hill, Varma, Harries, Norris, & Kay, 2012). Figure 1 illustrates the arrangements of the essential components.

Powertrain

The central components of the powertrain are the electric motor (EM), the DC/AC-inverter, and the control system. The EM has distinct advantages over an internal combustion engine (ICE). It generates a high initial torque, less noise, and is more energy-efficient (MacLean & Lave, 2003). Additionally, the EM can be turned into a generator to recuperate the mechanical energy when braking that is stored back into the battery. Mainly two construction designs for the EM are used in today's BEVs: the permanently excited synchronous machine (PSM) and the asynchronous machine (ASM) (Leidhold, 2015; Linssen et al., 2012; Mock, 2010). Both have their advantages and disadvantages. The PSM has the advantage of higher energy efficiency and power density, while the ASM has a simpler mechanical construction and can operate in a broader speed range without requiring a gear shift (Leidhold, 2015; Linssen et al., 2012; Mock, 2010). One disadvantage of the PSM is that it requires rare earth elements for their permanent magnets and the increasing demand strains the limited supplies that are already subject to export restrictions (Desai, 2018). Both motor types require a 3-phase alternating current (AC) input that needs to be transformed by the DC/AC-inverter from the direct current (DC) provided by the battery. It regulates the frequency and power input into the EM (Linssen et al., 2012).

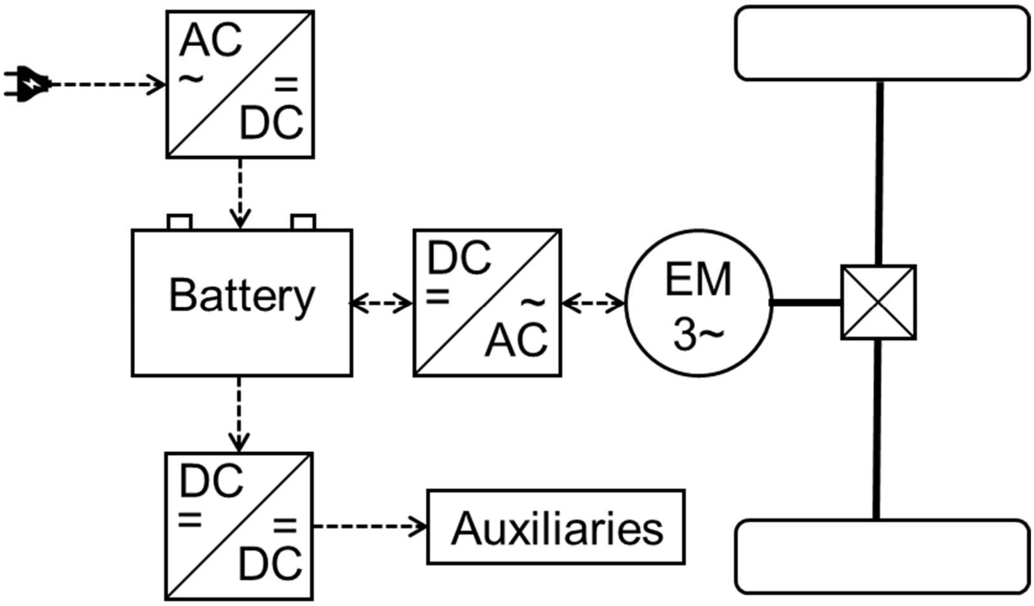

Figure 1: Basic schematics of a battery electric vehicle (own illustration following Leidhold (2015))

Additional to the powertrain there are other critical electric components: the onboard charging unit as well as the DC/DC-converter and auxiliaries (Linssen et al., 2012). The onboard charging unit converts the 1- or 3-phased AC provided by the charging station in DC at the battery voltage level (Linssen et al., 2012; Yilmaz & Krein, 2013)[1]. The DC/DC-converter transforms the battery voltage to 12 V required by the auxiliaries. The auxiliaries, such as light, power steering, and wipers, play an essential role in the BEV's energy consumption (Neubauer & Wood, 2014). Most challenging for the BEVs is the climatization of the passenger cabin. It can take up to 4 kW of additional power demand (Helms et al., 2013; Linssen et al., 2012; Tober, 2016).[2] Due to the limited battery capacity, it is a definite disadvantage in comparison to an ICEV. Especially, since ICEVs heat the passenger cabin with waste heat from the ICE. As a result, researchers and manufacturers are working on new, more efficient technologies, especially heat pumps, to reduce the auxiliaries' power demand (MAHLE, 2019; Mitsubishi, 2017; Qi, 2014).

Battery

The traction battery as energy storage is the heart of a BEV. Its properties determine the performance potential of the whole vehicle. Five fundamental properties for batteries are listed in the literature for assessing and comparing technologies: peak power and power density,

[1] Yilmaz & Krein (2013) offers an extensive review over the different design alternatives of BEV on-board chargers.

[2] Helms et al. (2013) and Tober (2016) provide a measured progression of more efficient heating and cooling power demand depending on the outside temperature for different current BEV.

energy capacity and energy density, durability, costs, and safety (Axsen, Kurani, & Burke, 2010). It remains a challenge to develop a technology that performs well in all of these five categories (Gerssen-Gondelach & Faaij, 2012).

Large format lithium-ion (Li-ion) cells have emerged as the dominant technology for vehicle traction batteries over the past years and are predicted to dominate in the nearer future (Thielmann, Sauer, & Wietschel, 2015; Thielmann et al., 2020; Yong, Ramachandaramurthy, Tan, & Mithulananthan, 2015a)[3]. In Li-ion batteries cells, oxidation-reduction reactions between the cell electrolyte and electrodes create the current (Cluzel & Douglas, 2012; EASE/EERA, 2017). The characteristics of their active elements limit the theoretical maximum performance (Julien, Mauger, Vijh, & Zaghib, 2016). In most current cells the anode is made of graphite while the cathode consists of different Lithium-metal-oxides, e.g., NCA, NMC or LFP (Graf, 2013; Thielmann et al., 2020).

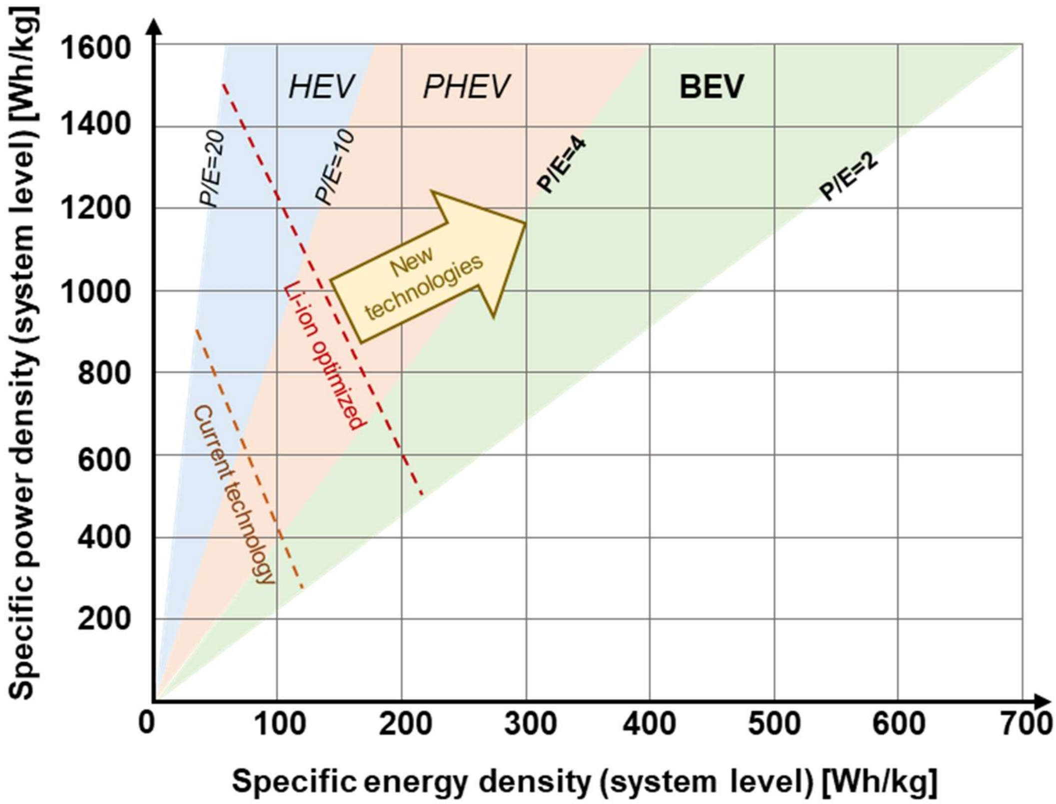

Figure 2: Battery technologies for different vehicle types (own illustration following Lamp (2013))

Li-ion batteries are used in BEVs for their superiority in power and energy density (Yong et al., 2015a). Their advantages over other current technologies are usually depicted in the Ragone diagram (Julien et al., 2016). The power density is responsible for vehicle dynamics. The battery needs to provide enough power to master different driving situations. The energy density and capacity determine the BEV's range. The values for power and energy density communicated in the literature and by manufacturers must be compared cautiously. Gravimetric and volumetric values can be distinguished as well as the aggregation levels cell or battery system. For example, the gravimetric energy density values on a system level are around 80% of the cell level values (Lamp, 2013). The relation of power to energy P/E is an essential characteristic of a traction battery. As can be seen in Figure 2, with all the energy

[3] Tesla vehicles form an exception. They use a large number of small format Li-ion cells (Thielmann et al., 2015).

required for the propulsion coming only out of the battery, BEVs require more energy density in comparison to PHEVs or HEVs. Future advances in Li-ion batteries like silicon anodes or new technologies like lithium-sulfur, lithium-air, and solid-state batteries are developed to increase the energy and power density beyond the technological boundary of Li-ion (Bloomberg, 2019a; Lamp, 2013; Yong, Ramachandaramurthy, Tan, & Mithulananthan, 2015b).

Li-ion battery durability and their aging process impose a challenge for their implementation in BEVs. The irreversible aging mechanisms of Li-ion cells are complex and influenced by a multitude of factors. The aging leads to a capacity decrease and an internal resistance increase. Cyclical and calendar aging can be distinguished. In most studies, both are considered to be additive (Hoke, Brissette, Smith, Pratt, & Maksimovic, 2014). Cyclical aging depends on the ways and intensity of use while calendar aging mostly depends on time and cell temperature. Detailed descriptions of the underlying electrochemical processes and the influence of charging power levels, State of Charge (SOC), temperature, depth of discharge, and others as well as different modeling approaches, can be found in the literature (Barré et al., 2013; Pelletier, Jabali, Laporte, & Veneroni, 2017; Vetter et al., 2005). One example of the influence of charging power levels is that loads lead to an increased likelihood of lithium plating on the anode, which can ultimately destroy the separator resulting in short circuits and potential thermal runways (Chandrasekaran, 2014; Kim, Albertus, Cook, Monroe, & Christensen, 2014; Offer, Yufit, Howey, Wu, & Brandon, 2012). Also, charging the battery at high and low SOC levels can cause unwanted secondary reactions and chemical effects. This effect can be worse than more frequent cycling in mid-range SOC levels (Agubra & Fergus, 2013; Ecker et al., 2012; Lunz, Yan, Gerschler, & Sauer, 2012; Vetter et al., 2005). Therefore, as one measure to slow down the aging process batteries in BEVs only use a certain net proportion of the available gross capacity (Hacker et al., 2015; Kley, 2011).

The cost of Li-ion batteries is considered one of the central barriers hindering the wide-spread introduction of BEVs (see chapter 2.3). However, in recent years, the prices have decreased to lower levels than predicted at the start of the decade (Nykvist & Nilsson, 2015; Thielmann et al., 2015). In 2017, a survey of more than 50 companies put the market price on the battery level at $209 per kWh coming down from around $1,000 per kWh in 2010 (Chediak, 2017). In 2019 the average prices have fallen to $156 per kWh (Bloomberg, 2019b). Reaching a cost level of $150 per kWh on battery level is commonly considered as the breaking point for broad commercialization (Nykvist & Nilsson, 2015). This point will presumably be reached soon, as battery prices are predicted to fall below $100 per kWh by 2024 (Bloomberg, 2019a).

In terms of safety, Li-ion cells also show shortcomings. First and foremost, they have no intrinsic safety mechanism (Fuchs, Lunz, Leuthold, & Sauer, 2012). A complex Battery Management System (BMS) is required to avoid overstressing the highly reactive materials into a thermal runaway. Also, active cooling can be required as part of the security measures to remove the heat generated by the internal resistance during charging and driving.

Despite the listed shortcomings, Li-ion batteries currently offer the best-balanced option for use as energy storage in BEVs. The further development of new technologies, such as Lithium-sulfur, Lithium-air or Lithium solid-state batteries, which promise higher energy and power densities, could lead to solutions that show a better overall performance in the five fundamental properties. However, so far the alternative technologies are only tested under laboratory conditions and based on current projections will fulfill the technical and economic requirements only by 2030 (Bloomberg, 2019a; Thielmann et al., 2015).

Efficiency

The overall efficiency of the BEV is vital from an economic as well as environmental point of view. Here, the powertrain, the onboard charging unit, and the battery are the most critical components. The powertrain efficiency directly translates into a range increase. Table 2 lists individual values for the components from empiric measurements (Apostolaki-Iosifidou, Codani, & Kempton, 2017; Helms et al., 2013; Landau et al., 2017) and a literature review (Kasper, 2015; Travesset-Baro, Rosas-Casals, & Jover, 2015). The range of values underlines the variation between different technologies as well as the dependence on the voltage and current levels. This variance is especially noticeable for the onboard charging unit. For example, a charging unit optimized for high voltages and currents can perform poorly at low battery voltage and currents with an efficiency of only 0.12 (Apostolaki-Iosifidou et al., 2017). The battery efficiency is relevant for charging, propelling the BEV forward, and recuperating the energy back into the battery. The losses occur in the electrical connections of the cells as well as over their internal resistance. Li-ion batteries are characterized by a high (dis-)charging efficiency (Table 2).

Table 2: Efficiency of mechanical and electrical BEV components

Component	Efficiency
Charging efficiency (onboard charging unit and cables)	0.12 - 0.83[1]
	0.84[2]
	0.86 - 0.91[3]
Battery	0.96[2]
	0.92 - 0.96[4]
	0.90 - 0.99[5] *(input)*
	0.93 - 0.98[5] *(output)*
DC/AC-inverter	0.95 - 0.97[4]
	0.96 - 0.98[5]
Electric motor	0.87 - 0.95[4]
	0.81 - 0.95[5]
Electric generator	0.82 - 0.95[5]
Transmission (fixed)	0.93 - 0.98[4]
	0.89 - 0.98[5]
Differential	0.92 - 0.98[4]

Sources: [1] Apostolaki-Iosifidou et al. (2017), [2] Helms et al. (2013), [3] Landau et al. (2017), [3] Kasper (2015), [4] Travesset-Baro et al. (2015)

When discussing the efficiency of BEVs and comparing it to ICEVs, it is crucial not only to include the different components but also to distinguish the boundaries of the energy carrier. Four different points of measurement can be distinguished: tank-to-wheel (TTW), grid-to-wheel (GTW), plant-to-wheel (PTW), and well-to-wheel (WTW) (Figure 3). TTW only considers the efficiency of the energy conversion from the battery to the tires. GTW includes the losses that occur when charging the battery from the grid. PTW additionally considers the losses during energy conversion and transport. WTW is the most holistic approach considering the whole value chain starting with the resources. When comparing the efficiency to other drivetrain technologies, different boundaries must be considered. The TTW efficiency of a BEV is important when estimating its range based on the battery capacity. From an economic point of view, the GTW efficiency of a BEV is comparable to the TTW efficiency of an ICEV since it measures the energy paid. From an environmental perspective, the PTW efficiency of a BEV is equal to the TTW of an ICEV since it includes the emissions caused by the conversion from the primary energy carrier.

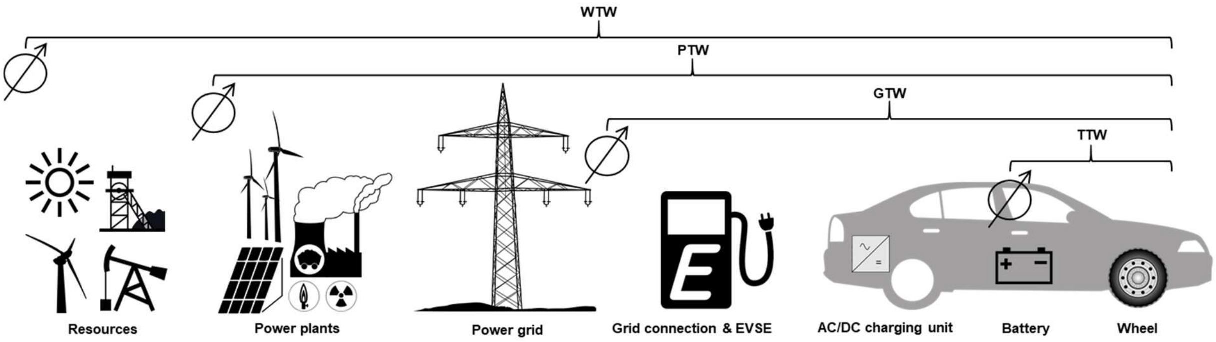

Figure 3: Efficiency measurement points of the BEV in the energy system (Ensslen et al., 2017)

Charging infrastructure

The charging infrastructure, in the following called electric vehicle supply equipment (EVSE), can be distinguished into four categories by their accessibility: private, semi-private, semi-public, and public (NPE, 2013). Private charging is installed at households, semi-private stands for charging at the workplace that is only open for employees, semi-public defines charging for example at a shopping center or a car park that is open to customers, and public charging requires on openly accessible infrastructure build on public land.

Table 3: Charging modes (IEC/DIN EN 61851)

Mode	Outlet	Current output	Present maximum current and voltage output in Germany	Connection & communication
1	Standard outlet	AC	1-phase, 230 V, max. 16 A	A direct passive cable connection to the BEV
2	Standard outlet	AC	1-phase, 230 V, max. 16 A	A semi-active connection; in Germany, it is found in combination with a standard outlet. In this case, the cable has an integrated regulation and communication device including an In-Cable Control and Protection Device (EN 62752) (Landau et al., 2017)
3	Wallbox, Charging station	AC	1-phase, 230 V, max. 16 A 3-phase, 400 V, max. 32 A	An active direct cable connection to the BEV, communication between the BEV and the EVSE by wire, allows controlled charging and potentially vehicle to grid (v2g)
4	Charging station	DC	600 V, max. 125 A	An active direct cable connection to the BEV, communication between the BEV and the EVSE by wire, allows controlled charging and potentially vehicle to grid (v2g)

The technical charging standards for conductive charging have been established and modified over recent years standardizing charging modes, plugs, and communication. The IEC/DIN EN 61851-1 distinguishes four different conductive charging modes (NPE, 2013). The countries' grid voltage and current level restrictions usually limited the maximum specifications. Table 3 presents the charging modes applied in Germany. Mode 1, that has practically disappeared for safety reasons, and Mode 2 are used in combination with standard power outlets. In Germany with 1-phase 230 V and a maximum AC of 16 A the charging power is limited to 3.7 kW. Mode 3 can be used for 1-phase and 3-phase AC charging. The maximum power in most presently used charging systems is limited to 22 kW (32 A at 400 V). Even though, as can be seen in Table 4, the most commonly used Type 2 plug works up to 62 A (IEC/DIN EN 62196-2). Mode 4 specifies DC charging that allows currents up to 400 A. However, the current combined charging system (CCS) (IEC/DIN EN 62196-3) and CHAdeMO system plugs limit it to 125 A (Table 4). Presently, there is an effort to increase the maximum DC fast charging power to 450 kW and the first charging stations are publicly available in Germany (Porsche, 2020). This increase requires raising the board net and battery voltage to around 800 V as well as cooling of the cables and plugs (Schäfer, 2018). The cables are cooled (or heated) with a glycol-water mixture (Schwierz, 2017). The standardization for the communication between the BEV and EVSE for mode 3 and 4 are laid out in the ISO/IEC 15118 Road vehicles - Vehicle to grid communication interface. However, it has not yet been implemented beyond BEV prototypes.

Inductive charging which eliminates the power cord is seen as a safer, more convenient alternative and significant technical development for future BEVs (Li & Mi, 2015; Yilmaz & Krein, 2013). Even though the underlying technology was developed a long time ago, wireless BEV charging has so far only been implemented in research projects and vehicle prototypes (Fortum, 2019; Panchal, Stegen, & Lu, 2018; Rajashekara, 2013). Especially the insufficient power rating, the distance between transmitter and receiver, the misalignment, the costs, the manufacturing complexity as well as the lack of norms and standards still pose challenges (Li & Mi, 2015; Rajashekara, 2013; Yilmaz & Krein, 2013). Nevertheless, customers prefer it (Fett, Ensslen, Jochem, & Fichtner, 2017). Therefore, it will most likely play an essential role in the future, especially in combination with autonomous vehicles.

Table 4: Charging plug systems (IEC/DIN EN 62196)

Plug system	Current output	Present maximum current and voltage output
Type 2	AC	1-phase, 230 V, 70 A (limited to 16 by the grid) 3-phase, 400 V, 62 A
Combined charging system (CCS)	DC	850 V, max. 125 A
CHAdeMO	DC	500 V, max. 125 A

Battery swapping is considered an alternative and faster approach to conductive or wireless charging. However, since the early rise and spectacular fall of the company Better Place which wanted to introduce standardized swapping stations for passenger cars it has more or less disappeared from the public discussion (Blum, 2017; The New York Times, 2013). The required level of universal standardization, as well as the additional investment in batteries and swapping stations, are considered the two main reasons that hinder a widespread implementation. However, in transportation research, it remains a commonly discussed concept. Especially for large delivery or taxi fleets with similar vehicles and a high degree of utilization, it is considered a potential alternative. Several optimization approaches for planning, locating, routing, and managing battery swapping stations can be found in the literature (Almuhtady, Lee, Romeijn, Wynblatt, & Ni, 2014; Kuppusamy et al., 2017; Mak, Rong, & Shen, 2013; Schneider, Thonemann, & Klabjan, 2017; Widrick, Nurre, & Robbins, 2018). Also, there are recurring attempts to introduce battery swapping in everyday life, e.g. the Chinese BEV manufacturer NOI has installed 18 swap stations in China (SAE, 2019). However, no scalable operating or business model has yet been established.

2.2 Commercial vehicle market and mobility patterns

Commercial transport is usually defined either by the type of vehicle owner or the purpose of the trip. Basing the identification of a commercial tour on the vehicle owner is more straightforward to implement since only the registration data is required (Gnann, Plötz, Funke, & Wietschel, 2015). However, it is often inconclusive since people commonly use company cars privately and private vehicles are used for business trips. Hence, setting the purpose as identification criteria delivers a more precise identification. This approach follows the definition of commercial transport as all trips by individuals within their occupation (Schwerdtfeger, 1976; Steinmeyer, 2007). A more detailed definition states that in *"commercial transport goods, news, and people are carried from one place to a destination in the execution of economic, public service or official activities"* (Wermuth et al., 2012). It can be divided into passenger transport and the transport of goods. From a top-down perspective, the distinction by registration is the only suitable choice while from a bottom-up approach with detailed data available it is possible to differentiate by purpose.

The publicly available database of the German Federal Motor Transport Authority (KBA) shows that commercial vehicles only make up for a small portion of the total number of registered vehicles, but they have the dominant share of first-time registrations. In Germany, of the 57.3 million vehicles registered in 2018 47.1 million were passenger cars (KBA, 2019b). Of these, only 10.8% were commercially registered (KBA, 2019b). On average 63% of commercially registered vehicles are company cars, while 37% are fleet vehicles (Hacker et al., 2011; Plötz et al., 2013). In 2018, 3.43 million new passenger cars were registered for the first time of which 63.9% had a commercial registration (KBA, 2019a). This relation has only seen small fluctuations over recent years (Radke, 2017).

Table 5: Major mobility studies in Germany

	KiD	**MiD**	**MOP**
Focus	Commercial transport patterns (up to 3.5 t)	Private mobility patterns	Private mobility patterns
Year	2002, 2010	2002, 2008, 2017	Annually since 1994
Method	Questionnaire	Questionnaire	Questionnaire
Duration	One day (spread out through a whole year)	One day (spread out through a whole year)	One week (September till December 2016)
Dataset	2010: 76,798 vehicles 173,054 trips	2017: 156,420 households 316,361 people 960,691 trips	2017: 1,881 households 3,867 people 71,977 trips
Detailed data set description	Wermuth et al. (2012)	Aust et al. (2019)	Ecke et al. (2019)

Several publicly funded surveys have recorded representative samples of mobility behavior in Germany (Table 5). The detailed micro data allows bottom-up studies. Their results can be scaled to the total market. Most notably are the three surveys Vehicles in Germany (KiD), Mobility in Germany (MiD), and the Mobility Panel (MOP). Since MiD and MOP analyze the mobility patterns of people and households, trips with a commercial purpose or taken by company car are also included. The KiD focuses solely on commercial vehicles as a unit of analysis and includes metadata concerning the vehicles and companies. The use of commercial vehicles in Germany strongly differs between the economic sectors according to the maximum and average daily distances traveled, the number of daily trips as well as their registration numbers, stock, and average holding periods (Gnann, Plötz, Kühn, et al., 2015; Ketelaer et al., 2014). This heterogeneity underlines the requirement of a case-specific analysis.

2.3 Potential and challenges of commercial electric mobility

Commercial transport shows notable differences to private vehicle use, which makes it more advantageous for an early BEV adoption. In general, commercial fleets are an attractive first market for the introduction of new vehicle technologies (Nesbitt & Sperling, 2001). Current numbers confirm that the commercial market is promising for the introduction of BEVs. Although the share of commercial owners in new electric vehicle registrations has fallen to 61.6% in 2018, the majority of all BEVs in Germany are still registered commercially (KBA, 2019b; Statista, 2019). Based on socio-economic research nine reasons can be stated to explain this observation (Barfod, Kaplan, Frenzel, & Klauenberg, 2016; Gnann, Plötz, Funke, et al., 2015; Ketelaer et al., 2014; Plötz et al., 2014; Robinson, Blythe, Bell, Hübner, & Hill, 2013):

1. Commercial mobility patterns are usually more regular than private ones and therefore enable an easier substitution assessment.
2. The future mobility patterns can be better predicted based on usually available data and a scheduling tool or fleet manager usually does the planning.
3. In mixed fleets trips over the maximum BEV's range can be done by an ICEV.
4. Commercial vehicles have higher daily mileages than private ones, which allow better utilization of the lower operational costs.
5. Organizations are more likely to use TCO calculations for investment decisions and therefore account for the advantages of lower operational costs.
6. Commercial vehicles have a much faster turnover rate than private vehicles with an average holding period of 3-4 years.
7. Own infrastructure can be installed at the organization's premises avoiding the need to rely on public charging.
8. Organizations can benefit from the positive public image and apply methods like carbon accounting to measure and present a positive environmental impact on the public.
9. BEVs can also be used indoors and in sensitive areas, e.g., when ICEVs are potentially banned from inner cities or night deliveries.

The simplicity, safety, reliability, and driving dynamics as well as being an early adopter are considered additional arguments for introducing BEVs into commercial fleets (Globisch & Dütschke, 2013; Hacker et al., 2011; Plötz et al., 2014; Sierzchula, 2014).

However, socio-economic surveys have identified several technical, operational, and economic barriers that hinder the widespread introduction of BEVs in commercial fleets. From a technical point of view, the charging time and the limited battery capacity are rated negatively (Globisch & Dütschke, 2013; Hacker et al., 2011; Sierzchula, 2014). Also, operational barriers need to be taken into consideration (Wikström, Hansson, & Alvfors, 2016). From an organizational perspective, fleet management that trains new users and considers the technical restrictions of charging and capacity is required. These technical and organizational barriers can be overcome. Managers of larger fleets perceive the limited range and the introduction of new processes already as less problematic (Plötz et al., 2014). Moreover, research shows that fleets with BEV experience show a higher perceived operational ease (Kaplan, Gruber, Reinthaler, & Klauenberg, 2016). However, the economic barrier of the higher investment is not overcome that quickly. The investment decision is not only based on cost, but it is usually the most relevant criterion (Barfod et al., 2016; Globisch & Dütschke, 2013; Hacker et al., 2011).

This thesis defines five identification criteria as a framework to find commercial use cases that have a high chance of an economically beneficial BEV introduction under the current technological and economic conditions. The criteria are designed to get the best possible use out of the above listed nine reasons. Applying these criteria reduces the impact of the existing technical, organizational, and economic barriers. In Table 6, the five criteria and the reasoning behind them are presented.

Table 6: Criteria list to identify suitable commercial use cases for BEV introduction

No	Identification criteria	Reasoning
1.	The predictability and regularity of the mobility patterns should be high.	The high predictability ensures that the technical requirements can be assessed ex-ante to a high degree of certainty. The low variability means that the battery capacity technically required for a full substitution is regularly utilized to a high degree.
2.	The driving profiles should consist of short but frequent trips.	Short trips require only a small battery meaning a smaller investment. The high frequency leads to high mileages which allows greater utilization of the lower operating costs.
3.	The vehicles should be used exclusively for one specific purpose.	Deploying vehicles for one specific purpose, e.g., the execution of a service, increases the predictability of the mobility demand.
4.	The deployed vehicle types should come from segments in which BEVs are available.	Most BEVs currently available on the market can be assigned to the mini, small or compact car segment. For use cases in which vehicles from these segments are usually deployed the user can already choose from a range of different models.
5.	There should be space on the organization's premises to set up own EVSE.	Due to the still limited available public charging infrastructure users cannot rely on their availability in terms of location and time. Therefore, depending only on its own EVSE can ease the introduction of BEVs.

These five criteria provide a first indication of which use cases are potentially suitable for an economic beneficial BEV deployment. A more detailed techno-economic replaceability analysis is indispensable and should be performed bottom-up and based on empirical data. The use of commercial vehicles differs distinctively between the different economic segments concerning the average and spread of daily travel distances and the number of trips (Ketelaer et al., 2014). Accordingly, differences in BEV adoption across industrial sectors and depending on the travel needs can be identified (Kaplan et al., 2016). One problem with assessing the BEV substitution potential based on the mobility studies such as the KiD is that it relies on one day of data recording and therefore harbors the danger of overestimating the market potential (Gnann, Plötz, Funke, et al., 2015). A longer time frame allows studying the individual regularity of the mobility patterns more thoroughly (Neubauer, Brooker, & Wood, 2012). Different studies have analyzed the substitution potential based on long-term empiric input data of commercial driving profiles in research projects (e.g., Hacker et al., 2015; Wagner et al., 2011).[4] One example of a more extensive database is the publicly available REM2030 data. It consists of 91.422 trips made by 630 commercial vehicles mainly used for commercial purpose recorded with a GPS logger over an average of three weeks (REM2030, 2015). In contrast to KiD, it is not representative but focuses on applications that promise an early BEV substitution potential (Plötz et al., 2013).

Several commercial mobility use cases show characteristics that make an early introduction of BEVs likely. BEVs can technically fulfill over 87% of the three-week REM2030 driving demand profiles (Gnann, Plötz, Funke, et al., 2015). Plötz et al. (2014) predict that in 2020 for 3-5% of all newly registered commercial vehicles BEVs would lead to a lower TCO than ICEVs. Exemplary applications identified by bottom-up analysis that promise early widespread introduction of BEVs are social, security, delivery, and postal services (Hacker et al., 2015; Ketelaer et al., 2014; Wagner et al., 2011).

In this thesis, three use cases are selected for a detailed analysis based on the five defined selection criteria: the commuting of shift workers (between France and Germany), business trips between two plants (in France and Germany), and the home nursing service. Table 7 lists the identification criteria for the three use cases. All three are analyzed under the premise that the mobility patterns of commercial vehicles and commuters do not change through the introduction of BEVs.

Table 7: Identification criteria for the three use cases

Identification criteria	Commuting of shift-workers	Business trips between plants	Home nursing service
The predictability and regularity of the mobility patterns should be high.	The fixed shift schedule and the constant groups provide entirely predictable and highly regular mobility patterns.	The route is fixed. The timing of the trips can vary throughout the workday making the patterns less predictable and regular.	The routes and the timing of the tours and trips can change. However, the area of operation is usually restricted, and two demand peaks occur during the day.

[4] An extensive overview of different studies focusing on specific commercial transport applications can be found in Gnann, Plötz, Funke, et al. (2015).

The driving profiles should consist of short but frequent trips inside the possible range.	Commuters usually live within a certain radius of the plant. They travel two trips per day with enough time for recharging on both ends.	The distance between the two plants should be small enough for frequent daily trips. Fast charging is required to ensure high availability.	The trips from one patient to the next patient are short and the overall tours usually in BEV range. Two tours per day are common which may require in between charging.
The vehicles should be used exclusively for one specific purpose.	At workdays, the minivans are only used for commuting.	The vehicles are exclusively used by the employees to travel between the sites.	The vehicles are only used for home nursing services. Sometimes the employees take the vehicles home overnight.
The deployed vehicle types should come from segments in which BEVs are available.	A few OEMs offer BEV in the minivan segment.	Several OEMs offer BEV in the compact car and a few in the minivan segment.	Several OEMs offer BEV in the mini and subcompact car segment.
There should be space on the organization's premises to set up own EVSE.	EVSE can be installed at the company parking lot and the homes of the workers.	EVSE can be installed at both sites.	EVSE can be installed at the required parking lot of the central office and if necessary, also at the homes of the employees.

The commuting of shift-workers as the first use case is selected since it fulfills four out of the five criteria. The mobility patterns are highly predictable and show almost no variations in timing and route. The working travel remains identical, the workers must arrive and leave at fixed times according to their work schedule, and the rolling system allows the use of one BEV by more than one group, increasing the frequency of travel. The investigated commuter groups have one-way distances of 60 to 80 km. With a frequency of traveling twice a day, the annual mileage lies above 30,000 km leading to high utilization of the lower operating costs. Also, the EVSE can be installed at home and work. The only limitation is that currently, not many manufacturers offer BEV minivans. An additional benefit of the cross-border commuting investigated in this thesis is that based on the rotating 24 h shift schedule it allows the comparison of electricity mixes at different times of the day and between the two countries. In general, commuting is widespread in Germany (Figure 4). Over 60% of all employees in Germany commute to work with an average one-way distance of 16.8 km; 1.3 million people have one-way commuting distances over 150 km (Pütz, 2017). 68% of commuters use a car (Statistisches Bundesamt, 2017a). However, from a strict purpose perspective commuting does not fall under commercial transport, even though company cars are used frequently and are sometimes, as in the presented case, provided as a full service by the employer.

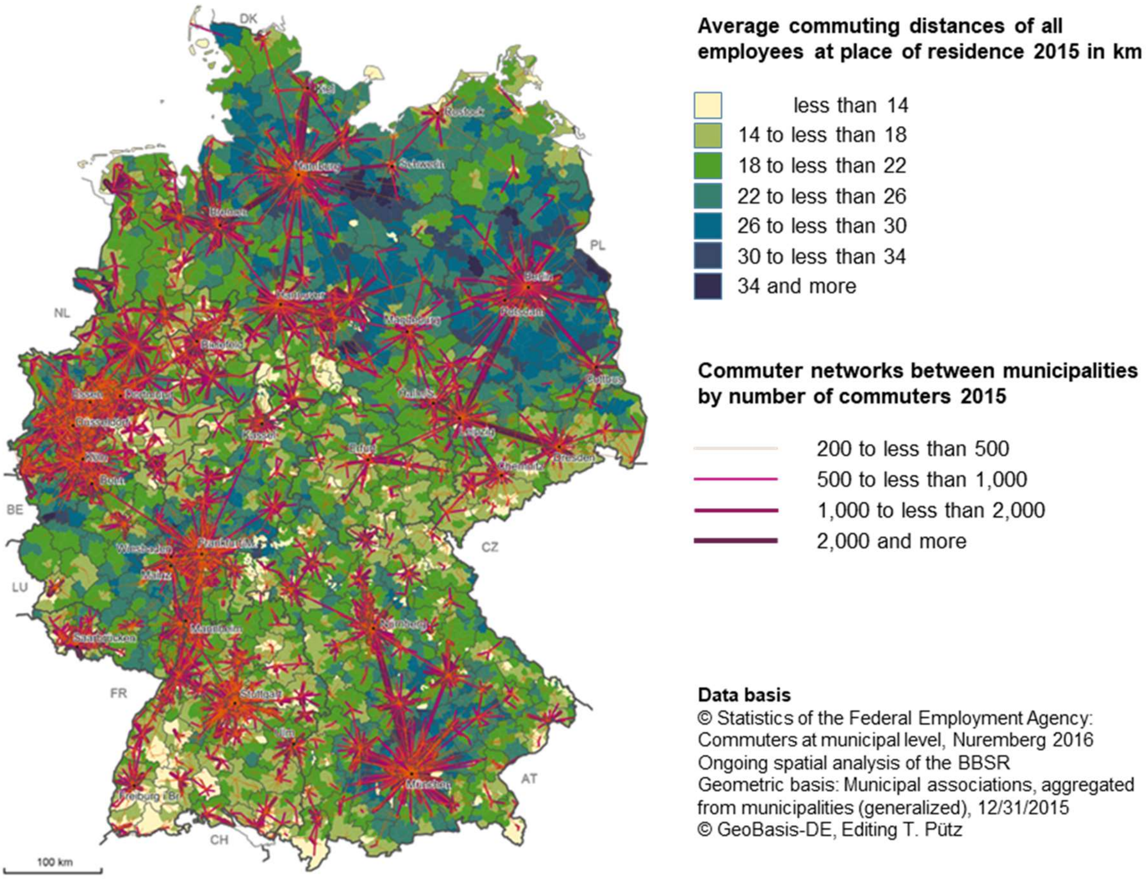

Figure 4: Commuting distances and networks in Germany (Pütz, 2017)

The business trips between two plants are chosen as an example of a use case on a fixed route with uncertain timing and frequency of travel. Hence, the predictability and regularity decrease significantly in comparison to the commuting of shift workers. Additional challenges in planning and operation arise. If required the fixed-route allows the installation of EVSE at both ends, but fast charging infrastructure is required to ensure a high BEV availability. In contrast to the commuter use case in the required compact car segment several BEV models are available allowing to choose the best fitting technical and economical option. The presented empirical case study has a one-way trip distance of 70 km. On average the employees make one tour every other day leading to an annual mileage of around 17,000 km, which is significantly less than the commuter BEVs. Quantifying the commonness of this use case is difficult. Nevertheless, due to historical development and location restrictions, companies often operate different sites nearby which can be covered by current BEVs without intermediate charging.

The home nursing service is chosen as the third use case. It stands as an example of a general commercial use case. Both the route and timing of the mobility patterns vary which makes the assessment of the techno-economic BEV deployment more challenging and suggests a stochastic approach. The home nursing service was selected since previous studies have shown that with an annual average mileage of 16,719 km, 17 single trips per day, and long-time parking overnight it is especially suitable for the early introduction of BEV (Ketelaer et al., 2014). In contrast to other commercial applications and private users due to the frequent short trips, it disproportionately benefits from higher charging power and shows a high economic potential (Gnann, Plötz, Kühn, et al., 2015; Wagner et al., 2011). With its near-zero profit margins, the effective utilization of resources and cost reduction potentials are of high importance (Milburn, 2012). Already, a wide range of BEV models is available in the mini or subcompact car segment. Due to the above-stated reasons, several providers have already introduced BEV to their fleets, mostly within publicly subsidized projects (APD, 2015; Block & Glinka, 2014; Goebel, 2015; Verholen, 2017). With 13,300 providers, over 350,000 employees, and around 700,000 patients in need of home care in 2015 it is a very common use case in Germany (Statistisches Bundesamt, 2017b). Despite its potential and scale this use case in particular, as well as service vehicles in general, are rarely in the focus of transportation research (Milburn, 2012; Yavuz & Çapar, 2017).

Amongst the reasons stated above, the three use cases were mainly chosen in their combination for two reasons. Firstly, they can be distinguished by an increasing degree of uncertainty in their mobility patterns. Secondly, they differ in their annual mileages allowing a comparison between the potential economic and environmental benefits of a high degree of utilization. For both, with the high predictability, regularity, and annual mileages the commuting of shift workers provides an almost ideal use case for the deployment of BEV. However, less regular and predictable mobility patterns, as well as lower annual mileages, are far more common. Therefore, business trips and home nursing services are also investigated to illustrate the challenges of uncertainty in mobility patterns and the effects of lower annual mileages on the economic and environmental evaluation.

3. Literature review and identified research gaps

In this thesis, the evaluation, simulation, and optimization of commercial electric mobility are separated into two perspectives, the techno-economic and the environmental. As generally valid in both research fields, the results are highly sensitive to utilization input data. Uncertainties can play a significant role, especially in the techno-economic analysis, but are often only indirectly implemented through scenarios and sensitivities or completely neglected in transport modeling (Jochem, 2016). Methodical approaches are always simplifications of the underlying significantly more complex systems. Hence, the taken assumptions, the local and system boundaries, the time resolution and horizon, the input data, as well as the level of technical detail significantly influence the results. For the assessment of the techno-economic potential as well as the environmental impacts, this must be considered when interpreting the input data. Usually, studies either take a microscopic view, which allows the drawing of specific conclusions or a macroscopic focus, which allows more general conclusions, but is less representative of a single-use case.

3.1 Techno-economic studies

Even though the price is not the only customer decision criterion, a widespread introduction of BEVs requires a favorable cost structure. In BEV research, the total cost of ownership (TCO) is commonly used to assess the economic potential and comparable break-even because it includes all expenses over the product lifetime and not just the initial price. It is applied as a supporting tool to understand the actual cost of a particular good or service (Ellram, 1995). It is usually used in combination with discounted value methods. The literature presents detailed introductions to the concept and history of the TCO and its use for BEV valuation (Kley, 2011). The TCO is commonly applied in the context of an economic comparison of BEVs to other technologies because the higher purchase price and the lower operational costs are both accounted for. Furthermore, it is already widely used in real-life commercial vehicle purchase decisions (Plötz et al., 2013). Overall, previous TCO studies focussing on the techno-economic potential of BEV can be classified by their methodology, perspective, transport data, energy model, the inclusion of battery aging, EVSE (alternatives) and load shifting or vehicle to grid (v2g), as well as by the scope and extent of their results. Table 8 gives an exemplary overview of the classification of previous studies.

Most commonly TCO is used as part of market diffusion models, but also for the evaluation and forecast of specific use cases and less commonly as the basis for cost optimization. Different methodical approaches exist to predict BEVs' market penetration (Al-Alawi & Bradley, 2013; Jochem, 2016). The approaches can be classified into econometric models with disaggregated data and agent-based simulation models as bottom-up approaches, econometric models with aggregated data, system dynamics, and integrated assessment models with general equilibrium models as top-down approaches as well as hybrid models that combine bottom-up and top-down approaches (Jochem et al., 2018). Most studies that assess the technical and economic substitutability focus on private users since they represent by far the larger share of the car market. For Germany, a few include or exclusively assess the market diffusion potential for commercial fleets (Gnann, Plötz, Kühn, et al., 2015; Hacker et al., 2015; Plötz et al., 2013; Richter & Lindenberger, 2010; Wagner et al., 2011).

Most studies using TCO build on simulation as methodology, fewer evaluate specific use cases or use optimization to assess the techno-economic potential. With a few exceptions, the simulation often includes some form of future extrapolation based on different input parameter developments (Table 8). Since the BEV numbers are increasing only slowly, the empirical database likewise is still limited. Only a few studies have evaluated first-hand data from BEV use cases (Muneer et al., 2015; Neubauer et al., 2012; Wagner et al., 2011). Optimization is commonly applied to various fields of BEV related planning and operating.

Energy system models are used to assess charging strategies from the perspective of a fleet manager (Iversen, Morales, & Madsen, 2014; Lan et al., 2012; Škugor & Deur, 2015a, 2015b; Xiaohua Wu, Hu, Moura, Yin, & Pickert, 2016), a grid operator (Atia & Yamada, 2015; Honarmand, Zakariazadeh, & Jadid, 2014; Pantoš, 2011) or a vehicle aggregator (Arnoldt, Klarner, Ritter, & Warweg, 2016; Baringo & Sánchez Amaro, 2017; Donadee, Ilić, & Karabasoglu, 2014). Examples from transportation research are the routing of BEVs (Goeke & Schneider, 2015; Nejad, Mashayekhy, Grosu, & Chinnam, 2017; Schneider, Stenger, & Goeke, 2014; Sweda, Dolinskaya, & Klabjan, 2017; Yavuz & Çapar, 2017), the allocation of (fast-)charging stations (Hwang, Kweon, & Ventura, 2017; Kuby & Lim, 2005; Lim & Kuby, 2010; Sadeghi-Barzani, Rajabi-Ghahnavieh, & Kazemi-Karegar, 2014; Tran, Nagy, Nguyen, & Wassan, 2018; Xiang et al., 2016; Zhu, Gao, Zheng, & Du, 2016) or the planning and operation of battery swapping stations (Almuhtady et al., 2014; Mak et al., 2013; Schneider et al., 2017; Widrick et al., 2018). However, optimization is only rarely applied considering both the investment and operation of the BEV. The few existing studies show a heterogeneous research focus. They analyze the competitiveness of electric delivery trucks (Davis & Figliozzi, 2013; Feng & Figliozzi, 2013), fleet size and mix vehicle routing problems (Hiermann et al., 2016; Lebeau et al., 2015; Sassi et al., 2015), fleet renewal for electric taxis with battery swapping stations (Kuppusamy et al., 2017) or suitable charging infrastructure and cost minimal battery capacities for private users (Kley, 2011; Lin, 2014). Some of these incorporate detailed technical models or analyze the effect of different scenarios. However, none of these models consider uncertainties in the utilization data even though several studies have shown their importance when optimizing BEV utilization charging from the perspective of the vehicle user or fleet manager (Iversen et al., 2014; Kley, 2011; Lan et al., 2012; Lin, 2014; Škugor & Deur, 2015a, 2015b; Widrick et al., 2018; Wu et al., 2016), the grid operator (Atia & Yamada, 2015;

Honarmand et al., 2014; Pantoš, 2011) or a vehicle aggregator (Arnoldt et al., 2016; Baringo & Sánchez Amaro, 2017; Donadee et al., 2014; Wei & Guan, 2014; Wu & Sioshansi, 2017).

The type, level of detail, and recording period of the transport data have a significant impact on the appropriate techno-economic assessment approaches. The literature provides detailed theoretical overviews of different transport models, their history, and their use for BEV assessment (Jochem, 2016). Depending on the quantity and quality of data both top-down and bottom-up approaches incorporating a TCO analysis can be found in the literature. Assumed average annual miles and daily traveled distances are sufficient for basic assessments, and consequently most studies use them (Table 8) (Wu, Inderbitzin, & Bening, 2015). The consideration of recorded data can increase the accuracy. High time and spatial resolution allow for a bottom-up analysis (Gnann, Plötz, Funke, et al., 2015; Kley, 2011; Plötz et al., 2013; Wagner et al., 2011). This type of data is usually only available for commercial users (Jochem et al., 2018). Different types of empirical data can be found in the literature. Most studies are based on ICEV data under the assumption that the mobility patterns will not change. Some studies use representative mobility studies based on target dates (Kley, 2011; Windisch, 2013). Others rely on long-term data of conventional fleets (Gnann, Plötz, Funke, et al., 2015; Greaves, Backman, & Ellison, 2014; Neubauer et al., 2012; Plötz et al., 2013).[5] Only a few base their analysis on empirically logged BEV movement data (Muneer et al., 2015). Spatial information such as how many vehicles are parked at a destination at one point in time is more critical for grid purposes or larger commercial fleets. Most studies neglect the uncertainties in mobility patterns.

A resilient TCO analysis of a BEV requires the inclusion of a technical model. The inclusion is essential since the technology of BEVs imposes notable restrictions. Especially the consideration of energy consumption, and battery aging is imperative due to their influence on the utilization potential. Even with the continuously increasing battery capacities of new BEV models, the maximum range on one battery charge is still less than on one tank filling of a common ICEV (Lutsey et al., 2018; Thielmann et al., 2020). Recharging requires more time than refilling at the gas station (Pelletier, Jabali, & Laporte, 2016). Therefore, the specific usability is much more sensitive to the actual energy consumption. Like ICEVs, the actual energy consumption has a strong influence on the TCO. In some studies, the estimation of energy consumption relies on standard driving cycles, e.g. the new European driving cycle (NEDC). These usually underestimate the real energy consumption (Muneer et al., 2015; Rangaraju, De Vroey, Messagie, Mertens, & Van Mierlo, 2015; Saxena, Gopal, & Phadke, 2014; H. Wang, Zhang, & Ouyang, 2015; Wu, Freese, Cabrera, & Kitch, 2015). Others account for it by assuming more substantial load levels and adding the auxiliary load (Bickert, Kampker, & Greger, 2015; Kley, 2011; Van Vliet, Brouwer, Kuramochi, Van Den Broek, & Faaij, 2011). Several studies implement their own mechanical vehicle dynamics model to predict energy consumption more thoroughly based on driving dynamics, resistances, efficiencies, and the use of auxiliaries. Some studies go more into detail and include an SOC progression model in their assessment. Others have measured empirical energy consumption (Saxena et al., 2014; Travesset-Baro et al., 2015; H. Wang et al., 2015; Wu et al., 2015). Only very few studies incorporate empiric energy consumption values into a techno-economic assessment (Muneer et al., 2015). The empirical values provide the possibility to evaluate and calibrate the theoretical models. Another important argument for including a detailed technical model is the impact of aging that depends on the way, intensity, and duration of use. Most TCO studies

[5] The advantages of using long-term data are stated in chapter 2.3.

simplify battery aging by neglecting the effects of a fading capacity during the utilization and only consider the required replacement of the battery system based on cycle or calendar life (Neubauer et al., 2012; Neubauer & Wood, 2014; B. Wang, Xu, & Yang, 2014).

The battery capacity and the maximum charging power are two key technical parameters that can be varied to assess the potential degree of substitution. The higher the battery capacity, the higher the degree of substitution (Kley, 2011; Lin, 2014; Neubauer et al., 2012). Alternative forms of mobility can be included which can be used when the range is insufficient (Lin, 2014). This approach is more sensible for individual long-haul journeys of private users than commercial use cases. For private users, the charging time in contrast to the battery capacity has little impact on the substitutability since the vehicles are parked most of the time (Greaves et al., 2014). For commercial fleets, integrated charging management is more critical (Ketelaer et al., 2014). Most studies set both the charging power and battery capacity as exogenous variables with only a few forming an exception. Hiermann et al. (2016) and Lebau et al. (2015) include different vehicle alternatives with battery capacity, payload, recharging rates, and energy consumption. Sassi et al. (2015) also include the charging power level as a decision variable with time-dependent charging costs. Lin (2014) endogenously identifies the cost-minimal range of BEV for private users based on battery price, electricity, and limitation cost. Wagner et al. (2011) implement an iterative algorithm to identify the required battery capacity endogenously accounting for the weight increase and higher energy consumption on empiric drive profiles. They also vary the charging power and show that for many commercial use cases 20 kWh battery capacity and 3 kW charging power is enough. In this study, only meals on wheels, the home nursing service, and taxis gain notably through higher charging power.

Most of the studies that incorporate a TCO approach draw similar conclusions in terms of relative competitiveness, break-even points, and sensitivities. Under average utilization scenarios, the TCO of BEVs is still higher than of comparable ICEVs (Wietschel et al., 2019). TCO studies on the first generation of mass-market BEVs show that they required an annual mileage of around 30,000 km to break even in Germany (Hacker et al., 2015; Kasten, Zimmer, & Leppler, 2011; Richter & Lindenberger, 2010). The average annual mileage for a commercial vehicle in Germany is 20,000 km. For other countries, these results varied due to the different fuel and electricity prices but were mostly in a range between 20,000 and 35,000 km (Feng & Figliozzi, 2013; Sharma, Manzie, Bessede, Brear, & Crawford, 2012; Tseng, Wu, & Liu, 2013; Windisch, 2013). The sensitivity analysis and the scenarios show that the results are highly sensitive to battery prices as well as the utilization input parameters such as energy prices and consumption (Gnann, Plötz, Funke, et al., 2015; Wu et al., 2015). Positive developments such as the rapidly falling battery prices can have an accelerating effect on the market penetration rate (Hacker et al., 2015; Nykvist & Nilsson, 2015; Plötz et al., 2013). Based on declining battery prices, price parity was forecasted to happen most likely between 2025 and 2029 depending on the vehicle segment (Soulopoulos, 2017; Wu et al., 2015). However, battery prices are decreasing faster than projected. Therefore, newer predictions state that price parity will be reached by 2022 to 2024 (Bloomberg, 2019b; Thielmann et al., 2020). By 2030 with an annual mileage of 15.000 km the TCO of a BEV is predicted to be 5-23% lower than the cheapest comparable ICEV (Kasten, 2018).

Table 8: Exemplary literature overview of studies using TCO analysis in combination with other methods for various research purposes

		Perspective			Methodology				Transport data			Energy consumption model							Results								
Paper	Region of deployment	Market diffusion	Focus on commercial market	Specific use case(s)	Simulation	Forecasting	Evaluation	Optimization	Average values & assumptions	Empiric values	High time resolution	Standard drive cycles	Detailed energy consumption model	SOC model	Empiric energy consumption	The inclusion of battery aging	The inclusion of EVSE (alternatives)	The inclusion of load shifting and/or v2g services	ICEV	HEV	PHEV	BEV	FCEV	Different vehicle types/battery capacities	Sensitivities & scenarios	Stochastically modeled uncertainties	Break-even analysis
Bickert et al. (2015)	Germany				X	X			X				(X)[1]						X			X		X	X		X
Chatzikomis et al. (2014)	Greece	X			X	X			X						X[2]				X	X	X	X			X		
Davis et al. (2013)	USA		X	X[3]				X	X				X						X			X			X		X
Gnann et al. (2015)	Germany	X	X	X	X	X				X	X		X	X					X		X	X			X		
Greaves et al. (2014)	Australia				X					X		X	X						X			X			X		
Feng et al. (2013)	USA		X	X[3]				X	X				X						X			X					X
Hacker et al. (2015)	Germany	X	X	X	X	X			X				X				X		X			X		X	X		X
Hiermann et al. (2016)	---		X	X[3]				X	X			X		X			X		X			X		X			
Kley (2011)	Germany	X						X		X	X		(X)[1]	X		X	X	X	X		X	X			X		
Kuppusamy et al. (2017)	USA		X	X				X	X			X					X		X			X		X	X		
Lebeau et al. (2015)	Belgium		X	X[3]				X		X			X	X	X				X			X		X			
Lin (2014)	USA							X		X					X[2]							X			X		
Muneer et al. (2015)	UK			X			X			X			X		X							X					
Neubauer et al. (2012)	USA						X			X			X			X		X	X			X			X		
Plötz et al. (2013)	Germany	X	X		X	X				X	X			X	X[2]		X		X		X	X		X	X		X
Propfe & Redelbach (2012)	Germany	X			X	X			X			X							X	X	X	X	X	X			
Richter & Lindenberger (2010)	Germany	X	X	X	X	X						X						X	X		X	X		X	X		X
Sassi et al. (2015)	France		X	X[3]				X	X					X			X		X			X		X			
Sharma (2012)	Australia				X				X			X							X	X	X	X		X	X		X
Tseng et al. (2013)	USA				X				X			X					X		X	X	X	X			X		
van Vliet et al. (2011)	Netherlands	X			X	X			X				(X)[1]				X	X	X		X	X			X		
Wagner et al. (2011)	Germany	X	X	X	X	X	X			X	X		X	X				X	X		X	X		X	X		
Wang et al. (2014)	China				X				X			X	X			X						X		X[4]	X		
Windisch (2013)	France	X			X	X				X		X							X		X	X		X	X		X
Wu et al. (2015)	Germany	X			X	X			X			X							X	X	X	X		X	X	X	

[1]standard values with assumptions for additional load and auxiliaries; [2]assumption based on literature; [3]analysis for delivery vehicles; [4]different EV powertrain designs

Optimizing the charging and integrating the vehicles into the energy system has the potential to lower the TCO. Under flexible tariffs, load shifting can reduce the electricity costs, especially when charging can be postponed to night time (Kristoffersen, Capion, & Meibom, 2011; Škugor & Deur, 2015b). Further integration of BEVs into the energy system by selling energy back at high prices, providing grid services or participating in the secondary control reserve market[6] is at the current state of markets and regulations less favorable, especially if the efficiencies and battery aging are considered (Bishop, Axon, Bonilla, & Banister, 2016; Gunter et al., 2016).

In summary, the literature focusing on the techno-economic assessment of BEVs allows three key observations. Firstly, the overview of previous studies shows that the TCO can be combined with other methods for various research purposes from top-down and bottom-up perspectives. Secondly, the results of the various approaches show that detailed utilization data is vital since the results are highly sensitive to mobility patterns and energy consumption and the utilization varies distinctively between different commercial applications. Thirdly, it can be observed that most studies address market diffusion and only a small number focuses on evaluating real BEV use cases or optimizing investment and operation of BEVs. These approaches are often missing detailed technical models and neglect the effect of uncertainties in the critical utilization data even though it has been shown that uncertainties in the input data, e.g., stochastic mobility patterns, can have a significant impact on operational optimization.

3.2 Environmental impact studies

The environmental impact assessment of BEVs in comparison to other technologies, mostly ICEVs, has become a common scientific research topic in recent years (Helmers & Weiss, 2017; Nordelöf et al., 2014). To evaluate the environmental impacts of BEVs beyond the direct evident benefit of no tailpipe emissions a wide range of different research questions has been addressed. On a high-level, past studies can be distinguished along two dimensions: the included emissions and pollutants and the covered vehicle life cycle phases (Figure 5).

Potential CO_2 or GHG emission savings from the deployment of BEVs in comparison to ICEVs is a frequent topic in the scientific and public discussion. Therefore, many studies address this issue. Some focus only on the utilization phase of the vehicles (Campanari, Manzolini, & Garcia de la Iglesia, 2009; Doucette & McCulloch, 2011; Faria et al., 2013; Jochem et al., 2015; Ketelaer et al., 2014; McCarthy & Yang, 2010; Muneer et al., 2015). This approach allows comparing the tailpipe emissions from ICEVs to the indirect emissions from the BEVs based on the electricity mix as well as indicating the potential benefits of load-shifting. Different methods can be applied to quantify the CO_2 of BEV emissions during utilization (Jochem et al., 2015). Some studies expand the focus from the utilization by including cradle-to-gate processes (Plötz, Funke, & Jochem, 2017; Robinson et al., 2013; Sharma, Manzie, Bessede, Crawford, & Brear, 2013) or expanding the analysis on the whole vehicle life cycle (Bickert et al., 2015; Chatzikomis, Spentzas, & Mamalis, 2014; Ellingsen, Singh, & Strømman, 2016; Garcia, Freire, & Clift, 2017; Ma, Balthasar, Tait, Riera-Palou, & Harrison, 2012; Yazdanie, Noembrini, Heinen, Espinel, & Boulouchos, 2016). Quantifying the CO_2 emissions over the life cycle constitutes a carbon footprint analysis (Ausberg et al., 2015). In these, the environmental impact is usually expressed in CO_2-eq., which is mainly the result of CO_2, CH_4, and N_2O emissions (Helms et al., 2011).

[6] Due to the communication required between the coordinating system, the charging stations, and the BEVs the secondary control reserve with 30 s reaction time is currently assumed to be the best suitable for BEV integration (Gunter et al., 2016).

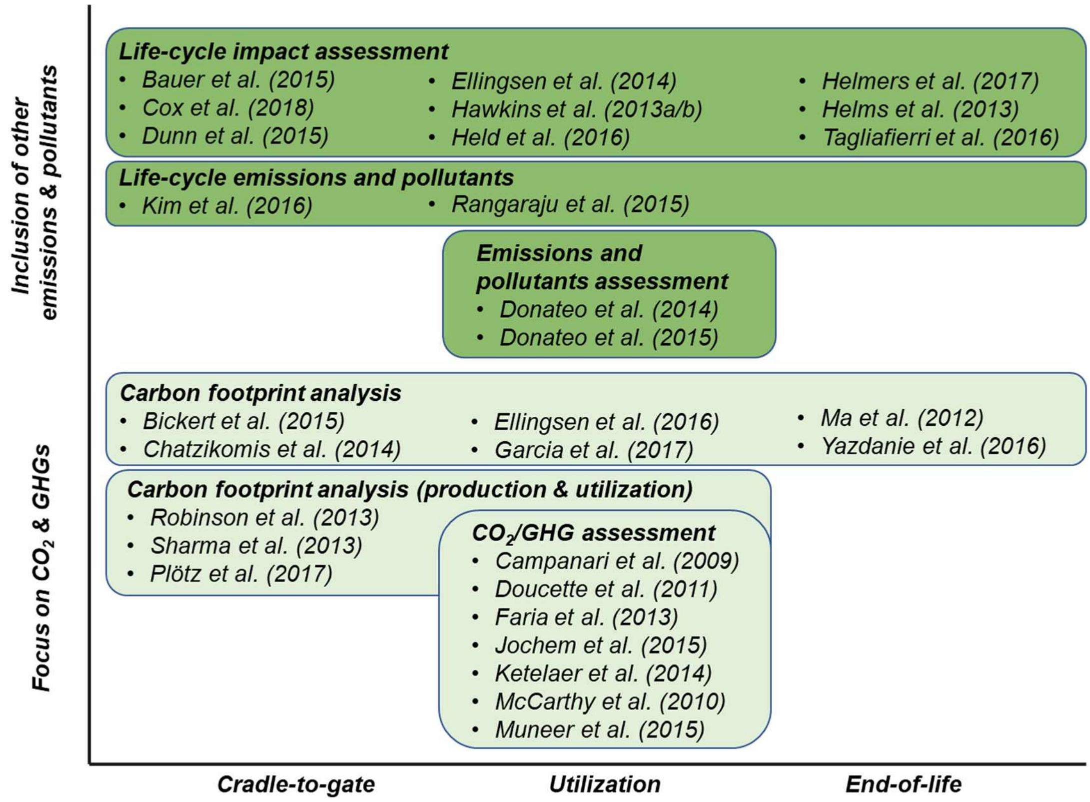

Figure 5: Overview literature on the environmental assessment of BEVs

However, next to GHGs other emissions and pollutants can be attributed to the BEV life cycle. Hence, studies include these, e.g. volatile organic compounds (VOC), carbon monoxide (CO), nitrogen oxides (NO_x), particulate matter (PM), and sulfur dioxide (SO_2), in their utilization assessment (Donateo, Ingrosso, Licci, & Laforgia, 2014; Donateo et al., 2015). Holistic approaches, which cover the whole vehicle life cycle from raw material extraction and material production, transport, part manufacturing, and product assembly, product utilization, maintenance, up to recycling and disposal for the different emissions, pollutants, are more frequent. A few studies only assess the emissions and pollutants over the full life cycle (Kim et al., 2016; Rangaraju et al., 2015). More commonly, the Life cycle Assessment (LCA) has established itself as the dominantly used method for attributing the effects of the pollutants and emissions over the full life cycle to different environmental impact categories (Figure 6). The LCA is an elaborated and standardized approach that considers the impacts of a functional unit during all life cycle stages. The idea of the LCA originates from an initiative by the Club of Rome in 1972 (Jolliet, Saadé-Sbeih, Shaked, Jolliet, & Crettaz, 2016). Over the years, different initiatives have continuously developed this approach until it was first transformed into DIN norms in 1997 (Hauschild, Rosenbaum, & Olsen, 2018). The DIN EN ISO 14040 & 14044 were last updated in 2006 and provide an internationally agreed-upon standardized framework for conducting an LCA (Klöpffer, 2014). The number of LCA studies analyzing BEVs has only increased recently. Between 2011 and 2015 approximately a quarter of all publications that analyzed potential environmental benefits from BEV introduction included other environmental impact factors than the GWP (Helmers & Weiss, 2017). The main argument of including other impact categories is to uncover potential problem shifting or rebound effects from GWP to other impact categories (Egede, Dettmer, Herrmann, & Kara, 2015; Ellingsen et al., 2014).

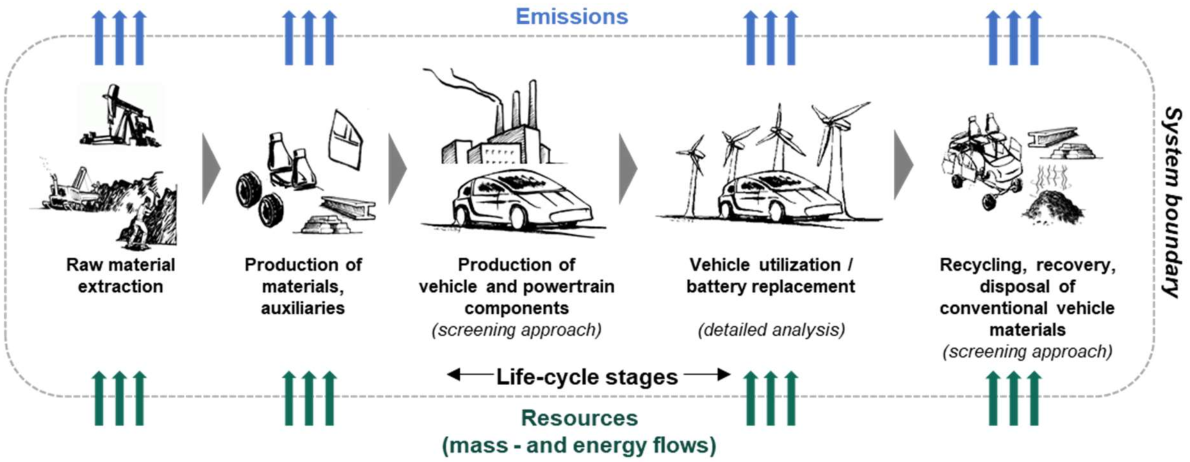

Figure 6: Life cycle Assessment of a BEV (Held & Schücking, 2019)

It is an ongoing discussion, which additional environmental impact factors should be included in the LCA of a BEV. Some studies focus on impact factors, such as acidification potential (AP), eutrophication potential (EP), summer smog, and fine particulates that are significantly influenced by utilization (Held et al., 2016; Helms et al., 2011). Others include up to 18 impact factors expanding the number of factors for example by separating the EP into freshwater eutrophication potential (FEP), marine eutrophication potential (MEP) and terrestrial eutrophication potential (TETP), by including depletion potentials, e.g. fossil depletion potential (FDP), ozone depletion potential (ODP), and metal depletion potential (MDP), as well as toxicity potentials, e.g. human toxicity potential (HTP) (Bicer & Dincer, 2017; Cox, Mutel, Bauer, Mendoza Beltran, & van Vuuren, 2018; Ellingsen et al., 2014; Hawkins, Singh, Majeau-Bettez, & Strømman, 2013a; Helmers, Dietz, & Hartard, 2017; Singh, Guest, Bright, & Strømman, 2014). Moreover, some studies include the primary energy demand (PED) which allows comparing the overall energy efficiency of the different technologies (Cox et al., 2018; Dunn, Gaines, Kelly, James, & Gallagher, 2015; Held et al., 2016; Helms et al., 2013; Yazdanie et al., 2016). The number of impact categories illustrates the complexity of providing a final positive or negative answer concerning the environmental impact of BEVs in comparison to other powertrain alternatives.

In addition to the two dimensions stated above, environmental BEV studies can also be distinguished by their perspective and approach (Table 9). A few publications take a macroscopic perspective by combining the overall environmental assessment with market diffusion models (Garcia et al., 2017; Jochem et al., 2015; Ketelaer et al., 2014; Singh, Ellingsen, & Strømman, 2015; Yabe, Shinoda, Seki, Tanaka, & Akisawa, 2012). Most publications take the microscopic view. These studies compare different technologies on vehicle level under varying conditions (Bauer, Hofer, Althaus, Del Duce, & Simons, 2015; Cox et al., 2018; Hawkins et al., 2013a; Hawkins, Singh, Majeau-Bettez, & Strømman, 2013b; Held et al., 2016; Helms et al., 2013; Notter et al., 2010a; Tagliaferri et al., 2016). Most papers with either a macroscopic or a microscopic perspective are simulations based on average data (Table 9). Some also predict future developments based on scenarios (Bauer et al., 2015; Cox et al., 2018; Jochem et al., 2015; Ma et al., 2012; McCarthy & Yang, 2010; Singh et al., 2015; Tagliaferri et al., 2016). Only a few studies evaluate detailed empirical BEV utilization data or specific use cases (Donateo et al., 2014, 2015; Faria et al., 2013; Ketelaer et al., 2014; Muneer et al., 2015; Rangaraju et al., 2015; Robinson et al., 2013).

Table 9: Exemplary literature overview of different BEV environmental impact studies

			Emissions & impact categories		Focus			Approach			LCA		Energy system boundaries			Mobility patterns		BEV data				Electricity data					Results							
Paper	**Region of deployment**	**Energy mix data**	**Global warming potential/CO_2**	**Others**	**Macroscopic**	**Microscopic**	**Specific use case(s)**	**Simulation**	**Evaluation**	**Prognosis**	**Full life-cycle**	**Focus on utilization**	**WTW**	**PTW**	**TTW**	**Average values**	**Empiric values**	**Different segments**	**Standard drive cycles**	**Empiric energy consumption**	**Time of charging**	**Emission intensity average**	**Emission intensity disaggregated**	**Electricity mix average**	**Electricity mix marginal**	**Different electricity mixes**	**ICEV**	**HEV**	**PHEV**		**FCEV**	**Emission targets**	**Load shifting**	**Break-even analysis**
Bauer et al. (2015)	Europe	2012/30	X	X		X		X		X	X		X			X			X	(X)[2]		X		X		X	X	X	X	X	X			
Bickert et al. (2015)	Germany	2013/14 & 2020/30	X			X		X			X[1]		X					X	X	(X)[2]		X		X		X	X			X				X[1]
Campanari et al. (2009)	Italy	2007	X			X		X				X	X			X			X			X		X		X	X			X	X			
Cox et al. (2018)	Global	2017	X	X[10]		X		X		X	X		X			X				X[6]		X		X		X[9]				X				
Chatzikomis et al. (2014)	Greece	2012 & 30	X		X			X			X[1]		X			X		X		X[6]		X		X		X	X	X	X	X				
Donateo et al. (2014)	Italy	2013	X	X		X	X		X			X		X			X			X	X[3]		X	X						X		X		
Donateo et al. (2015)	Italy	2013	X	X		X			X		X[7]			X			X			X	X		X	X		X				X		X		
Doucette et al. (2011)	USA, France, India, China	2009	X			X		X				X			X	X		X	X			X		X		X	X			X				
Dunn et al. (2015)	USA, California	---	X	X[10]		X		X			X		X			X			X			X		X		X	X		X	X				
Ellingsen et al. (2014)	Norway	---	X	X		X		X			X		X			X			X			X		X		X[9]				X				
Ellingsen et al. (2016)	Europe	2013	X			X		X			X[1]		X			X		X	X			X		X		X	X			X				X[1]
Faria et al. (2013)	Portugal, Poland, France	2011	X			X		X				X	X			X		X		X		X	X[4]	X		X	X		X	X				
Garcia et al. (2017)	Portugal, Europe	2010/15 & 2020/30	X		X			X		X	X[1]		X				X	X				X	X	X	X	X	X			X				
Hawkins et al. (2013a/b)	Europe	< 2010	X	X		X		X			X		X			X			X			X		X		X	X			X				
Held et al. (2016)	Germany	2009-11	X	X[10]		X					X		X			X		X		X		X		X		X	X		X	X				X
Helmers et al. (2017)	Germany	2013	X	X		X		X			X		X			X				X		X		X			X			X				
Helms et al. (2013)	Germany	2008-12, 2020/30	X	X[10]	X			X		X	X		X			X				X		X		X	X	X	X		X				X	
Jochem et al. (2015)	Germany	2030	X		X			X		X		X		X		X				(X)[5]			X	X	X					X		X	X	
Ketelaer et al. (2014)	Germany	2010	X		X		X		X			X		X			X		X			X		X		X	X			X				
Kim et al. (2016)	USA	---	X	X[10]		X		X			X		X			X			X			X		X			X			X				
Ma et al. (2012)	England, California	2015	X			X		X		X	X[1]		X			X		X		(X)[2]		X		X	X	X	X	X	X	X				
McCarthy et al. (2010)	California	2009/10	X		X			X		X		X	X			X			X				X		X		X	X	X	X	X			
Muneer et al. (2015)	Scotland, Slovenia	2010/11	X			X	X		X			X	X				X	X		X		X		X		X				X				
Plötz et al. (2017)	Germany	2013	X			X		X			X[7]		X			X				X		X		X		X	X		X	X				
Rangaraju et al. (2015)	Belgium	2011	X	X		X			X		X		X				X			X	X		X	X		X	X			X			X	
Robinson et al. (2013)	England	2011/12	X			X			X			X	X				X			X	X		X	X		X				X			X	
Sharma et al. (2013)	Australia	2011	X			X		X			X[8]		X			X		X	X			X		X			X	X		X				
Singh et al. (2015)	Norway	2012/20	X		X			X		X	X[1]		X			X			X			X		X		X	X			X		X		
Tagliafierri et al. (2016)	Europe	2014	X	X		X		X		X	X		X			X			X			X		X		X	X	X		X				
Yazdanie et al. (2016)	Switzerland, Europe	2011/12	X	(X)[10]		X		X			X[7]		X			X		X	X			X		X		X	X	X	X	X	X			

[1]only carbon footprint; [2]standard values with assumptions for additional load and auxiliaries; [3]small data set; [4]only monthly values; [5]different battery types; [6]assumption based on literature; [7]only carbon footprint based on average literature values for production emissions; [8]only carbon footprint excluding recycling and disposal; [9]also for cradle-to-gate processes; [10]plus Primary Energy Demand (PED)/Cumulative Energy Demand (CED) assessment

Conducting an environmental assessment, especially a carbon footprint analysis or an LCA, for a BEV requires a large amount of different inventory data which provides challenges in comparison and the need for standardization. For cradle-to-gate and end-of-life (EOL), there are a few publications that provide detailed first-hand BEV specific databases and descriptions of processes for the life cycle inventory (LCI) (Cerdas, Egede, & Herrmann, 2018; Dunn et al., 2015; Ellingsen et al., 2014; Kim et al., 2016; Notter et al., 2010a, 2010b). Due to the high diversity in data and the increasing importance of the issue, there are attempts to establish standardized frameworks concerning guidelines, methods, assumptions, and data for BEVs based on the International life cycle data system (ILCD)[7] (Cerdas et al., 2018; Del Duce et al., 2013; Del Duce, Gauch, & Althaus, 2016). Besides the LCI different life cycle impact assessment (LCIA) characterization models exist. Most focus on mid-point indicators that measure scientifically describable impacts, e.g., ReCiPe, CML 2002, Eco-Indicator or IMPACT2002+ (Ausberg et al., 2015; Huijbregts et al., 2017; Rosenbaum et al., 2017). In contrast to the upstream and downstream life-cycle processes, the input parameters and processes for the utilization phase are more transparent since primary data can be directly recorded. However, as stated above only very few studies evaluate specific use cases based on first-hand data. Especially in terms of a full LCA, a detailed analysis of site-specific use cases based on long-term empirical values is missing from the literature (Egede et al., 2015).

The results of previous environmental BEV studies show the same overall tendencies but vary significantly on a more detailed level (Helmers & Weiss, 2017; Nordelöf et al., 2014). The different scopes, system boundaries, inventories, and research assumptions explain the divergence. Table 9 provides an exemplary overview and classification of recent publications addressing the environmental impact of BEVs. The key utilization input parameters for all environmental studies are the vehicle and battery parameters, the user behavior and mobility patterns, and the electricity mix (Cox et al., 2018; Egede et al., 2015; Ellingsen et al., 2014).

Due to the deviations of the real energy consumption from the one measured on the NEDC for all drivetrain technologies, it is crucial to rely on realistic mechanical simulations or empirical values when calculating the environmental impact of utilization. This procedure is particularly relevant for BEVs where the auxiliaries, which are not considered in standard driving cycles, can have a strong influence on energy consumption (see chapter 2.1). However, several studies rely on the standardized energy consumption values stated by the manufacturers since or simulated based on the NEDC (Ellingsen et al., 2016; Hawkins et al., 2013a, 2013b; Tagliaferri et al., 2016). Others attempt to simulate more realistic values by using the Worldwide harmonized Light vehicles Test Procedure (WLTP) (Bauer et al., 2015; Cox et al., 2018; Garcia et al., 2017). Some studies add the additional demand of the auxiliaries to their simulations (Bauer et al., 2015; Bickert et al., 2015; Cox et al., 2018; Faria et al., 2013; Li, Zhang, & Li, 2016). Only some papers use empirical data recorded at BEV or EVSE level for the environmental assessment (Donateo et al., 2014, 2015; Helmers et al., 2017; Plötz et al., 2017; Rangaraju et al., 2015; Robinson et al., 2013). Of these, some include other pollutants than CO_2 (Donateo et al., 2015; Rangaraju et al., 2015) and even less conduct a full LCA (Held et al., 2016; Helmers et al., 2017). None of these incorporate use case-specific long-term empirical values as input for a full LCA or a detailed assessment of the CO_2 emissions from utilization.

[7] The European Commission initiated the International Life-cycle Data System (ILCD) as a database of life-cycle inventory data and a series of methodological guidelines to guide consistent, and quality assured LCA data and studies (EC-JRC, 2010).

The studies conclusively show that the indirect emissions resulting from the used energy carrier in utilization take a significant influence on the environmental impact of BEVs (Helmers & Weiss, 2017; Nordelöf et al., 2014). The electricity mix is the largest source of variability in the prognosis of future LCA development (Cox et al., 2018). It is vital to compensate for the higher cradle-to-gate environmental impacts from BEV (Hawkins et al., 2013a, 2013b). To illustrate the sensitivities towards the electricity mix studies compare the influence of different energy markets (Doucette & McCulloch, 2011; Egede et al., 2015; Faria et al., 2013; Woo, Choi, & Ahn, 2017), average mixes and individual renewable energy sources (RESs) (Held et al., 2016; Helmers et al., 2017; Helms et al., 2013; Muneer et al., 2015), different regional grids (Macpherson, Keoleian, & Kelly, 2012), as well as an electricity system with or without a high storage capacity (Garcia et al., 2017). The electricity mix can also vary between seasons or the time of day especially for countries with a large share of volatile RESs (Donateo et al., 2015; Jochem et al., 2015; Rangaraju et al., 2015; Robinson et al., 2013). When the time of charging varies throughout the day hourly disaggregated data of the electricity mix becomes essential. Since the effect of hourly disaggregated electricity mixes influences the emissions, the controlled delay of the charging into a period of a less emission-intensive electricity mix, called load shifting, can significantly reduce the emissions (Jochem et al., 2015; Rangaraju et al., 2015). However, just shifting the load to times with less energy demand does not necessarily lower the environmental impact, especially when, as in Germany today, coal is used to cover a significant proportion of the baseload. Despite the potential benefits, only a few studies include timely disaggregated input data (Garcia et al., 2017; McCarthy & Yang, 2010; Sharma et al., 2013). Even fewer studies contain the empirical time of charging data (Donateo et al., 2014, 2015; Rangaraju et al., 2015; Robinson et al., 2013). Concerning the electricity mix, another important distinction between the average and the marginal mix is required especially in the context of load shifting. Marginal emissions are the ones that are additionally caused by the last connected consumer. Depending on the energy source they are likely to be more emission-intensive than the average mix (Jochem et al., 2015; Ma et al., 2012; McCarthy & Yang, 2010). It is an on-going discussion of whether and under which circumstances environmental impact studies should consider the average or marginal mix. There is a strong argument that if the load is shifted the marginal mix should be chosen since the additional demand is consciously created.

The results of the BEV environmental impact assessments are regularly put into context by comparing them to other technologies such as ICEVs, HEVs, PHEVs or FCEVs. In comparison, the environmental impacts of BEVs from cradle-to-gate exceed those of ICEVs in many impact categories due to the higher energy requirements for cell production as well as due to the extraction and production of the particular materials (Cox et al., 2018; Egede et al., 2015; Hawkins et al., 2013a, 2013b; Held et al., 2016; Kim et al., 2016). Some of the higher environmental impacts can be compensated through comparable lower emissions and fewer pollutants during operations. Some studies illustrate this effect of compensating the initial higher offset with a break-even analysis over the lifetime mileage (Bickert et al., 2015; Cox et al., 2018; Ellingsen et al., 2016; Held et al., 2016). This approach provides a good illustration of the potential compensation and the influence of the operating grade on the overall environmental performance of BEVs. Depending on the research settings, the break-even points vary. The GWP break-even under the carbon-intensive German average electricity mix lies between 60,000 and 125,000 km and at around 40,000 km when relying on an electricity mix from RESs (Bickert et al., 2015; Held et al., 2016). Depending on the type of car under the European electricity mix the break-even points lie between 20,000 and 110,000 km (Ellingsen et al., 2016). For other impact categories, the results differ. Especially for the acidification potential (AP) due to the high emissions in the material extraction and processing of active materials no significant improvement is reached over a lifetime (Held et al., 2016). Again, an extensive analysis based on long-term empirical data is missing.

In summary, the literature overview on environmental impacts and emissions of BEVs allows several conclusions. The differences between the studies underline the complexity of the issue and the importance to distinguish scope, system boundaries, and input data clearly. Even though the utilization takes a high influence on the environmental impacts of BEVs, most publications neglect specific use cases and long-term empirical energy consumption values. They rely on general assumptions concerning lifetime mileage and mixed route profiles (urban, interurban or motorway) not considering the substitution potential of BEVs in detail. The few papers that use actual data from BEV deployment either lack a full LCA or do not focus on specific use cases.

3.3 Research gaps in the literature

For the techno-economic as well as the environmental evaluation and optimization of BEVs there are notable gaps in the literature. These underline the need for further research presented in this thesis's research papers. Since BEVs had only recently been introduced to the mass market when the research started, there was limited data available concerning their real performance in utilization. Due to the sensitivity of the techno-economic and environmental results on the utilization parameters, including this data sets the research on a more solid foundation and provides new insights into the economic and environmental beneficial deployment of BEVs.

From a techno-economic point of view concerning the current state of BEVs, two different strategies have the potential to accelerate BEV introduction into commercial applications.
Both strategies were developed under the condition of full ICEV substitutability without changes in individual mobility behavior. Considering a fixed BEV endowment, the first strategy is to increase the operating grade inside the set technical boundaries, which increases the competitiveness by making greater use of the lower operating costs. This approach demonstrated by specific commercial use cases has not been presented in the literature. Considering a flexible BEV endowment, the second strategy is to minimize the investment and operational costs in a comprehensive TCO optimization model. Current studies on electric vehicles' TCO often neglect two important factors that influence the investment decision and operational costs: firstly, the trade-off between battery and charging capacity; secondly the uncertainty in energy consumption. Jointly optimizing investment and cost of operations under uncertainty requires a stochastic approach. In the literature, several stochastic approaches can be found that optimize BEV operations taking uncertainties into account. However, to the best of the author's knowledge, an approach that jointly minimizes the investment and operational costs for BEV under uncertain energy consumption is missing

From the environmental perspective, various impact factors and, as a consequence thereof, the environmentally beneficial deployment of BEVs are highly sensitive to the operational conditions. Firstly, this applies to the assessment of timely disaggregated CO_2 emissions resulting from BEV operations. The detailed assessment requires combining long-term case-specific empirical input data, e.g., the mobility patterns, the energy demand, and the exact charging time with data from different electricity markets. Secondly, several environmental impacts resulting from the full BEV life-cycle are directly dependent on the circumstances of utilization. The electricity mix and energy efficiency are directly related to the emissions from the operation. As indicated in the literature, favorable conditions and a high degree of utilization can lead to a comparable break-even over the BEV life-time in several impact categories. There is a gap concerning this kind of commercial case-based LCA in the literature. Most previous publications neglect specific use cases, make general assumptions on lifetime mileage, and do not consider case-specific technical substitution restrictions of BEVs in detail. Both approaches could provide vital contributions to the literature since they allow the drawing of specific conclusions concerning the environmental impacts of BEVs and provide recommendations for their environmentally beneficial deployment.

After unifying the stated gaps in the literature an overall research question arises: based on case-specific utilization data what are the critical conditions, prerequisites, and measures required for a joint economic and environmentally beneficial deployment of BEV in commercial applications?

4. Contribution and organization of the thesis

This thesis follows a holistic approach to assess the potential of BEVs in commercial fleets. It addresses the overall research question and individual gaps in the literature stated above by presenting methodical approaches for optimizing the techno-economic potential and evaluating the environmental impacts of BEVs deployed in commercial fleets and used by commuters. The research in all papers is based on empiric utilization data recorded over an extensive period of different BEVs, ICEVs, and EVSEs. This detail and the quality of empirical data allow a detailed techno-economic and environmental analysis. In summary, the papers present an interdisciplinary approach to evaluate, simulate, and optimize the utilization of commercial BEVs.

The presentation of the five research papers' methodical approaches, main results, and contributions are separated into three subject areas (Table 1). Subject area 1 consists of Schücking et al. (2016) which has a technical focus. Subject area 2 consists of Schücking et al. (2017) and Schücking & Jochem (2020) which both have a techno-economic focus. Subject area 3 focuses on the environmental impacts of BEVs with the papers Ensslen et al. (2017) and Held & Schücking (2019). These five papers build a holistic framework of methodical approaches to optimize the techno-economic potential and evaluate the environmental impacts (Figure 7).

One set of papers (Paper I, II and IV) sets the focus solely on the use of BEVs answering technological, economic or environmental research questions. Schücking et al. (2016) assesses the empiric energy consumption of BEVs in deployment. The processed data and the calibrated vehicle dynamics model are vital contributions to the other studies presented in this thesis. Schücking et al. (2017) develops charging strategies that can be applied to increase the utilization of BEVs and facilitate a faster economic break-even under the given technical restrictions. The newly developed key performance indicators (KPIs) of the mobility patterns help to illustrate the differences in the two use cases presented. They can also be used to assess the potential of increased utilization in other commercial applications. Ensslen et al. (2017) focuses on the utilization from an environmental perspective. It simulates the time-dependent CO_2 emissions from BEV in cross-border operation building on high-resolution mobility and electricity mix data. The results indicate the influences of the regional mixes and point out the CO_2 emission reduction potentials in BEV operation.

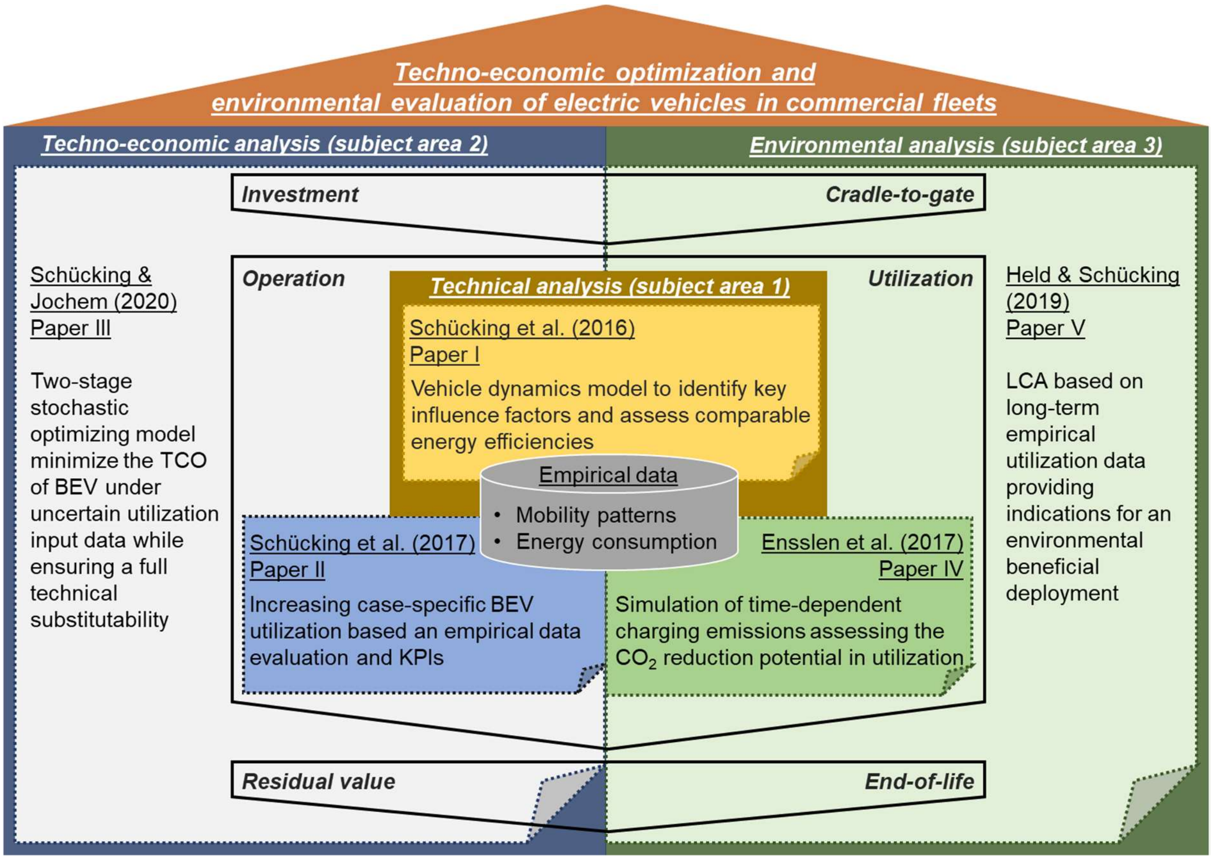

Figure 7: Overview framework of methodical tools applied in this thesis

The other set of papers (Paper III and V) take a more holistic approach by expanding the system boundaries to the whole life-cycle of the BEVs. Addressing the identified gap of a missing comprehensive TCO optimization approach that jointly considers both the trade-off between battery and charging capacity and uncertainty in energy consumption in the investment decision and operational costs Schücking & Jochem (2020) proposes a two-stage stochastic program. It minimizes the TCO of a commercial electric vehicle under uncertain energy consumption induced by mobility patterns and outside temperature. The optimization program is solved by sample average approximation (SAA). Based on practical experience, the study assumes that only limited information on mobility patterns, e.g. from a logbook, is available in everyday commercial mobility applications. Therefore, a hidden Markov model (HMM) is introduced as an approach for generating mobility scenarios that provide suitable input for a detailed energy consumption model based on limited empirical data. Furthermore, the paper presents a new scenario reduction heuristic to facilitate a more efficient approximation of the optimal TCO value based on the key first-stage decision variables and the output performance of the scenarios. All things considered, several methodical approaches and small advancements are newly combined into a comprehensive stochastic TCO optimization framework. Held & Schücking (2019) provides a full LCA based on the long-term empirical data suggesting conditions for an environmentally beneficial deployment of BEVs based on a simplified screening model. Even though the two papers assess the overall life cycle, detailed long-term case-specific data is paramount for both methodical approaches.

In their combination, all five papers address the overall research questions and contribute valuable insights into the conditions, prerequisites, and measures required for a joint economic and environmentally beneficial deployment of BEV in commercial applications.

The five papers originate from research undertaken by the author in the capacity as an assistant in the research group Energy and Transport at the Institute for Industrial Production (IIP) and at the Battery Technical Center (previously Competence E), which are both entities of the Karlsruhe Institute of Technology (KIT). In relation to the existing literature, the five research papers in this thesis combine several existing methods into new approaches that are applied based on unique long-term empirical data. Furthermore, Paper III also introduces an HMM-based approach for predicting commercial mobility patterns and develops a new scenario reduction heuristic that allows approximating the solution of the proposed two-stage stochastic approach more efficiently by considering the key first-stage decisions and output performance of the individual scenarios. To the best of the author's knowledge, each paper, as well as all of them combined, provide a new contribution to the field of commercial BEV research. The papers include a comprehensive literature review addressing not only the domain but also methodology as well as a detailed empirical data collection process. The complex issues were analyzed in cooperation with co-authors who provided valuable input especially concerning the methods and data for the environmental assessment. The central techno-economic ideas and applied methods, as well as the literature reviews, the data analysis, and the preparation and discussion of the results, were to the most substantial extent provided by the author of this thesis.

4.1 Subject area 1: Technical analysis of the BEVs' energy consumption

The following part summarizes the contribution, applied methods, used data, and key results of the technical paper in the subject area 1.

Paper I *Influencing factors on specific energy consumption of electric vehicles in extensive operations* (M. Schücking et al., 2016) presents a detailed technical energy consumption and efficiency model for BEVs. The vehicle dynamics model is calibrated based on long-term empirical measurements of the commuter and business trip use cases supplemented with detailed measurements on a dynamometer. Especially the intensive use with monthly mileages over 3,000 km and the horizon of over 2.75 years provided a unique data set. The results underline the influence of speed level and variance as well as the influence of the auxiliaries' power demand. On the one hand, a higher travel speed increases the loss to drag and therefore the specific energy consumption. On the other hand, under the assumption of constant power demand by the auxiliaries during a trip, a higher average speed leads to a lower auxiliaries' impact on the specific energy consumption. Depending on the vehicle type and auxiliaries' power demand, these opposing effects lead to a minimum value between 22 and 42 km/h for specific energy consumption, which determines the longest possible trip without recharging. As the results show, this is not necessarily the operating point where BEVs are most competitive compared to ICEVs, which usually lies at lower average speeds. However, the worst-case energy consumption determines the substitution potential, which is more sensitive to the higher use of auxiliaries at lower speeds. The results suggest that a higher average speed, which allows the constant operation on longer routes and therefore increases the annual mileage, can overcompensate the losses in relative efficiency. This study underlines the complexity of the technical substitution assessment as well as the requirement of considering the influence of mobility patterns and outside temperatures on energy consumption.

4.2 Subject area 2: Techno-economic evaluation and optimization

The following paragraphs present the research questions, applied methods, used data, and critical results for the two techno-economic papers in subject area 2.

Paper II *Charging strategies for economic operations of electric vehicles in commercial applications* (M. Schücking et al., 2017) presents and discusses five BEV charging strategies during an early stage long-term field test from 2013 to 2015 in the French-German border region. The primary objective of the charging strategies is to propose conceptual suggestions and provide empirical evidence for increasing the BEV's utilization to a high operating grade within the technological restrictions. The research distinguishes itself from others not only by the taken approach but also based on the intensive use of the deployed vehicles which drove more than 450,000 km and the inclusion of DC fast charging. Both were unique characteristics when the research was conducted. The purpose of the high utilization is to benefit from the lower operational cost and to facilitate a faster economic break-even. Three of the charging strategies focus on commuting shift workers while the other two strategies focus on business trips. For four out of five presented charging strategies, the inclusion of DC fast charging is indispensable. Based on the case studies five KPIs are developed. These indicators allow a straightforward assessment of commercial mobility profiles according to economic potential. The results indicate that a prudent mix of conventional and DC fast charging allows a high annual mileage while at the same time limiting avoidable harmful effects on the battery. Overall, the results demonstrate that the higher predictability of the commuting use case in comparison to the business trips allows finer tuning of charging strategies. The uncertainty concerning the timing of the trips significantly limits the appliance of simple strategies to increase utilization indicating that for less predictable use cases the inclusion of uncertainty in mobility patterns in the investment decisions and operations is indispensable.

Paper III *Two-Stage stochastic program optimizing the total cost of ownership of electric vehicles in commercial fleets* (Maximilian Schücking & Jochem, 2020) addresses this issue by proposing a two-stage stochastic program that minimizes the TCO of a commercial electric vehicle under uncertain energy consumption induced by mobility patterns and outside temperature. In contrast to the first paper in subject area 2, it does not increase the utilization of a given BEV but sets the battery and charging capacity as variables for the investment decision, which both form a trade-off. Four major contributions are made in this paper. Firstly, an overall investment and operations choice formula, which considers battery capacity, charging capacity, and uncertain energy consumption under the constraints of a detailed technical BEV model is developed. Secondly, the stochastic mobility patterns are predicted based on limited empirical time-series data by training and using an HMM for scenario generation. Thirdly, three scenario reduction heuristics, one of which is a newly developed advancement, are compared to identify the one that most efficiently approximates the optimal value of the two-stage stochastic model. Fourthly, the newly developed approach is applied to a home nursing service case study, which, despite being a common mobility application, has received little research attention. The results show the large influence of the uncertain mobility patterns on the optimal solution. Concerning the methodology, the results of the home nursing service case study demonstrate that using HMM is a suitable way to model stochastic mobility patterns. Moreover, the results indicate that the inclusion of the first-stage decision variables and the overall output performance in the scenario selection process can improve the solution approximation efficiency. In the case study, by including the trade-off between battery and charging capacity the TCO can be reduced by up to 3.9%. The introduction of variable energy prices can lower energy costs by 31.6% but does not influence the investment decision in this case study. Overall, this study provides valuable insights for real applications to determine the techno-economic optimal electric vehicle and charging infrastructure configuration. The model is easily transferable to other commercial mobility applications that promise early BEV introduction such as security, delivery or postal services.

4.3 Subject area 3: Environmental evaluation

The following part reviews the research questions, applied methods, used data, and critical results of two papers in subject area 3.

Paper IV *Empirical carbon dioxide emissions of electric vehicles in a French-German commuter fleet test* (Ensslen et al., 2017) presents the results from measuring the time-dependent electricity consumption of BEVs during driving and charging. It contributes to the discussion concerning the quantification of real CO_2 emission reduction potentials. Three research questions are addressed in this paper. Firstly, how much energy was charged and consumed by the BEVs on the individual trips during the commuter fleet test and to what extent does this amount depend on the chosen measurement points or assessment method (e.g., GTW, TTW, NEDC)? Secondly, what are the CO_2 emissions caused by the BEVs considering the time-dependent national PTW CO_2 emissions and the different assessment methods? Thirdly, how high are the real CO_2 emission reduction potentials of different BEV use cases based on the previous results? The high-resolution empirical data originates from the use case of shift workers commuting between France and Germany from March to August 2013. 639 individual charging events were recorded. The study matches the vehicle data on electricity consumption to the disaggregated electricity generation data with time-dependent national electricity mixes and corresponding CO_2 emissions with an hourly temporal resolution. The results indicate that charging in France causes only about 10% of the CO_2 emissions compared to Germany. In Germany, the carbon intensity is more diverse and depends on the time of day or season. Solely based on the German electricity mix the specific emissions of the use case are higher than the European fleet target for 2022 of 95 g CO_2/km. The results confirm that delayed charging can reduce electric vehicle-specific CO_2 emissions by shifting the load into periods with high shares of renewables, i.e., particularly into afternoon hours, when the sun is shining or into windy periods. At the presented high utilization level this requires the installation of higher maximum charging powers. Reducing the CO_2 emissions, the utilization phase is an essential step in the effort to cut the overall environmental impact of BEVs.

Paper V *Utilization effects on battery electric vehicle life-cycle assessment: A case-driven analysis of two commercial mobility applications* (Held and Schücking 2019) conducts an LCA to investigate the environmental impact categories GWP, AP, EP, and PED as an indicator for the depletion of nonrenewable energetic resources from BEVs deployed in the cross-border commuter and business trips use cases. The paper analyzes the effect of the high operating grade, different energy mixes on both sides of the border, and vehicle types on the lifetime environmental impact as well as the respective break-even points to ICEVs. The research is based on empirical powertrain and GPS data. The approach follows the standardized LCA framework. However, since no car manufacturer was directly involved in this study for exchanging specific inventory data on the vehicle and powertrain components in a consistent level of detail, a simplified internal LCA screening model approach is applied to estimate the environmental impacts from production and the EOL of the investigated vehicle types. Depending on the level of detail and quality of available data, the parameterization of the screening model allows a comprehensive adjustment of the vehicle specifications as well as for single components according to their technical properties. The LCA software GaBi is used for the screening model with access to the detailed LCA database. In the LCIA, all the emissions are classified according to their environmental effects, and the emissions are summarized using the CML2001 as a characterization model. The findings of this article indicate that regular and predictable mobility patterns in combination with high vehicle utilization are favorable conditions for an environmentally beneficial deployment of BEVs. These characteristics allow tailoring the battery capacity to the requirements and avoiding an unnecessary offset from production. When charging the vehicles with electricity from RESs, the high operating grade utilizes the comparatively lower environmental impacts per kilometer. A high lifetime mileage allows breaking-even to comparable ICEVs in most investigated impact categories. Since regular and more predictable mobility patterns, as well as a high operating grade, are commonly found in commercial applications, these are especially suitable for replacing ICEVs with BEVs from an environmental perspective.

5. Summary and outlook for future research

BEVs have the potential to play a vital role in the decarbonization of our future transportation system. This thesis presents an interdisciplinary framework of methodical approaches consisting of five scientific papers that evaluate, simulate, and optimize the economic benefits and environmental impact of commercial and commuter BEVs. Combined they answer the overall research question: what are the essential conditions, prerequisites, and measures required for a joint economic and environmentally beneficial deployment of BEV in commercial applications? The presented framework can be applied to assess and optimize the potential economic and environmental benefits of BEVs deployed in specific commercial applications based on long-term utilization data.

In their results, the five papers confirm previous research, address open gaps in the existing literature and suggest methodical advancements. As a technical analysis, Schücking et al. (2016) focuses on the empirical energy consumption of BEVs and presents a calibrated vehicle dynamics model. The paper demonstrates the effect of speed and outside temperature on the actual energy consumption. The results underline that a resilient BEV dynamic model or detailed empirical utilization data is a central component for bottom-up economic and environmental analysis of potential BEV benefits. The two techno-economic papers present two different bottom-up approaches for assessing the individual BEV's deployment potential and facilitating a faster economic break-even. Schücking et al. (2017) focuses on the utilization. The new empirical insights and conceptual suggestions show that under high predictability and, with the inclusion of DC fast charging, a high operating grade can be reached allowing for a faster economic break-even. However, increasing uncertainty in the mobility patterns limits the potential benefits of this cost optimization strategy. To address this issue, Schücking & Jochem (2020) develops a more holistic TCO approach to minimize the investment and operational cost of a BEV under the consideration of uncertainty in energy consumption due to mobility patterns and outside temperature. The results of the home nursing service case study demonstrate the benefit of the stochastic approach. Both techno-economic papers advocate the importance of taking an incremental approach when assessing the BEV substitution potential. The two papers focusing on the environmental impacts of BEVs in the cross-border commuter case and business trips emphasize the influence of the electricity mix, the operating grade, and the battery capacity on the overall environmental performance. The specific focus on the quantification of real CO_2 emission reduction potentials during utilization presented in Ensslen et al. (2017) shows the timing and potential delaying of the charging can lead to notable emission savings. Held & Schücking (2019) expand these results by highlighting the importance of the utilization phase on the environmental impact over the whole life cycle. The paper shows that a high utilization can lead to an environmental break-even in most but not all the evaluated impact categories.

Following the overall research ambition, the results of the individual research papers allow overall overarching conclusions concerning the economic and environmental beneficial deployment of BEVs, specifically in commercial applications. Two essential criteria defined in this thesis to identify commercial applications with a high potential for a beneficial economic deployment "*The predictability and regularity of the mobility patterns should be high*." and *"The driving profiles should consist of short but frequent trips."* also increase the likeliness of an environmentally beneficial BEV introduction. Allowing for an ex-ante assessment of the required battery and charging capacity and avoiding unused excess battery capacity reduces not only the investment but also the significant environmental burden resulting from the cradle-to-gate and EOL processes. Aiming for a high operating grade in combination with electricity from RESs not only facilitates a faster economic but also environmental break-even in several impact categories. Therefore, the utilization characteristics that make many commercial vehicle applications a promising introduction market for BEV from an economic perspective (Gnann, Plötz, Kühn, et al., 2015; Plötz et al., 2013), can also lead to significant environmental benefits resulting from BEV introduction when combined with electricity from RESs. Increasing the deployment of BEVs in commercial applications also benefits the introduction of BEVs by private users since the commercial market provides an essential lever to the private market (Brand, Cluzel, & Anable, 2017; Plötz et al., 2014).

The presented research is subject to various limitations. The specific limitations are listed in the individual research papers. This paragraph summarizes the general limitations that arise from the case-based approach followed in this thesis. To a large extent, the research presented in this thesis is based on specific use cases and the recorded empirical data. Transferring them from the use case level into a broader context must be done cautiously. The cross-border commuting of shift workers is a unique use case. Even though commuting by car is very common in Germany, it is usually done by private or company cars which are also used for other purposes reducing the regularity and limiting the predictability. Also, in this thesis the thermal battery management is neglected in the presented technical BEV models. Under intensive use and high charging loads, which are vital to the presented models, the battery temperature can become a restriction resulting either in higher energy consumption through the need for active cooling or a restriction of charging power to avoid overheating. The latter effect was observed in the commuter case study. Furthermore, the analyzed BEVs were from an early generation. Recent technological advances already show increases in component efficiencies, lower load requirements by the auxiliaries, and increased battery energy and power densities as well as significant decreases in battery and vehicle prices. These technological and market maturity advances increase BEV competitiveness from an economic as well as environmental point of view.

Future research could apply the developed methodical approaches to other use cases, address the stated limitations, expand the presented models, as well as combine the economic and environmental analysis into one methodical approach. The validity of the proposed methodical approaches can be tested by applying them to other use cases based on current BEV technology and different mobility patterns. A future methodical advancement lies in the combination of the different methodical approaches presented in this thesis into one model. One potential approach could be to combine the environmental impacts of an LCA with the TCO in a multi-objective (stochastic) optimization. Multi-objective optimization could have effects on the results for the optimal battery and charging capacity depending on the monetary valuation or weighting factors. The investment in charging capacity, for example, has the potential to reduce the environmental impacts by lowering the battery capacity and shifting the charging to times with a low emission electricity mix. An alternative approach could be to conduct a life cycle sustainability assessment (LCSA), which consists of an LCA, life cycle costing (LCC), and a social life cycle assessment (SLCA). The results of future research can potentially accelerate the growing market penetration of (commercial) BEVs further and minimize the associated environmental impact.

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Part B – Papers

Contents

EVS29 Symposium
Montréal, Québec, Canada, June 19-22, 2016

Influencing factors on specific energy consumption of EV in extensive operations

Maximilian Schücking[1,*], Patrick Jochem[1], Wolf Fichtner[1], Olaf Wollersheim[2], Kevin Stella[2]

*[1](*corresponding author) Chair of Energy Economics, Institute for Industrial Production (IIP), Karlsruhe Institute of Technology (KIT), Building 06.33, Hertzstraße 16, D-76187 Karlsruhe, Germany*
Tel.: +49 721 608 44559, E-Mail: maximilian.schuecking@kit.edu

[2]Project Competence E, Karlsruhe Institute of Technology (KIT), Building 276, Hermann-von-Helmholtz-Platz 1, D-76344 Eggenstein-Leopoldshafen, Germany

Abstract

The sensitivities of electric vehicle (EV) energy consumption become significant when operating at long distances. This study analyzes these sensitivities based on empirical data of seven EV over 2.75 years with individual monthly mileages above 3,000 km and a specifically adopted energy consumption model. The results underline the influence of average speed, the distribution of speed and the auxiliaries as well as their opposing effects. It is demonstrated that the point of lowest specific energy consumption is not necessarily identical to the point where EV are most competitive compared to conventional internal combustion engine vehicles.

Keywords: EV (electric vehicle), energy consumption, demonstration, fleet

1 Introduction

The economic break-even for electric vehicles (EV) in comparison to internal combustion engine vehicles (ICEV) can be reached in most countries through a high mileage based on their lower energy costs. Due to the limited charging speeds and battery capacity for most currently available EV this requires operating them at their upper technical boundary. In this context assessing and forecasting their actual energy consumption is key. Empirical studies have shown that empirical energy consumption is usually higher than proclaimed by the manufacturers based on standardized driving cycles for EV [1–6] and for ICEV. This depends on various factors, e.g. driving profiles, driver behavior, battery technology, and the auxiliaries, which leads to specific energy consumption minima between 30 and 40 km/h depending on EV type and other conditions [7–9]. However, the possibility of energy recuperation changes the sensitivities of EV energy consumption in comparison to ICEV.

In this line of research we present the results of a long-term demonstration project, where seven EV were deployed with the goal to reach an economic break-even. The EV were provided to commuting shift workers and for business trips between two sites in France and Germany. The route profiles can therefore be characterized as mostly inter-urban with a significant share of motorways, which does not represent the usual deployment field of EV. However, both applications offer the potential to reach high mileages. In fact the monthly average mileage per EV in this field-test was above 3,000 km and required the regular use of DC fast charging.

2 Method & Data

In order to identify influencing factors and investigate the energy consumption sensitivity three steps were taken. Firstly, the long-term empirically measured energy consumption was evaluated. The changes in state of charge (SOC) values between the start and end of one trip proved unreliable by showing high sensitivities to factors such as temperature and load profiles. Therefore, to calculate the energy consumption for each trip (E_{Trip}, eq. 1) the recorded sum of the average values of battery current (I_{Bat}) and voltage between (U_{Bat}) two data points multiplied by the time difference ($\Delta t_{i,i-1}$) was taken. In the next step the specific energy consumption for each trip ($E_{Trip,spec}$, eq. 2) was calculated by dividing the total energy consumption by the distance covered (D_{Trip}).

$$E_{Trip,total} = \sum_{i=Start+1}^{End} \frac{(I_{Bat,i}-I_{Bat,i-1})}{2} \times \frac{(U_{Bat,i}-U_{Bat,i-1})}{2} \times \Delta t_{i,i-1} \quad (1)$$

$$E_{Trip,spec} = \frac{E_{Trip}}{D_{Trip}} \quad (2)$$

In the following analysis average monthly values were taken. This was done due to the observed high variance of energy consumption for the individual trips on identical routes, most likely depending on factors such as time of day, direction of travel, or current driver, etc., which are not investigated in this study.

Secondly, to analyze the observed effects average driving profiles for both EV types were created based on recorded data (e-Wolf Delta 2 Route 1 and Nissan Leaf Route 7). Identical to the data loggers as the constant equidistant time difference between two data points for the e-Wolf Delta 2 20 s and for the Nissan Leaf 1 s was taken. These artificial diving profiles were put into an individual adjusted theoretical energy consumption model considering the specific efficiency values of the powertrain components (Fig. 2), which were provided by the manufacturers and validated by putting the EV on the dynamometer (Fig. 1) and comparing to values from the literature [10], as well as the individual recuperation algorithms.

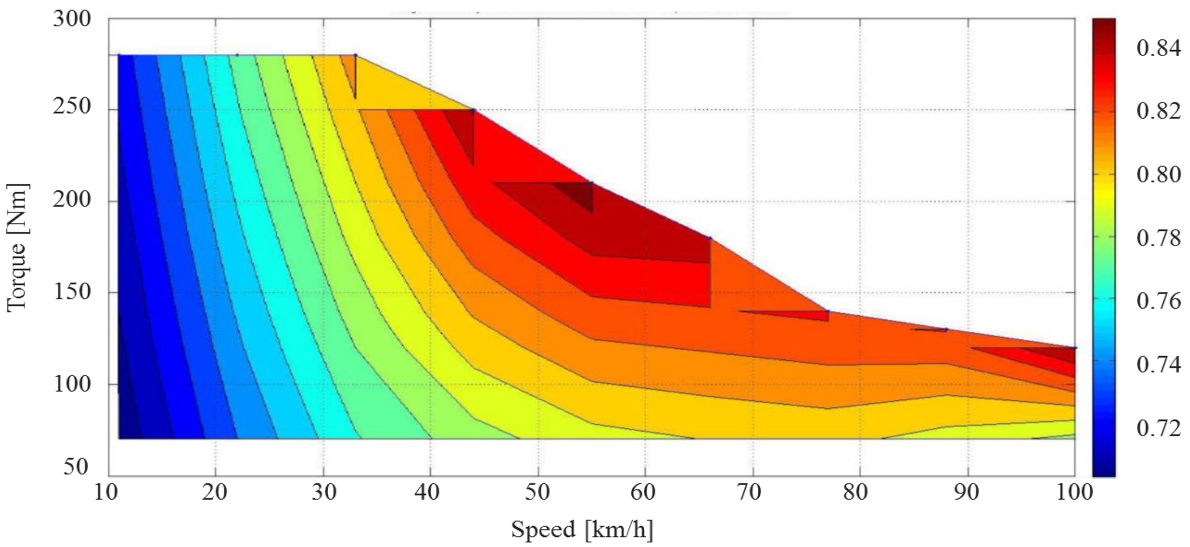

Figure 1: Range of efficiency for Delta 2 powertrain (measured in 11 km/h and 70 Nm intervals)

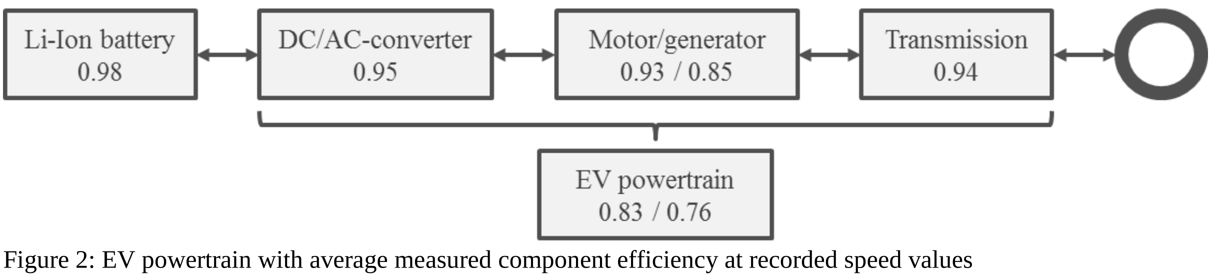

Figure 2: EV powertrain with average measured component efficiency at recorded speed values

The developed energy consumption simulation model distinguishes two driving states at different points of time during the trip (index k): taking electric energy from the battery for propelling the EV forward ($P_{k,el.sup}$, eq. 4) and recuperating electric energy back into the battery ($P_{k,el.rec}$, eq. 5.1 – 5.3). For both driving states an individual powertrain efficiency ($\eta_{pt,sup}$, $\eta_{pt,rec}$) is considered dependent on speed (v), torque (τ), and Temperature (T). The required power at the wheels ($P_{k,wheels}$, eq. 3) is the sum of the power for acceleration ($P_{k,acc.}$), the power necessary to climb an ascending slope ($P_{k,climb}$) as well as the power to overcome the rolling resistance ($P_{k,roll.res}$) and drag ($P_{k,drag}$). It is calculated based on the current speed (v), the change in speed ($\dot{v}$), the additional load (m), and the road gradient (α). The energy required for acceleration as well as to climb an ascending slope can potentially be recuperated, while the one used to overcome rolling resistance and drag is lost. The equations for the recuperation below exemplary show the calculation for the e-Wolf Delta 2 based the specific design of the algorithm: only recuperating energy above the speed of 20 km/h (eq. 5.1) and only up to a maximum of 22 kW battery charging power (eq. 5.3). The power demand or supply for each point in time of the driving cycle was added to the power demand of the auxiliaries ($P_{k,aux}$), which was then multiplied by the equidistant time difference ($\Delta t_{k,k-1}$), added up, and divided by the temperature dependent battery efficiency (η_{bat}) to calculate the total energy consumption for a single trip (E_{Trip}, eq. 6). To get the specific energy consumption ($E_{Trip,spec}$, eq. 7) the total energy consumption was again divided by the covered distance (D_{Trip}). To validate the model the results of the total energy consumption as well as the progression for different individual trips were subsequently compared to the energy consumption empirically measured confirming the accuracy of the developed model for the analyzed EV types.

$$P_{k,wheels} = P_{k,acc.}(v,\dot{v},m) + P_{k,climb}(v,\alpha) + P_{k,roll.res}(m,v,\alpha) + P_{k,drag}(v) \tag{3}$$

$$P_{k,el.sup} = P_{k,wheels} \times \frac{1}{\eta_{pt,sup}(v,\tau,T)} \tag{4}$$

$$P_{k,el.rec} = 0 \quad if \ \frac{\sum_{i=k-1}^{k+1} v_k}{3} < 20\ km/h \tag{5.1}$$

$$P_{k,el.rec} = P_{k,wheels} \times \eta_{pt,rec}(v,\tau,T) \quad if\ P_{k,wheels} \times \eta_{pt,rec}(v,\tau,T) \leq 22\ kW \tag{5.2}$$

$$P_{k,el.rec} = 22\ kW \quad if\ P_{k,wheels} \times \eta_{pt,rec}(v,\tau,T) > 22\ kW \tag{5.3}$$

$$E_{Trip} = \frac{1}{\eta_{bat}(T)}\left[\sum_{k=Start+1}^{End} (\Delta t_{k,k-1} \times (P_{k,el.sup} + P_{k,aux})) + \sum_{k=Start+1}^{End} (\Delta t_{k,k-1} \times (P_{k,rec} + P_{aux}))\right] \tag{6}$$

$$E_{Trip,spec} = \frac{E_{Trip}}{D_{Trip}} \tag{7}$$

In this study the developed simulation model was mainly used to investigate the effects of auxiliaries and drag in relation to travelling speed. Since the EV were deployed on constant routes and the individual driver was unknown, influence factors such as driving style, or drivers experience were excluded in this study. Also the vehicle load influencing the power to overcome the rolling resistance as well as the power required for acceleration was only estimated with the average number of passengers. It was the only way, because for privacy reasons for the individual trips there was no data available at which points on the route the workers where embarking or disembarking the EV or how many workers were using the EV for a business trip. To specifically examine the sensitivities to drag and the use of the auxiliaries of the energy consumption in relation to the average driving speed for both EV types the speed values of the created average driving profiles were put into the model and varied proportionally.

Thirdly, to not only study the relation to average speed, but also to investigate the effects of a greater distribution of speed values the recorded data of the Nissan Leaf was analyzed, by comparing the standard deviation of the speed values to the specific energy consumption and the average speed. The Nissan Leaf was taken since the data logger had a higher measurement resolution and therefore allowing a more precise calculation of the statistical distribution. The empirical and simulated values for the total and specific energy consumption are based on a tank-to-wheel (TTW) system boundary.

Both EV types in the project were chosen based on the technical and user specific requirements of the two applications. The main technological selection criteria were the possibility of DC fast charging, sufficient battery capacity to ensure a one-way trip even under restrictive conditions, and cycle stability under the intensive and frequent use of DC fast charging. In addition to the technological requirements the EV needed to fit the demands of the travelers concerning size and comfort. According to these criteria only two EV models were available at that time: the e-Wolf Delta 2 (and the updated EVO-version) for the commuters and the Nissan Leaf for the business trips. The technical specifications can be found in Table 1.

Table 1: Technical specification of the deployed EV (Source: Technical datasheet provided by manufacturers)

	e-Wolf Delta 2	e-Wolf Delta 2 (EVO)	Nissan Leaf
Number of EVs deployed	3	3	1
Specific energy consumption (NEDC) [Wh/km]	187	200	173
Max. motor power output [kW]	90	90	80
Cabin heating	Biodiesel	Biodiesel	Battery
Nominal battery capacity [kWh]	24.20	32.00	24.00
Real battery capacity [kWh]	22.26	29.44	20.85
Battery chemistry	Li-ion NMC	Li-ion NMC	Li-ion G/LMO-NCA
Drag coefficient	0.31	0.31	0.285
Frontal area [m^2]	3.32	3.32	2.6
Vehicle mass [kg]	1,660	1,650	1,525

All EV were equipped with data loggers connected to the CAN bus recording powertrain and GPS data. For the e-Wolf Delta 2 EV amongst others the following powertrain and GPS data was recorded: date and time, parameters of the high-voltage-battery, such as voltage, battery current, medium cell temperature, and SOC, speed and odometer based on axis turning, GPS height, GPS odometer, GPS speed, GPS position latitude and longitude. For the Nissan Leaf a data logger directly connected via Bluetooth to the on-board diagnostic system (OBD) was installed. This allowed detailed access to a wide range of powertrain data, e.g. battery currents, voltages, temperatures, SOC, charging status as well as GPS data. Over the duration of 2.75 years for the seven EV over 450,000 km were logged. Additionally the EV were set on a dynamometer to assess their energy consumption and power train efficiency under controlled conditions.

3 Results

In order to investigate the effect of the influence factors on the specific energy consumption the results presented in the following are the recorded energy consumption values, the simulated effects of drag and auxiliaries in relation to average speed, and the consequence of a higher speed variance in the driving profile.

3.1 Long-term specific energy consumption

As first step of identifying influence factors the values for the long-term energy consumption are analyzed. Even though all EV were deployed on constant routes, for the two applied EV types significant differences in the energy consumption over the time of use can be observed (Fig. 3). For the specific energy consumption of the e-Wolf Delta 2 vehicles differences between the routes and time of year can be detected. As one reason for the variations between the routes the different shares of inter-urban and motorway route parts can be stated. Route 4 is mostly motorway and shows the highest average speed of all commuter routes with 60 km/h also leading to the highest specific energy consumption. Concerning the fluctuations a clear identification of causing factors is more difficult. Sometimes one worker being on holiday changes the route of the commuting group and therefore the specific energy consumption varies. Some fluctuations however can be explained by the changes in outside temperature. Especially between November 2014 and March 2015 an increase in specific energy consumption for almost all e-Wolf Delta 2 of around 20 Wh/km can be observed. Since the heating for the e-Wolf Delta 2 is done with Biodiesel the increase cannot be directly explained with an increase in auxiliary demand. Further analysis indicated that in the cold months the increase can be explained by a combination of battery chemistry and battery management design: Lower outside temperatures also cool down the battery temperature leading to a higher battery's inner resistance which decreases battery efficiency. Additionally the battery management system reduces the recuperation power depending on the current cell temperature to avoid potentially harming effects on the cell chemistry by charging with higher currents. The energy instead is lost through mechanical breaking, leading to a higher specific energy consumption. Other potential factors can be a more frequent use of specific auxiliaries such as headlights, wipers, and cabin fan. Secluding it should be noticed that on average the specific energy consumption lies around 235 Wh/km, which is significantly higher than the NEDC value stated by the manufacturer (Table 1).

The Nissan Leaf, due to the lower weight and better aerodynamics in comparison shows lower specific energy consumption, with the lowest point at 150 Wh/km (Fig. 3), which even lies below the NEDC value stated by the manufacturer (Table 1). On the other hand it shows a much higher variance between winter and summer. Even though different reasons for this increase in months of lower average temperatures can be adduced, the data shows that the cabin heating, that takes energy from the battery instead of an additional heating device, has the biggest influence. A maximum value of close to 4 kW was recorded for cabin heating power taken from the battery. This indicates the significant influence of the cabin heating on the specific energy consumption even at the relatively high average speed: At the measured average speed of around 70 km/h for the business trips the full heating power of 4 kW leads to an additional specific energy consumption of 57 Wh/km, which is an increase of 33% to the NEDC. Under these circumstances short term test measurements on urban routes showed specific energy consumption values up to 280 Wh/km.

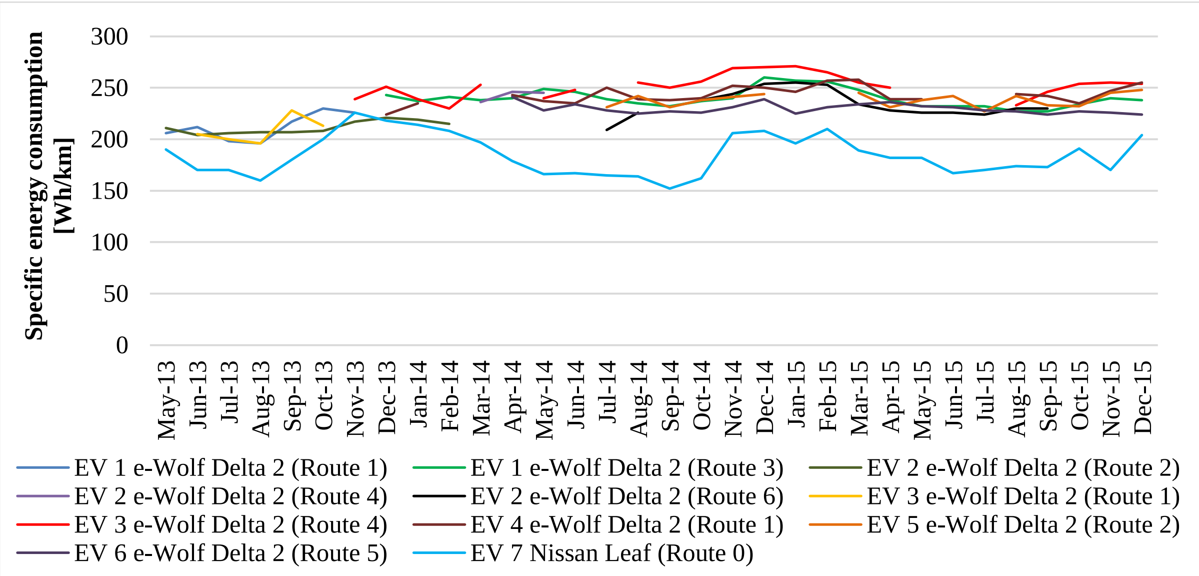

Figure 3: Measured monthly average specific energy consumption of the RheinMobil EV

3.2 Effect of drag and auxiliaries on specific energy consumption

The results of the specifically for both EV types developed energy consumption simulation model for the averaged recorded empirical driving profiles with proportionally varied speed values clearly underline the reverse effects of the auxiliaries and drag in relation to average speed on the specific energy consumption. Figure 4 shows the total specific energy consumption taken from the battery depending on the average speed for both EV types and two levels of auxiliary demand. The auxiliaries' power demand levels of 1.1 kW as average and 4 kW as maximum were chosen according to the recorded values. At the same level of auxiliaries' power demand the energy consumption at low average speeds for both EV types is very similar. With an increase in average speed the difference between the two curves increases. At higher average speeds the discrepancy between the different auxiliary demand levels diminishes. The progression of the curves illustrates the relatively changing influence of auxiliaries and drag at different speed levels. At a constant use of 1.1 kW auxiliaries under these driving conditions the minimum specific energy consumption lies at 22 for the Delta 2 and 28 km/h for the Leaf. The maximum auxiliaries' power demand of 4 kW leads to a minimum of specific energy consumption at 38 or 42 km/h respectively.

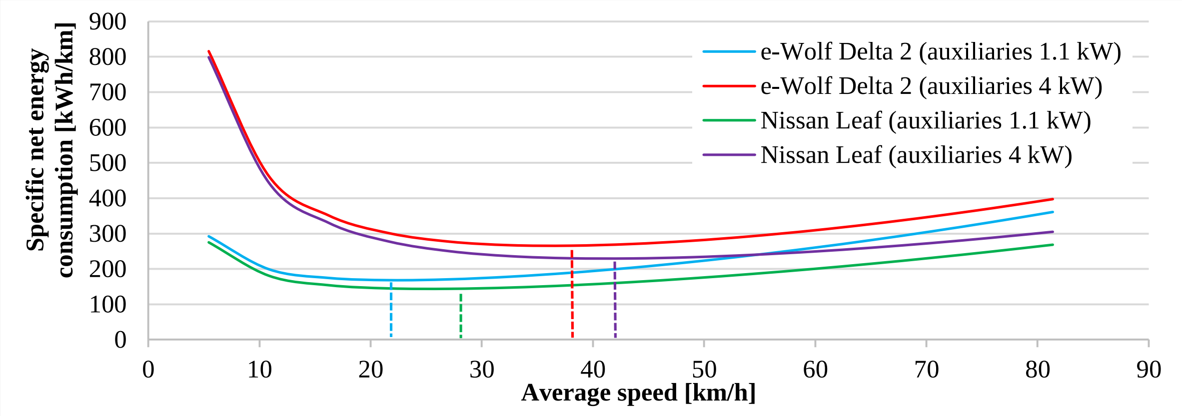

Figure 4: Energy consumption model e-Wolf Delta 2 and Nissan Leaf based on average empiric driving profiles

3.3 Effect of speed variance on energy consumption

Furthermore the empirical results suggest that even at high average speed values the distribution has an effect on the specific energy consumption that should not be neglected. Figure 5 shows the relation of specific energy consumption and recuperation to the standard deviation of the speed values for one trip as well as its relation to average speed. Even for the limited range of average speed values from 56 to 73 km/h, due to the constant mostly inter-urban and motorway driving profile the, clear correlations can be detected. The specific energy consumption as well as the specific recuperation increases with a higher standard deviation of speed values. The increase in recuperation does not fully compensate the increase, which is understandable due to efficiency rates, imperfect driving, and the quadratic with speed increasing losses due to drag. Therefore the specific net energy consumption increases with a higher speed variance. The data also shows that with a higher average speed the standard deviation of speed values for one trip decreases. This has to be interpreted carefully since the EV was deployed on a fixed route and therefore cannot be accounted to changes in the route profile, but might be the effect of traffic density or driving style.

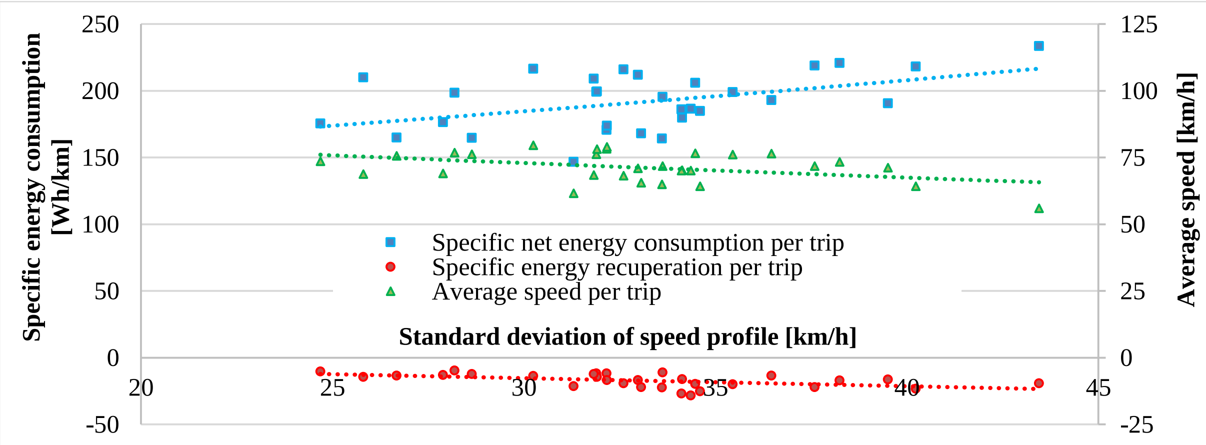

Figure 5: Measured effects of speed volatility on specific energy consumption and recuperation Nissan Leaf

4 Discussion & Outlook

The empirical results and the adapted theoretical model underline the importance of a careful EV energy consumption assessment and forecast. They specifically demonstrate the opposing effects of auxiliaries and drag at different average speed levels on the specific energy consumption. Furthermore, they substantiate that not only the average speed, but also the volatility of speed and therefore the amount and amplitude of acceleration and deceleration processes has a significant impact. The ramifications of these influencing factors become particularly relevant when operating EV on fixed routes at their upper technical boundary, with the goal of reaching an economic break-even.

Considering the presented influence factors in the context of economic deployment from a technological point of view the maximum specific energy consumption even under the most challenging circumstances must be low enough to allow a full one way tour on a single battery charge. As the empirical results (cf. Fig. 3) and the simulation results (cf. Fig. 4) show a changing use of auxiliaries plays a significant role when it comes to variations in energy consumption on constant routes – even more so at lower average speeds. They can lead to a high variance between specific energy consumption in winter (represented by a high auxiliary energy demand) and milder temperatures. Therefore, the worst case assumption, the constant maximum energy demand of the auxiliaries, has to be taken as restriction limiting the maximum distance. In this context the TTW energy consumption is relevant variable, since the EV battery capacity sets the limit.

The empirical and simulation results further suggest that the presented influencing factors have a direct effect on the point where EV deployment is most economical in comparison to ICEV. An intuitive approach would be to identify the point of the comparable highest relative energy efficiency. The values in Table 2 show energy consumption values measured by ADAC for identical vehicles with different means of propulsion. They indicate that the point of most comparable energy efficiency between EV and ICEV is not necessarily identical to the EV specific consumption minimum. It rather lies at low speeds on inner-city routes characterized by frequent starts and stops. The values in Table 2 however do not consider a variation in auxiliary energy demand. As the results of this field-test show, to provide a more comprehensive analysis, the variance in energy consumption based on the auxiliary demand must be taken into consideration. This is especially true for the effects of an additional energy demand for passenger cabin heating. For ICEV the required energy can be taken from the excess heat of the combustion process and is not increasing the total energy consumption. Therefore, from an economic point of view the realistic long-term average energy consumption including all relevant influencing factors has to be taken for EV ICEV comparison. Regarding the system boundary in this context the ICEV fuel consumption needs to be compared to the EV grid-to-wheel (GTW) energy consumption, since this way also losses occurring in the charging process, which are hence payed for when charging the EV, are included.

Table 2: Empiric TTW consumption EV & ICEV (Source: ADAC EcoTest Data base, last accessed 01.03.2016)

	NEDC	**ADAC EcoTest**				
	Average	**Average**	**Inner-city**	**Inter-urban**	**Motorway**	
Smart fortwo electric drive (55 kW)	15,1	19,0	13,2	17,1	26,8	[kWh/100km]
Smart fortwo (gas, 52 kW)	4,1	5,1	5,5	4,5	6,3	[l/100km]
Energy saving EV vs. ICEV[1]	57%	56%	72%	55%	50%	
VW e-up! (60 kW)	11,7	13,7	10,4	11,6	18,6	[kWh/100km]
VW up! (gas, 55 kW)	4,7	5,5	5,9	4,1	6,4	[l/100km]
Energy saving EV vs. ICEV[1]	71%	71%	79%	67%	66%	
VW e-Golf (85 kW)	12,7	18,2	12,7	16,3	25,1	[kWh/100km]
VW Golf (diesel, 77 kW)	3,8	4,5	5,1	3,9	5,3	[l/100km]
Energy saving EV vs. ICEV[1]	66%	59%	75%	57%	52%	
Nissan e-NV200 (80 kW)	16,5	21,8	11,5	21,8	32,4	[kWh/100km]
Nissan NV200 (diesel, 81 kW)	5,5	6,2	6,3	5,0	8,0	[l/100km]
Energy saving EV vs. ICEV[1]	69%	64%	81%	56%	59%	

[1] neglecting the losses occurring during EV charging, which should be considered for an economic comparison

When considering the worst-case energy consumption as technological limitation for the one way distance and the realistic long-term average energy consumption as basis for economic valuation it can be deduced that the point of the highest comparable energy efficiency just based on the energy required for propulsion might not be the best for EV deployment when aiming for the fastest economic break-even. On the contrary the results indicate that deploying EV on constant routes profiles with higher average speeds accrues advantages that can redeem the lower comparable energy efficiency. The lower maximum specific energy consumption at full use of auxiliaries means that the EV can be deployed constantly on routes with longer one way distances. This increases the possible maximum annual mileage and hence the multiplier for reaching the economic break-even. As the values in Table 2 show the loss in relative efficiency between inner-city and inter-urban or even motorway route profiles is not high and the relative efficiency still lies above 50%. Therefore, increasing the annual mileage through longer one-way distances has the potential to more than compensate the losses in relative efficiency. When operating on a system with flexible EV deployment under predictable conditions the maximum energy consumption has only be considered under the current conditions and therefore the utilization of the economic potential could be increased further.

Considering the research method, setting, and focus of this field-test, transferring the findings and conclusions into a broader context must be done cautiously. Several limitations can be identified that could be addressed in future research. The empirical results are limited to the two analyzed EV types and are restricted for deployment on constant routes with average speed ranges between 55 and 75 km/h. This especially limits the validity for the influence of speed variance, which should be investigated in detail for urban profiles. Also under these conditions with more frequent starts and stops and a potentially higher share of energy recuperation the driving style can also play a more significant role. Furthermore, the volatility of auxiliary use is based on the changes in German climate conditions throughout the year. In other climate zones these effects might be stronger or less relevant. Lastly, the results of this case study can only indicate a potentially different way of thinking about economic EV deployment when considering the current state of technology. No direct empirical comparison of ICEV and EV deployment under identical conditions over a longer time frame is presented. To verify the presented suggestions this should be done while varying the route profiles between inner-city and motorway and carefully considering the right energy measurement system boundaries.

Acknowledgments

The authors thank the BMVI – Federal Ministry of Transport and Digital Infrastructure for enabling this project within the framework of the Schaufenster Elektromobilität and the LivingLab BWe mobil. They also thank their colleagues from the Institute of Vehicle System Technology (FAST) at KIT for granting access to their dynamometer and providing their expertise for measuring the EV energy consumption and power train efficiency under controlled conditions.

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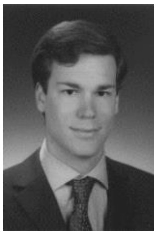
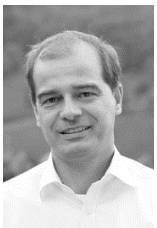


Maximilian Schücking is a scientist at project Competence E (PCE) at the Karlsruhe Institute of Technology (KIT). He is responsible for the data analysis in the research project RheinMobil. He is also a Ph.D.-student at the chair of energy economics. He holds a Master's degree in Industrial Engineering from the KIT.

Patrick Jochem is research group leader at the KIT-IIP, -DFIU, -KSRI, and chair of energy economics. In 2009 he received his Ph.D. in transport economics from KIT. He studied economics at the universities in Bayreuth, Mannheim and Heidelberg, Germany. His research interests are in the fields of electric mobility and ecological economics.



Wolf Fichtner is director of the KIT-IIP, -DFIU, and -KSRI. He is full professor and holder of the Chair of Energy Economics at KIT. His main areas of research are energy system modelling and the techno-economic analysis of energy technologies.

Olaf Wollersheim is head of PCE, which bundles all work in the field of electric energy storage for mobile and stationary applications at the KIT. He studied physics in Bonn, where he received his Ph.D. His research focuses on the development of lithium-ion-based batteries for stationary and mobile applications.

Kevin Stella is project manager and scientist for the application of storage technologies at PCE (KIT). Since 2013 he is the leader of the research project RheinMobil. 2012 he completed his MBA studies at the Collège des Ingénieurs (Paris, Munich, Turin). In 2011 he received his Ph.D. in physical chemistry from the University of Duisburg-Essen.

Transportation Research Part D 51 (2017) 173–189

Contents lists available at ScienceDirect

Transportation Research Part D

journal homepage: www.elsevier.com/locate/trd

Charging strategies for economic operations of electric vehicles in commercial applications

Maximilian Schücking [a], Patrick Jochem [b], Wolf Fichtner [b], Olaf Wollersheim [a], Kevin Stella [a,*]

[a] Project Competence E, Karlsruhe Institute of Technology, Hermann-von-Helmholtz-Platz 1, D-76344 Eggenstein-Leopoldshafen, Germany
[b] Institute for Industrial Production (IIP), Karlsruhe Institute of Technology, Hertzstraße 16, D-76187 Karlsruhe, Germany

ARTICLE INFO

Article history:
Received 24 October 2015
Accepted 28 November 2016
Available online 19 January 2017

Keywords:
Battery electric vehicles
Charging strategies
DC fast charging
Key performance indicators

ABSTRACT

When substituting conventional with electric vehicles (EV) a high annual mileage is desirable from an environmental as well as an economic perspective. However, there are still significant technological limitations that need to be taken into consideration. This study presents and discusses five different charging strategies for two mobility applications executed during an early stage long-term field test from 2013 to 2015 in Germany, which main objective was to increase the utilization within the existing technological restrictions. During the field test seven EV drove more than 450,000 km. For four out of five presented charging strategies the inclusion of DC fast charging is indispensable. Based on the empirical evidence five key performance indicators (KPI) are developed. These indicators give recommendations to economically deploy EV in commercial fleets. The results demonstrate that the more predictable the underlying mobility demand and the more technical information is available the better the charging strategies can be defined. Furthermore, the results indicate that a prudent mix of conventional and DC fast charging allows a high annual mileage while at the same time limiting avoidable harmful effects on the battery.

1. Introduction

The electrification seems to be a very promising way to cut future CO_2 emissions from road transport (Creutzig et al., 2015). This is especially true if the underlying electricity demand of electric vehicles (EV) is generated by carbon-free energy resources (such as wind or solar energy) (Ensslen et al., 2017; Jochem et al., 2015; Sohnen et al., 2015). Furthermore, EV show potential to reduce the oil dependency of western societies and decrease local emissions in urban areas, i.e. noise and local air pollutants such as SO_x, particle matters, CO and NO_x (Jochem et al., 2016). Concerning both aspects, a high life-time mileage is desirable to fully utilize the EV emission saving potential (Stella et al., 2015).

However, EV are still a new technology and therefore face some hurdles that are currently limiting their market success considerably (Ensslen et al., 2014). Two of those hurdles are the limited range of current vehicles (about 150 km) and their purchase prices that are considerably higher than the ones of their internal combustion engine driven counterparts (ICEV) (Dumortier et al., 2015). In commercial transport both limitations are easier to overcome than for private passenger car applications (Ketelaer et al., 2014). This is mainly due to the fact that for many applications trips are more predictable, single trips above the maximum range are more easily replaced by conventional cars, and the high purchase price of EV can be

* Corresponding author.
E-mail addresses: maximilian.schuecking@partner.kit.edu (M. Schücking), patrick.jochem@kit.edu (P. Jochem), wolf.fichtner@kit.edu (W. Fichtner), olaf.wollersheim@solarwatt.net (O. Wollersheim), kevin.stella@de.bosch.com (K. Stella).

http://dx.doi.org/10.1016/j.trd.2016.11.032
1361-9209/

negated by the higher annual mileage of commercial cars due to the lower variable costs of EV operation compared to ICEV (Bickert et al., 2015; Gnann et al., 2012; Plötz et al., 2015; Sierzchula, 2014).

Therefore, for environmental as well as economic motives the aim of this study is to increase the number of trips and hence the annual mileage of EV in commercial fleets. One essential part is the development of specific charging strategies that allow a high operating grade. These include the usage of fast charging infrastructure in order to show an economic advantageous application of current EV compared to conventional vehicles in an empirical field test (a detailed description of the research aim can be found in Section 2.4). The field test with several cross-border commuters from Alsace (France) to Karlsruhe (Germany) lasted from early 2013 till the end of 2015. The research project behind was comprised of two different user groups: the first were fixed car-pooling commuter groups that travelled on average 75 km one-way from their homes in France to work in Germany; the second were employees on business trips during the day between two plant sites around 70 km apart, one in Germany and one in France. The EV were equipped with data loggers tracking battery as well as GPS data to allow a detailed technological and economic analysis.

The article is structured as follows: the second section provides an overview of the existing literature focusing on charging strategies, economic reasons as well as limitations of fast charging. It illustrates the gap in the literature and states the underlying research aim. The third section introduces the research project RheinMobil and the method by explaining the research design, setting and data collection. The fourth section is divided into five subsections; each describes and analyzes a different charging strategy that was implemented for the two mobility applications. The fifth section discusses the presented strategies in reference to the literature and introduces key performance indicators (KPI) for comparison. It also includes a small Total Cost of Ownership (TCO) analysis as well as a discussion of the technological implications. The last section concludes by summarizing the results, outlining the limitations and suggesting topics for future research.

2. Literature review

There are two main perspectives in the literature on the impacts of charging EV. One comprehensive focus deals with the impact on the electricity system (1) and the second focus considers the impact on the vehicle and the battery (2). There are several dimensions for focus (1). Some studies take a macroscopic point of view by looking at the impact on the electricity load and the resulting implications on the power plant portfolio and electricity grid (Babrowski et al., 2014; Camus et al., 2011; Dharmakeerthi et al., 2014; Hadley and Tsvetkova, 2009; Hahn et al., 2013; Harris and Webber, 2014; Jansen et al., 2010), another emphasis is on additional emissions caused by electricity generation based on the timely distribution of charging (Bickert et al., 2015; Donateo et al., 2015; Ensslen et al., 2017; Jochem et al., 2015; Khoo et al., 2014; Muneer et al., 2015; Rangaraju et al., 2015; Sohnen et al., 2015; Thompson et al., 2011), still others aim on maximizing the input from (local) renewable energies (Atia and Yamada, 2015; Kier and Weber, 2015; Pantoš, 2011; Škugor and Deur, 2015; Wu et al., 2016). These topics are sometimes connected to different charging technologies such as controlled charging or even vehicle-to-grid (V2G) systems, providing virtual energy storage for grid services in the local electricity system (Bishop et al., 2016; Kristoffersen et al., 2011; Tomić and Kempton, 2007). The second focus (2) is on vehicles and their batteries. Previous studies investigate the development of an optimized charging strategy from an EV perspective considering factors such as the state of health (SOH) of the battery, cost optimized charging, including V2G, and parking time (Bashash et al., 2011; Neubauer et al., 2012). Other studies go even more into battery-related technical details by evaluating the charging and discharging behavior of the battery packs or even of individual cells (Kim et al., 2014; Onda et al., 2006; Rahimian et al., 2011).

2.1. Charging strategies for EV

The understanding of the term charging strategy presented in this study differs from the one commonly used in the literature. In previous studies "charging strategy" is mostly applied in terms of timing the charging event (from an electricity grid perspective). Three options are mainly discussed: instant charging (uncontrolled charging), controlled charging (load and time), and V2G. The idea of controlled charging mainly focuses on avoiding load peaks and improving the electricity market efficiency by offering load shift potentials (flexibilization of electricity demand/demand response) (Axsen et al., 2011; Babrowski et al., 2014; Kang and Recker, 2009). Some studies analyze the real charging behavior of EV users in the context of timing, distribution, and type of charging (Khoo et al., 2014; Sun et al., 2015a, 2015b). Other "charging strategies" focus on sustaining a high SOH of the battery (Lunz et al., 2012). Our perspective starts from a mobility application that is focused on increasing the annual mileage of EV in order to replace mileage of ICEV. Therefore, not only the time and power of charging, but also the location is highly relevant.

Currently, many authors assume that charging takes place at home, at work or at other public electric vehicle supply equipment (EVSE) (Axsen et al., 2011; Neubauer et al., 2012; Speidel and Bräunl, 2014). The configuration of the EVSE varies between locations and countries depending on charging power, grid connections, and other technological standards (Azadfar et al., 2015). Previous research suggests that for first-time EV users, home charging is most convenient and most probable – especially for households in rural areas, in suburbs or for people with access to city parking garages. However, charging at work or in public is also seen as realistic. Consequently recharging at work or public places leads to less demand for charging at home (Kang and Recker, 2009; Neubauer et al., 2012).

Developing a suitable charging strategy is highly dependent on the ratio of driving to parking time and the constraints set by customers, EV and the grid (Hahn et al., 2013). Lunz et al. (2012) suggest the following order of priorities: first, the vehicle owner's interest, second, grid stability, and as third priority grid support. The vehicle owner's interest is a combination of ensuring that the EV meets the personal mobility needs combined with economic aspects such as sustaining the battery SOH as well as personal attitude and further interests (Graham-Rowe et al., 2012). Concerning the ratio of driving to parking time many studies of conventional driving patterns or EV user behavior indicate that particularly privately used EV are not in use most of the time and are therefore available for charging; in average more than 22 h per day (Guille and Gross, 2009), or 80–96% of their lifetime (Camus et al., 2011; Lunz et al., 2012; Speidel and Bräunl, 2014). The EV spend more time than technologically required for the charging process at the EVSE (Speidel and Bräunl, 2014), and the charging time therefore has in average little impact on the EV feasibility (Greaves et al., 2014).

2.2. Economic advantages and reasons for fast charging

The high production costs of EV at the time of the field test in 2013, which were essentially the consequence of high battery prices (Plötz et al., 2013), have motivated research effort to identify and quantify potential savings in EV operations. In the context of charging some propose that potential economical savings lie in the use of V2G load shifting potentials during parking time. Simulations based on real driving patterns, different dynamic tariffs, and electricity market prices show that the potential cost reductions through controlled charging and V2G might reduce the TCO of EV in the future (Bunce et al., 2014; Dallinger et al., 2011; Ensslen et al., 2014). Even though commercial applications of EV seem to be more convenient there are only a few studies in this field, especially with empirical EV data (Kier and Weber, 2015; Škugor and Deur, 2015; Tomić and Kempton, 2007). In terms of driving patterns, Robinson et al. (2013) show in their investigation of over 30,000 EV trips that commercially used pool vehicles have the highest amount of daily trips, but also the shortest trips on average. This underlines the technical and economic potential for EV in commercial fleets.

Besides using potential savings through controlled charging, maximizing the availability and durability of the EV, to achieve a high annual as well as lifetime mileage might increase the competitiveness of commercial EV for some applications. The lower variable costs (fuel costs per km) (Alexander and Davis, 2013; Linssen et al., 2012; Plötz et al., 2013) are mainly based on the higher efficiency of EV and the spread of fuel and electricity prices, which differ considerably between countries (cf. Table 1). In some countries, e.g. Norway, the benefits amount to 15 Euro-Ct/km. Furthermore, the costs for maintenance are seen to be 50–60% lower compared to ICEV (Alexander and Davis, 2013; Richter and Lindenberger, 2010). However, due to limited long time experience there is still a high uncertainty in the real maintenance costs of EV.

One way to increase the availability of EV is the implementation of fast charging. Fast charging in the context of this paper is defined as C-rates of 1 C or higher. The C-rate stands for the relation of the applied charging current to the battery cell's capacity: e.g., for battery cells with a capacity of 40 Ah a charging current of 120 A means a C-rate of 3. According to IEC 61851-1 there are three different charging modes that are able to deliver charging power that goes beyond the standard single-phased outlet, which in Germany has a maximum charging power of max. 3.7 kW (one phase 16 A/230 V). In Germany two of them are used for passenger cars. In mode 3 the EV is charged with alternating current (AC). For passenger cars this is usually limited to 22 kW (three phases 32 A/400 V) charging power. In mode 4 the EV is charged with direct current (DC), allowing maximum charging currents of up to 400 A. Besides some exceptions, the few in 2013 available EV that were equipped with DC charging technology allowed a maximum charging power of 50 kW. For EV with battery capacities around 20 kWh (at that time most common in the market), AC charging with 22 kW leads to a charging rate of around 1 C, and 2 C for 50 kW DC charging. As a result a complete recharge would take 1 h or 30 min respectively (Bashash et al., 2011). Disadvantages of fast charging are the significant increase of investment for the EVSE (Neubauer et al., 2012), as well as the stronger impact and stress placed on the battery cells, which could harm them in the long run.

2.3. Challenges of fast charging for the Li-ion battery

One of the major problems at higher C-rates is the increased likeliness of lithium plating occurring on the anode. Plated lithium can destroy the separator resulting in short circuits and possible thermal runaways. Several studies have been reported dealing with these effects (Chandrasekaran, 2014; Kim et al., 2011, 2014; Offer et al., 2012; Onda et al., 2006; Vetter et al., 2005).

Fast charging also increases ageing effects depending on various battery conditions. Battery degradation can have many causes, some of the key factors are the depth of discharge (DOD) and temperature (Fernández et al., 2013). At high and low SOC, due to chemical effects and secondary reactions, high currents stress cells more than in the mid SOC range (Agubra and Fergus, 2013; Broussely et al., 2005; Ecker et al., 2012; Vetter et al., 2005). Furthermore, high SOC is far worse for battery health than cycling (Lunz et al., 2012; Vetter et al., 2005). Too high or too low temperatures can also harm the cells (critical values depend on the cell chemistry and set-up). Higher charging currents lead to measurably higher local heating, which can result in a departure from the temperature range for ideal performance. A detailed explanation of ageing is beyond the scope of this article, but the potentially harmful effects underline the limitations and consequences of using fast charging to increase EV availability.

Table 1
Fuel costs for EV and ICEV in selected countries for 2013 (based on data from Dudenhöffer et al. (2014), IEA (2014), OECD (2015), and Wagner (2014)).

	Variable cost (EV, Industry) [Euro-Ct/km]	Variable cost (EV, Household) [Euro-Ct/km]	Fuel costs (ICEV, gasoline) [Euro-Ct/km]
Canada	1.347	1.599	8.580
China	1.309	1.686	8.905
France	1.899	2.913	12.415
Germany	2.551	5.840	12.740
India	1.515	1.667	8.125
Japan	2.958	4.112	13.000
Norway	1.101	2.379	16.445
US	1.033	1.836	6.305

Even though fast charging is potentially harming the SOH of the battery, the time-limiting requirement by vehicles users is a serious challenge for the deployment of EV. Therefore, the US government has gone as far as setting 6 C as an objective for future charging standards (Chandrasekaran, 2014).

2.4. Research aim

From the ecological as well as the economic point of view, a high annual EV mileage, resulting in emission and potential cost savings, is desirable when substituting ICEV with EV. On the other hand, there are the above-mentioned technological limitations that need to be taken into consideration. Therefore, this study proposes conceptual suggestions and provides empirical evidence from a long-term field test in Germany of how charging strategies for EV that enable a high annual mileage under the technological restrictions can be implemented, assessed, and optimized based on different KPI. The concepts developed and conclusions drawn are based on real charging and mobility data as well as experience gathered in the development and execution of five different charging strategies in two mobility applications.

3. Research method and data

In order to answer the proposed research questions this paper takes a holistic experimental research approach, analyzing the development and application of different charging strategies according to their operational implications in two commercial applications. The field test was part of the research project RheinMobil, which itself was part of a greater publicly subsidized initiative financed by three different German Federal Ministries (Transport, Economics, and Research). RheinMobil itself was financially supported by the Federal Ministry of Transport and Digital infrastructure, which took no influence on the study design, data collection, analysis and interpretation of data. Its main objective was to demonstrate how EV are able to technologically and economically substitute ICEV and to maximize environmental benefits in commercial day-to-day operations: commuting and business trips (Stella et al., 2015). For this reason, three companies and two research institutions launched the project together in 2013. In order to demonstrate an economical application of EV, the annual mileage should be high enough to compensate for the higher investment in purchasing the car. Accordingly, one key part of RheinMobil was the development and adaption of charging strategies that enable these high annual mileages and allow to prove the reliability of EV components under stringent conditions.

3.1. Research setting

RheinMobil focused on two different mobility applications: the commuting of car-pooling shift workers and internal business trips of employees between two plant sites. The two applications were selected according to a distinctive set of conditions:

- Firstly, the deployment and routing of the vehicles is constant.
- Secondly, the distance of a one-way trip does not exceed the realistic maximum range of the EV.
- Thirdly, short recharging cycles allow for more than one or two trips per day on the selected routes.

Fulfilling these criteria ensures on the one hand that the EV offer an adequate range for the selected application, and on the other hand that, due to the high mobility demand on the route, a high operating grade and therefore mileage per year can be achieved. For both reasons it is essential that the routes travelled remain more or less constant and that the frequencies of use and charging time are almost completely predictable.

In the first mobility application, the commuting of shift workers in established car-pool groups provides a sensible application for an economically feasible e-mobility transport solution. Different studies have already identified the high potential of EV for commuting (Brunnert, 2012; Linssen et al., 2012; Richter and Lindenberger, 2010; Tomić and Kempton, 2007). Our application fulfills the criteria of fixed travel times and routes: the groups leave and arrive at regular times based on the shift schedule and they keep to their usual commuting routes. Furthermore, all parking places are equipped with EVSE and the commuting distances are rather long, on average 75 km one-way (cf. Table 2). This leads to an annual mileage for a single shift worker of about 36,000 km.

In the second mobility application, the business trips of employees between two production sites, not all of our set criteria are met. Trips are in this case less predictable, the user groups change and also the time of use varies. This creates uncertainty for charging times. Nevertheless, the route remains (more or less) constant and distances are similar, on average 70 km. One single trip per workday leads to an annual mileage of about 34,000 km.

All EV in the project were chosen according to technological and user specific requirements of the two applications. The first main condition was that batteries had to have sufficient capacity to ensure that even under restrictive conditions such as cold temperatures the EV would still be able to travel at least one way without the need of recharging. The second main condition was DC fast charging. In Germany at the starting time of the project, in 2013, the only available technology for DC fast charging (mode 4) was with the CHAdeMO system with a charging rate of up to 50 kW. Besides the sufficient range and option to fast charge, the EV were also selected according to the installed cell technology. The battery cells needed enough cycle stability under the planned fast charging conditions to sufficiently allow the proposed intensive use of fast charging without quickly showing significant capacity losses. In addition to the technological requirements the EV needed to fit the demands of the travelers concerning size and comfort. Since the commuters travelled in groups of up to seven people and the employees on business trips were travelling in groups of one to four people the EV had to have at least that amount of seats (cf. Table 2). The only two EV that were fulfilling these conditions and were available in Germany in early 2013 were the e-Wolf Delta 2 and the updated EVO-version for the commuters and the Nissan Leaf for the business trips. In total seven EV were deployed in the field test. The detailed technological data for both EV can be found in Table 3.

Besides the differences listed in Table 2, the applications can be distinguished from each other by their different requirements on charging technology. Similar to the EV, the conductive charging infrastructure was selected according to the technological requirements set by the two different mobility applications. In the case of commuting, EV can be deployed without the necessity of fast charging EVSE. Both time spans at home and at work are sufficient for conventional full charging cycles. However, during the field test it became necessary to install a fast charging station at the plant site in order to create the potential to increase the annual mileage significantly (c.f. Table 4).[1] This goes hand in hand with a developed car sharing principle between all commuting groups, which is described in Section 4.1 below. For the business trips between the two plant sites the time span is heterogeneous and mostly not sufficient for conventional charging; in particular, usual meetings with durations of less than two hours do not mesh with the conventional charging technology. Accordingly, on both ends DC fast charging EVSE was installed right from the beginning (c.f. Table 4).

3.2. Data collection

During the field test the EV were equipped with data loggers. The e-Wolf Delta 2 data loggers (VIKMOTE VX 20, Vikingegaarden) were connected directly to the CAN-bus of the vehicle and constantly send their data via UMTS to the online server data base. With timely equidistant data points, the following vehicle and GPS data was recorded: date and time, voltage in the 12 V-battery, voltage in the low voltage-circuit, several parameters of the high-voltage-battery, such as voltage, mean cell voltage, battery current, medium cell temperature, and SOC, as well as remaining range, speed and odometer based on axis turning, GPS height, GPS odometer, GPS speed, GPS position latitude and longitude, and address according to GPS. The data can be ascribed to the individual cars and user groups. The data logger was active while the ignition was switched on as well as during charging processes. For the data collection of the Nissan Leaf two different approaches were taken. Mainly a conventional online platform provided by the OEM to review the energy consumption and operation of the EV was used. This database shows the current SOC, the remaining range, and whether the vehicle is currently charged or not. Additionally, it lists historical data such as trips made, distances travelled, energy consumed by the engine, energy consumed by the auxiliaries, energy recuperated through regenerative breaking and travel time. To record the charging curves as well as to assess the accuracy of the online data for a five-month period an extra data logger directly connected via Bluetooth to the EVs on-board diagnostic system (OBD) was installed. This allowed detailed access to a wide range of additional data, e.g. battery currents, voltages, temperatures, SOC, SOH, charging status as well as GPS data. From early 2013 to the end of 2015, over 450,000 km of fully electrically driven mileage as well as over 5000 conventional and 650 DC fast charging events were logged.

4. Charging strategies for an economical application of electric commercial cars

In the following we present and evaluate five different charging strategies, which allow a significant increase of the EV operating grade. The first three (1.1–1.3) refer to the commuting application: the first solely relying on conventional AC charging, the other two including DC fast charging for achieving a higher annual mileage. The remaining two charging strategies (2.1 and 2.2) belong to the business trip application.

[1] Since the e-Wolf EV had a board voltage above 600 V, for which both DC-fast standard charging plugs CHAdeMO and CCS are not certified, e-Wolf built a special charging station, which worked on the open source CHAdeMO protocol, but used the Harting plug, which comes from railway technology and is certified up to 1000 V.

Table 2
Overview of the two selected mobility applications.

	Application 1: Commuting of car-pooling shift workers	Application 2: Business trips between sites
User group	Employees in shift production	All employees
User per EV	5–7 people	1–4 people
Fixed user group	Yes, fixed group(s) per EV	No, changing each trip
Time of use	Around the clock, 7 days a week	7 am to 8 pm, 5 days a week
One-way distance	75 km	70 km
Average speed	55 km/h	71 km/h
EV	3 e-Wolf Delta 2, 3 e-Wolf Delta 2 (EVO)	1 Nissan Leaf
Charging locations	Home and at work	Both plant sites
Charging infrastructure	12 standard outlets (max. 3.7 kW) 1 e-Wolf CHAdeMO (max. 30 kW)	1 standard outlet (max. 3.7 kW) 2 S CHAdeMO (max. 50 kW)

Table 3
Technological data of the applied EV.

Technical data	e-Wolf Delta 2	e-Wolf Delta 2 EVO	Nissan Leaf
Number of deployed EV	3	3	1
Traction battery capacity (nominal)	24.2 kWh	32 kWh	24 kWh
Traction battery voltage (max.)	720 V	720 V	360 V
Cell technology	Li-ion NMC	Li-ion NMC	Li-ion LMO-NCA
Energy consumption (NEDC)	187 Wh/km	200 Wh/km	173 Wh/km
Maximum range (NEDC)	154 km	165 km	175 km
Peak performance	90 kW	90 kW	80 kW
Cabin heating	Bio-Diesel	Bio-Diesel	HV-Battery
Vehicle mass (empty)	1666 kg	1650 kg	1525 kg
AC charging power (nominal)	2.6 kW	2.5 kW	2.3 kW
AC plug type	Type 2 (EN 62196-2)	Type 2 (EN 62196-2)	Type 1 (SEA J1772)
AC charging mode	Mode 1	Mode 1	Mode 2
DC charging power	Up to 30 kW	Up to 30 kW	Up to 50 kW
DC communication protocol	CHAdeMO	CHAdeMO	CHAdeMO
DC plug type	Harting	Harting	CHAdeMO
Data logger	On-board CAN and GPS Logger	On-board CAN and GPS Logger	Online overview, On-board OBD and GPS

Table 4
Technical parameters of fast charging EVSE installed in the project.

	e-Wolf EW-DC-30	Siemens CP3000
Input voltage	3-phased 340–460 V AC	3-phased 400 V AC
Input current	64 A	80 A
Efficiency	<95.5%	<94%
Output voltage	500–700 V DC	50–500 V DC
Output current	Max. 50 A	Max. 120 A
Output power	Max. 30 kW	Max. 50 kW
Plug type	Harting	CHAdeMO
Communication protocol	CHAdeMO	CHAdeMO
DC charging mode	Mode 4 (IEC 61851-1)	Mode 4 (IEC 61851-1)

4.1. Charging strategies for commuting shift workers

The three charging strategies applied for the commuting case can be directly connected to the premises set by the shift schedule as well as the travelling routes and times. In the current shift system, the car-sharing groups leave their home roughly two hours before the start of the shift, drive about 75 km to the plant and pick up colleagues on the way. They arrive about 30 min before the start of the shift at 6 am, 2 pm, or 10 pm. Each shift lasts 8 h and after the shift they immediately start their journey back to their homes where they arrive about one and a half hours later. Each new charging strategy represents an increase in the possible annual mileage.

4.1.1. Strategy 1.1: Relying on conventional charging (mode 2) only for one user group per EV

The first charging strategy was developed based on the technological data of the charging processes (mode 2), the energy consumption of the EV and the shift schedule of one commuter group. With 8.5 h at work and 12.5 h at home available for recharging (cf. Fig. 1) and an effective measured power after considering charging losses of around 2.30 or 2.19 kW respectively (c.f. Fig. 2 and Table 5), the theoretical maximum energy that can be recharged at work is about 18.7 kWh and 27.5 kWh at home. With a measured average energy consumption of about 230 Wh/km (NEDC is 187/200 Wh/km, c.f.

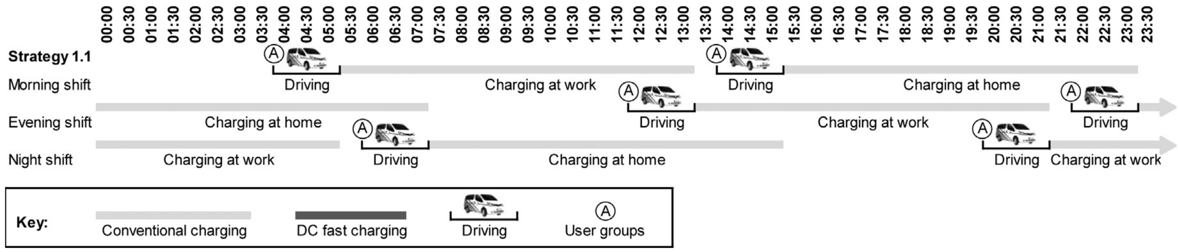


Fig. 1. Illustration of the commuting charging strategy 1.1.

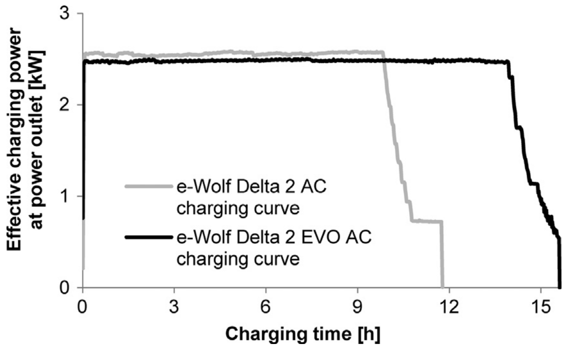


Fig. 2. Conventional AC charging curves of the e-Wolf Delta 2 and Delta 2 EVO.

Table 3) the maximum distance that can be covered by a recharge at work is about 81 km. The average distance of a one-way journey lies at around 75 km and the energy consumption therefore is 17.25 kWh, which requires about 8 h of recharge. Accordingly, for each EV deployed one conventional charging point is required on each end of the route. The calculations show that during the working shift almost the whole time is required for charging. At home only around 2/3 of the available time is needed for charging. With this charging strategy an annual mileage around 36,000 km a year can reached. Based on the average distance of 75 km the total charging time is about 16 h (66.7%), the total driving time is 3 h (12.5%), and finally the idle time equals 5 h (20.8%). The complexity for the vehicles users of this strategy is very simple since it did not involve switching EV or using different charging technologies.

4.1.2. Strategy 1.2: Using fast charging to enable three or four user groups to share two EV

In order to increase the annual mileage, it becomes necessary to assign more than one commuter group to each EV. Based on the shift schedule, three or four groups that work different shifts are required to share two EV amongst them. While the travel distances and the time for recharging at the plant remain constant, the time available for recharging at home changes: once a group arrives at home another group uses the EV to get to their next shift. The available charging time is reduced to 4.5 h. Fig. 3 illustrates the strategy 1.2 by showing the driving and charging schedule over three days for one EV and three user groups.

The shorter available charging time at home requires the installation of DC fast charging at the plant site. Calculating with an effective conventional AC charging rate of 2.19 kW (cf. Fig. 2) and the energy consumption of about 17.25 kWh per trip, it becomes obvious that the reduced charging time at home, in which only about 9.9 kWh can be recharged, is insufficient. As can be seen in Fig. 4 both the Delta 2 and Delta 2 EVO cannot constantly operate under these requirements. While the Delta 2 can accomplish only one round-trip, the Delta 2 EVO comes to an end after three round-trips. Only the fast charging infrastructure at the plant site allows sustainable operation of this strategy.

Based on the charging power and duration of the DC fast charging process as well as the energy consumption of the EV the charging strategy 1.2 was elaborated (cf. Fig. 3). The reduced charging time of 4.5 h is compensated by the use of fast charg-

Table 5
Data conventional AC charging curves of the e-Wolf Delta 2 and Delta 2 EVO.

	e-Wolf Delta 2	e-Wolf Delta 2 EVO
SOC span	0–100%	0–100%
Charging time for a full recharge [h]	11.78	15.60
Max. effective charging power at outlet [kW]	2.58	2.50
Max. effective battery charging power [kW]	2.30	2.19

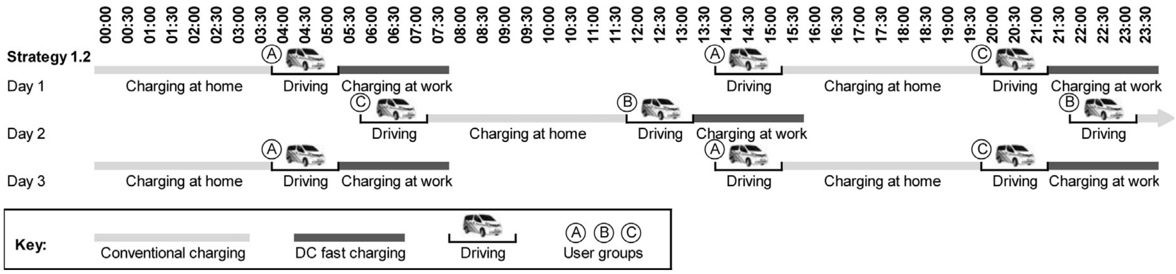


Fig. 3. Illustration of the commuting charging strategy 1.2.

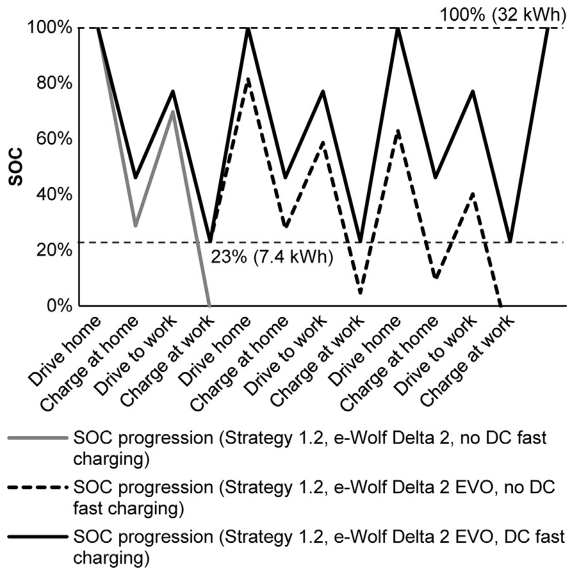


Fig. 4. Development of SOC for strategy 1.2 with and without DC fast charging station.

ing at the plant. With the maximum effective charging power of about 26 kW and a maximum time of 2.5 h for a full recharge (c.f. Fig. 5 and Table 6) the parking time at the plant is more than sufficient. Therefore, the time lacking for recharging at home can be more than compensated through DC fast charging at work. In this strategy the Delta 2 EVO's battery capacity of 32 kWh is sufficient to ensure that there is enough energy remaining for the way to the plant, including a satisfactory additional energy reserve. This operation schedule leads to an annual mileage of between 54,000 km (for three groups sharing two cars) and 72,000 km (for four groups sharing two cars) per EV. The total charging time is either 13.5 h (56.25%, day 1) or 7.5 h (31.25%, day 2). The total driving time per day is constant with 4.5 h (18.75%). In the remaining 6 or 12 h the EV is neither being charged nor used, respectively. The number of conventional and fast charging events is different for the two days. During day one, two fast and only one conventional charging events are started; on day two, two conventional and one fast charging event take place, on average 1.5 per day. Even though on average the number of charging events is equal, distinctly more energy is effectively recharged through fast charging. In 1.5 charging events 36.9 kWh are recharged by DC charging and only 14.84 kWh through conventional charging. All the groups using the EV have to work in different shifts as can be seen comparing day 1 and day 2 in Fig. 3. Hence for the two EV shared by the three or four commuting groups only one fast charging outlet is required.

4.1.3. Strategy 1.3: Using fast charging to enable three or four user groups to share one EV

Charging strategy 1.3 provides the opportunity to increase the annual mileage of the EV even further. The underlying model allows three of four different shift groups to continually share one EV as follows: (i) the first group drives to work, arrive about 30 min before the start, and immediately charge the EV; (ii) the second group leaves the plant 30 min later and travels back home, where the EV has 4.5 h for recharging until (iii) the third group takes it to drive to the plant and after a recharge of 30 min hands it over again to the first group, and so on. Fig. 6 illustrates an EV on two consecutive days deployed in this model.

Under the field test conditions strategy 1.3 could not be implemented. The idea of this strategy was developed before the start of the project. With an average distance of 75 km per journey, an average energy consumption of 230 Wh/km, and

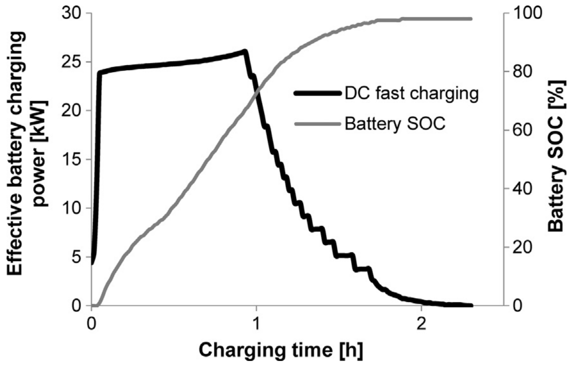


Fig. 5. DC fast charging curve of the e-Wolf Delta 2 EVO.

charging times of 0.5 or 4.5 h respectively the model proved unsustainable. As can be seen in Fig. 7, after the second recharge at home the energy stored in the battery is insufficient to drive the EV back to the plant.

Reducing the average commuting distance can make the charging strategy and the underlying occupancy model sustainable. Reducing the average distance has two positive effects. Firstly, the shorter distance reduces the energy consumption per trip. Only 11.5 kWh are required for a 50 km journey. Secondly, a shorter distance also reduces the travelling time from 1.5 to 1 h and therefore enhances the available time span for recharging at home from 4.5 to 5.5 h (cf. Fig. 6).

At an average distance of 50 km the charging strategy 1.3 becomes sustainable. The required energy per trip of 11.5 kWh can be charged conventionally at home, where the maximum recharge in 5.5 h is 12.1 kWh, and at work, where the maximum recharge in the 30 min is 13.5 kWh. Due to the fact that the DC fast charging power is significantly reduced at high SOC (cf. Fig. 5) the charging status of the EV never again reaches 100% SOC. After a few trips the process with its fixed time slots for charging stabilizes by utilizing the higher available DC charging power. Then the SOC range lies between 51% (16.34 kWh) and 89% (28.44 kWh) (cf. Fig. 7). This way of deployment leads to an annual mileage of around 100,000 km. The total charging time per day is 18 h (75%) and total driving time 6 h (25%) respectively. For this strategy the number of fast and conventional charging events started per day is 3 each. In these 36.3 kWh is charged conventionally and 32.7 kWh is recharged through DC fast charging. Since all the groups participating have to work in different shifts, again one DC fast charging EVSE is required.

4.2. Charging strategies for business trips between plants

For the business trips application there was no fixed schedule available to fit the charging strategy to. The groups consist of up to four people which travel between the two plant sites that lie 70 km apart (cf. Table 2). For these trips the EV was accessible from 8 am until 8 pm. The available time for charging on both ends could only be estimated with an average duration of 2 h, i.e., the average duration of one meeting or the time frame between the arrival of one group and the departure of the next.

4.2.1. Strategy 2.1: Solely relying on fast charging

Strategy 2.1 was developed by taking into account the technological data of the charging process, the energy consumption, and the required availability. A complete AC charge (mode 2) lasts up to 10 h. The effective charging power measured at the outlet is about 2.3 kW, and the effective charging power of the battery is 2.1 kW (cf. Fig. 9 and Table 7). With the available charging times during the day of about two hours between trips, the conventional 2.1 kW charging does not provide a sustainable solution for this strategy. Hence, at both plant sites the installed DC fast charging EVSE with 50 kW peak charging power was used. However due to local grid limitations the charging power in France was limited to 20 kW. Under ideal conditions the 50 kW fast charging process is ended by the Nissan Leaf's battery management system (BMS) after reaching around 90% SOC at about 30 min. Independent from the charging power and the SOC level, the DC fast charging process is ended by this vehicle's BMS after one hour latest. In both cases a manual restart is possible (cf. Fig. 10 and Table 8).

Table 6
Data DC fast charging curve of the e-Wolf Delta 2 EVO.

	e-Wolf Delta 2 EVO
SOC span	0–100%
Charging time for a full recharge [h]	2.30
Max. effective charging power at outlet [kW]	30.00
Max. effective battery charging power [kW]	26.04

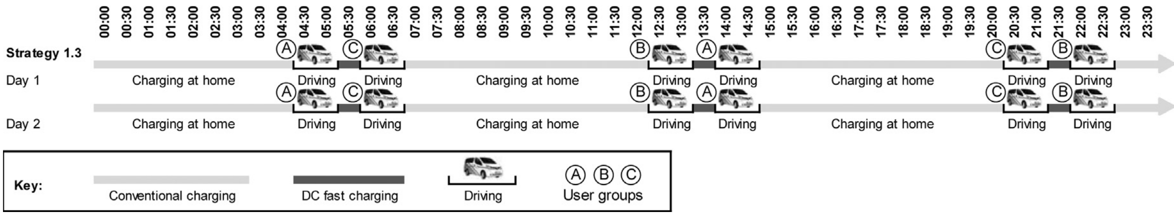


Fig. 6. Illustration of the commuting charging strategy 1.3 (distance 50 km).

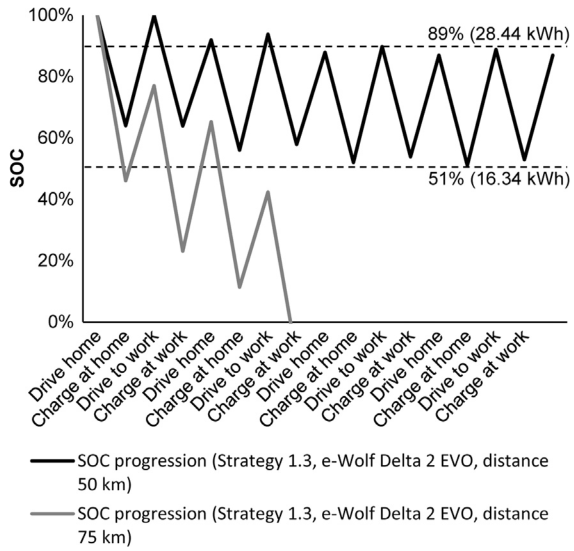


Fig. 7. Development of SOC for strategy 1.3 for 75 and 50 km average distance.

Fig. 8 illustrates the strategy's timeline for two example days, the first with one and the second with two trips and retours per day. By doing 1.5 trips on average per day, which was roughly the number of total trips before the deployment of the EV, the result would be an annual mileage of around 50,000 km. With one hour per tour, one hour (20 kW) in France and 30 min (50 kW) in Germany per charge, this leads on average to three hours of driving, 2.25 h of charging, and 18.75 h of idle time per day (cf. Fig. 8).

During operation two problems occurred with this charging strategy. Both can directly be linked to the exclusive use of DC fast charging and the fact that this vehicle version's BMS automatically limits the fast charging process to one hour latest (cf. Fig. 10). The first problem was the fading of the battery's capacity: after only about 4000 km the vehicle's SOH display indicated a considerable decrease. The reason identified for this fast capacity fade was the missing passive balancing of the individual battery cells' voltage. The passive balancing process takes time; since the charging process is ended by the EV after one hour at the latest, there was no time for passive balancing of the battery. The second problem with the autonomous switch-off was an insufficient charging level. Due to SOH considerations depending on the temperature the charging power is automatically reduced by the BMS. The forced switch-off after one hour lead in extreme situations to an insufficient SOC to ensure a safe journey back. Based on these problems with the execution of charging strategy 2.1, strategy 2.2 was set up.

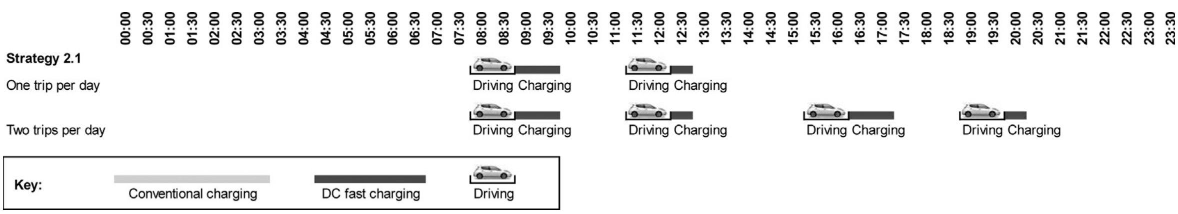


Fig. 8. Illustration of the business trip charging strategy 2.1.

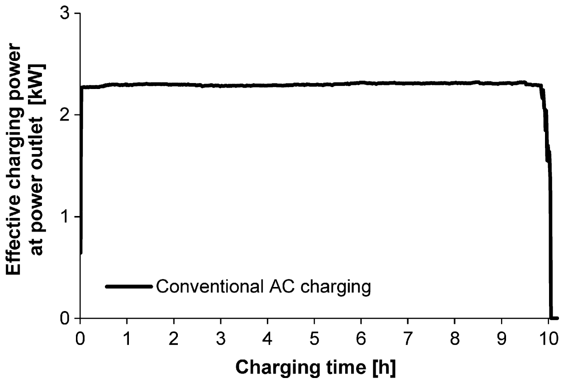


Fig. 9. Conventional AC charging curve of the Nissan Leaf.

4.2.2. Strategy 2.2: Relying on fast charging for the day and conventional charging (mode 2) at night

Charging strategy 2.2 includes not only fast charging during the day, but also conventional AC charging overnight (cf. Fig. 11). This addresses both problems that occurred in strategy 2.1: the conventional charging overnight provides more than enough time for passive balancing voltage levels of battery cells. After the introduction of overnight conventional AC charging, the SOH remained constantly at the reset level. The AC charging also allows preconditioning of the EV. The Nissan Leaf can be heated or cooled before use in the morning by energy taken directly from the power grid, which in turn increases the range of the vehicle. The new charging strategy ensures that even under low temperatures all the requirements concerning functionality and availability are met, while at the same time protecting the SOH. In this charging strategy the average time of driving and fast charging per day remains constant at 3 or 2.25 h respectively. However, about 12 out of the remaining 18.75 h are now used for recharging, balancing, and preconditioning.

5. Discussion

The outcomes of this field test provide evidence for an ecologically and economic sensible application of EV. Furthermore, they support previous findings and claimed concepts, but also provide new insights and conceptual suggestions for the optimal outlay of EV charging strategies for a predetermined mobility application. The presented charging strategies are based on three types of input factors originating from the charging processes, the deployed EV, and the mobility applications.

Contrary to most studies investigating charging behavior and strategies, for the five presented strategies the charging places and times are predetermined by the underlying application. The charging points considered (at plant sites and at private homes) concur with current empirical research studies, which show that most EV are charged at home and at work; public charging plays a less important role (Robinson et al., 2013; Skippon and Garwood, 2011).

In the literature, the main distinction with regard to the timing of charging relates to the electricity market. Therefore, the start of the charging process relative to the arrival and the time of day are focused on. With all five presented strategies, which try to maximize the annual mileage, there was significantly less flexibility in timing of the charging process compared to most other applications (Franke and Krems, 2013; Robinson et al., 2013). Considering the distribution of charging events during the day, the commuter strategies lead to an almost even distribution due to the 24 h rolling shift schedule. For the business trips most charging events happen during the day, which on a greater scale would mean putting additional electricity demand on the grid during peak times.

5.1. Key performance indicators to assess and compare EV charging strategies

To our knowledge the analysis of charging strategies at this level of detail is new in current literature. To characterize and compare the five different charging strategies it became clear that using only the ratio of driving time to parking time as can be found in other studies (Camus et al., 2011; Lunz et al., 2012; Speidel and Bräunl, 2014) was insufficient. Therefore, this study proposes five KPI using different technical dimensions: the average daily distance travelled, the average idle time

Table 7
Data conventional AC charging curve of the Nissan Leaf.

	Nissan Leaf
SOC span	0–100%
Charging time for a full recharge [h]	10.26
Max. effective charging power at outlet [kW]	2.32
Max. effective battery charging power [kW]	2.10

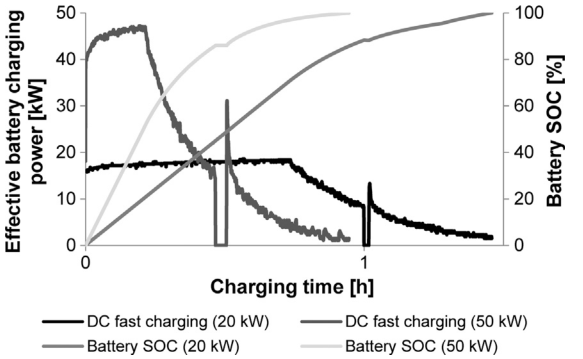


Fig. 10. DC fast charging curves of the Nissan Leaf.

per day, the average ratio of driving to charging hours per day, the average ratio of fast to conventional charging events per day, and the average ratio of energy charged through fast and conventional charging per day.

The comparison of these key indicators amongst the five strategies illustrates the individual advantages and shortcomings (cf. Table 9). The increase in the daily distance travelled between the commuting strategies 1.1, 1.2, and 1.3 does not lead to a constant reduction of idle time. On the contrary, due to the introduction of fast charging, the average idle time actually almost doubles from 5 to 9 h in strategy 1.2. However, in strategy 1.3 the EV virtually have no idle time. Between 1.2 and 1.3 even though the daily distance covered increases by almost 50% and the number of charging events increases from 3 to 6, due to a more balanced charging distribution the ratio of driving to charging time decreases and less energy is recharged through fast charging in total as well as relative to the amount conventionally charged. The highest amount of idle time and the highest ratio of driving to charging can be found in the business travel strategy 2.1, where on average the EV is charged faster than it is discharged through driving. This combination illustrates the reasoning behind the adaptation from 2.1 to 2.2: not only is the objective of high availability fulfilled, but also the potential degeneration of battery cells is limited. Since the EV is not used overnight, the fast charging can be combined with conventional charging, even if it is mainly done for balancing and preconditioning. Three of the five strategies have an average daily distance of over 200 km, but differ significantly in the remaining values of their key indicators. Strategy 2.2 has the lowest amount of idle time, but strategy 1.2 is more balanced between conventional and fast charging. These examples illustrate that the KPI individually are insufficient to characterize and evaluate a charging strategy. In combination they can serve as a sufficient basis for comparing and evaluating charging strategies based on constant mobility applications.

Comparing the time distribution of charging and driving in the different strategies to the values in the literature it becomes evident that even in the strategies with high annual mileage, driving only makes up a small proportion of the total time of day. The values in this study lie between 3 h in strategy 1.1 (12.5%) and 6 h in strategy 1.3 (25%). Accordingly, 75–87.5% of the day consist of charging and idle time. Compared to the 91.7% (22 h) by Guille and Gross (2009), the 95% by Camus et al. (2011), and 96.15% by Speidel and Bräunl (2014) the values reached are significantly lower. A comparison of these values has to be done carefully, since the distribution of charging and driving time is highly dependent on the average speed and therefore average discharge power. Nevertheless, in this project, even when travelling 300 km per day, most of the time the EV stands still.

5.2. Lessons learned

The conclusions drawn from evaluating the charging strategies, the adaptations made in the process, and the KPI introduced reveal three distinctive outcomes concerning the nature of the underlying application, the required input parameters, and the choice of charging power.

The differences in the charging strategies between the commuting and the business trips show that, the more predictable the underlying mobility application the better the charging strategy can be adapted to it. Based on the fixed shift schedule for commuters all the charging times were fully predictable. Therefore, the timing of the charging and the required charging power could be chosen accordingly. Since for the business trips the duration of meetings or the departure of the next group

Table 8
Data DC fast charging curves of the Nissan Leaf.

	Nissan Leaf (20 kW)	Nissan Leaf (50 kW)
SOC span	0–100%	0–100%
Charging time for a full recharge [h]	<1.5	<1.0
Max. effective charging power at outlet [kW]	20	50
Max. effective battery charging power [kW]	18.4	47.5

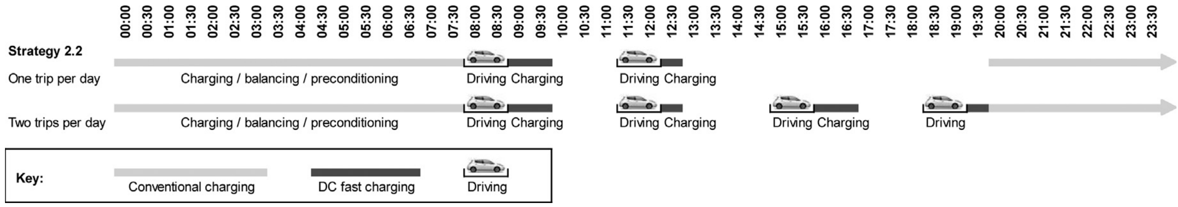


Fig. 11. Illustration of the business trip charging strategy 2.2 including AC charging overnight.

Table 9
Key performance indicators of the presented charging strategies.

Key performance indicators (daily average)	Strategy 1.1	Strategy 1.2	Strategy 1.3	Strategy 2.1	Strategy 2.2
Distance travelled	~150 km	~225 km	~300 km	~210 km	~210 km
Idle time	5 h	9 h	0 h	18 h	6 h
Ratio of driving time to charging time	0.19 (3 h/16 h)	0.43 (4.5 h/10.5 h)	0.33 (6 h/18 h)	1.33 (3 h/2.25 h)	0.21 (3 h/14.25 h)
Ratio of started fast charging to conventional charging events	0 (0/2)	1 (1.5/1.5)	1 (3/3)	undef. (1.5/0)	1.5 (1.5/1)
Ratio of energy recharged through fast and conventional charging	0 (0/34.5)	2.49 (36.9/14.85)	0.90 (32.7/36.3)	*Only fast charging*	*Conventional mainly for balancing*

was unknown, during the day the maximum charging power was always applied, even though it places more strain one the battery and the grid. A higher predictability not only leads to a less excessive use of fast charging, but also opens up the possibility for including other objectives such as decreasing the degradation of the battery or providing services to the electricity grid.

The field test indicates that in addition to the characteristics of the underlying mobility application, such as the starting and ending points, the travel times and distances covered, two factors need to be considered when developing a charging strategy: the features of the charging curve and the real (temperature and driving style dependent) energy consumption.

The comparison of the five charging curves presented in this study indicates that three characteristics are essential to develop a sustainable charging strategy: the maximum charging power, the duration of a full recharge, and the shape of the charging curve. The conventional AC charging curves for both EV types are similar, differing only slightly in their shape (cf. Figs. 2 and 9), whereas the charging power remains constant relative to the maximum charging power. Hence, the maximum charging power can be taken as a reliable indicator to simulate the recharge process. The DC fast charging curves on the other hand show a different progression (cf. Figs. 5 and 10). Therefore, for including fast charging in a sustainable charging strategy it is not sufficient just to rely on the nominal maximum charging power (C-rate) – the shape and the total duration of the charging process also need to be considered. This is illustrated by strategy 1.3: since the higher charging power is only available at lower SOC, even though the strategy is sustainable the SOC value never rises above 90% (cf. Fig. 7). Accordingly, various EV manufacturers provide not only estimations for a full fast charging recharge, but also for the duration of an 80% recharge. Strategy 1.2 shows that for an optimal charging strategy two distinct charging levels are not enough: the conventional charging is insufficient, but the fast charging requires far less time than the 8.5 h available. To allow the setting of a flexible charging power in a predetermined range could even further benefit the system. Concerning the application-specific real EV energy consumption, the results of this field test emphasize that real consumption can be significantly higher than values based on the New European Drive Cycle (NEDC) stated by the manufacturers depending on various factors, such as route profile, driving behavior, or the use of auxiliaries (Lorf et al., 2013; Muneer et al., 2015; Travesset-Baro et al., 2015; Wu et al., 2015). For the present field test the high occupancy rate of the EV (about 5 people per EV in average) and high average speed of around 55 km/h can be identified as one reason for the observed discrepancy.

5.3. Technological and economic implications

Considering the charging strategies and the market technology available at the time of the field test, it becomes evident that with high utilization of EV the cycle life of the battery cells becomes an issue. Apart from the standard degradation of parts such as tires, brakes, etc., the battery ages in intensive use. Over the course of a year the strategies in use lead to a different number of charging events as can be seen in Table 10. The DOD for each trip is considered constant for each strategy, since the travelled distances do not change. Applying a higher number of charging cycles allows a higher (daily) mileage, but due to cyclical effects it also affects battery life (Neubauer et al., 2012). Many battery cell manufacturers state a ten year lifetime based on calendar life and at least 3000 full charge and discharge cycles before reaching their end of life at 80% capacity (Azadfar et al., 2015; Kley, 2011). For the presented charging strategies and the associated DOD per trip, neglecting effects due to fast charging or different SOC levels regarding the cell chemistry, which goes beyond the scope of this work, the estimated cycle life of 3000 cycles varies from 4.2 to 11.1 years. As can be seen from these values in Table 10 the calendar life of

Table 10
Prediction of cycle life in different charging strategies.

EV	e-Wolf Delta 2 EVO			Nissan Leaf	
Strategy	1.1	1.2	1.3	2.1	2.2
Annual mileage	~36,000 km	~72,000 km	~100,000 km	~50,000 km	~50,000 km
Number of conventional charging events per year	500	500	1000		*Passive balancing*
Number of fast charging events per year		500	1000	750	750
Total charging events per year	500	1000	2000	750	750
SOC range used (in stable conditions)	~46–100%	~23–100%	~51–90%	~32–100%	~32–100%
Depth of discharge per trip (Energy consumed/capacity)	54%	54%	36%	58%	58%
Number of full charging cycles per year (Charging events*DOD)	270	540	720	435	435
Estimated cycle life (based on 3000 cycles)	11.1 years	5.6 years	4.2 years	6.9 years	6.9 years

the battery of ten years and beyond plays no significant role, since for all but one charging strategy the predicted cycle life values are distinctly lower than the calendar life. The actual SOC range used on both trip directions indicates that for all strategies there is potential to avoid high and low SOC levels (cf. Table 10). Due to the fact that at these levels it is more likely that harmful chemical side reactions occur, it is always good to avoid these states. This could prolong the battery life, but it requires external control of the EV BMS to limit the maximum SOC.

Evaluating the technologically possible annual and EV lifetime mileage from an economic point of view, the deployment of EV in the considered mobility applications can potentially become less costly than the use of ICEV. Various studies have compared and discussed the TCO of EV and ICEV (Plötz et al., 2013; Tseng et al., 2013; Windisch, 2013). In general, the TCO is influenced by two kinds of factors: technological factors and regional factors. Technological factors are for example the price and durability of the EV, especially that of the battery cells, or the basis of comparison to the ICEV, e.g. engine power. Regional factors can be energy prices, taxes, incentives, and other market circumstances, which are dependent on the respective country (Feng and Figliozzi, 2013; Plötz et al., 2013; Sharma et al., 2012). Considering the high sensitivity of a TCO analysis to these various factors no definite statements can be made based solely on the annual or lifetime mileage of an EV. In particular due to a lack of empirical evidence and fast technological progress, the residual value of the battery and therefore a successful market penetration of EV is still uncertain (Plötz et al., 2013). However, taking the annual or lifetime mileage can serve as an indicator for potential competitiveness. Various TCO analyses have shown that despite the savings in variable costs at current market prices and production processes, an annual mileage of 20,000 km, which is about the average of the German commercial fleet (Wermuth et al., 2012), is insufficient to reach an economic break-even in comparison to ICEV in Germany (Plötz et al., 2013). Hacker et al. (2015) calculate that in 2014 the barrier lies at 30,400 km in an optimistic scenario; Richter and Lindenberger (2010) estimate that for Germany in 2020 at least 27,000 km annual mileage is required while Kasten et al. (2011) even state a required annual mileage of 34,750 km in 2020 to break even. For the US market Feng and Figliozzi (2013) come to the conclusion that for commercial vehicles the competitiveness starts at 16,000–22,000 miles (25,750–35,400 km), depending on the conditions; Tseng et al. (2013) state a total of around 150,000 miles (241,000 km) over a lifetime of ten years for passenger cars. For the Australian market Sharma et al. (2012) show that a mileage of 150,000 km in ten years under the current conditions is insufficient. For France Windisch (2013) calculate a minimum of 30,000 km per year for seven years leading to a total of 210,000 km as break-even point. However, based on the average EU market conditions Faria et al. (2013) come to the conclusion that for the Nissan Leaf an annual mileage of 20,000 km in 8–9 years is sufficient to become competitive. The high discrepancy in the results illustrates the difficulty of feasibility statements solely based on mileage. Comparing all the listed mileages to the annual as well as lifetime mileages that can potentially be reached with the presented charging strategies and technology at hand, it becomes evident that the values in this study are significantly higher than the break-even values that can be found in the literature. This clearly indicates that the presented charging strategies can distinctly contribute to a potentially competitive EV use in commercial applications.

6. Conclusion

This study adds new empirical insights and conceptual suggestions to the EV charging literature by presenting and discussing charging strategies for two commercial mobility applications with constant mobility demand and fixed routes: the commuting of shift workers and business trips of employees. The five charging strategies, which were developed to increase the economic feasibility and therefore the annual mileage of EV in two mobility applications, were tested in a French-German field test from early 2013 to the end of 2015. During this time over 450,000 km were travelled by the seven EV deployed. First and foremost, the results demonstrate how specifically developed and adapted charging strategies can lead to a high annual mileage by relying on more than one level of charging power. In particular, the inclusion of DC fast charging with charging rates of 1 C or higher is shown to be indispensable when trying to reach a high EV operating grade. Nevertheless, the results also provide indications that there are limits to fast charging, that to avoid unnecessary damage to the battery cells it should only be applied when required by the underlying mobility demand. To illustrate and assess charging strategies five KPI are suggested. They can also be applied to evaluate and compare different charging strategies, by for example revealing an avoidably high amount of idle time as a consequence of an unnecessarily frequent use of fast charging. The results further reveal that the more predictable the underlying mobility application the easier the charging strategy can be adapted accordingly. For this adaptation the empirical examples suggest a range of input parameters required for developing a balanced charging strategy, such as the features of the charging curve and the real energy consumption of the EV in use. Overall, the results and discussion underline how important a carefully designed charging strategy is for technological, environmental and economic sensible EV deployment and that charging time under the condition of high mobility demand becomes a critical component on the way to feasible EV deployment.

Considering the research method, setting, and focus of the study, the transfer of the findings and conclusions into a broader context must be carried out carefully. Limitations lie especially in the research method: the early stage long-term field test of two mobility applications served with two different types of EV is insufficient for a broad generalization. The results show that particularly the technological features of EV have a strong influence on the charging strategies. The charging curves for example, which are a substantial part, are highly dependent on the EV individual BMS, and thus they vary for each EV. All charging curves presented in this study are recorded under ideal circumstances. Our experience in the project shows that especially under high or low battery temperatures the BMS lower the charging power of both conventional and DC fast charging processes to avoid harming the battery cells.

Based on the results future research could expand into three directions. Firstly, it could take the presented field test as an empirical starting point for developing an optimization model of charging patterns comparable to Bashash et al. (2011). However, instead of only using one charging power level to balance the annual mileage with the cost of cycle ageing it could allow for more levels of charging power. As indicated by the used SOC range (cf. Table 10) for most charging strategies the battery capacity could be reduced, which could lower the production costs. However, there is a trade-off with increasing ageing effects. Hence, a different approach with a fixed target mileage could allow different levels of battery capacity as additional decision variables in the optimization model. Secondly, the presented mobility applications show highly predictable demand patterns. However, for many commercial applications and private users the demand per vehicle is less predictable. Therefore, future research could also expand the detailed analysis of charging strategies by including stochastic models for optimization similar to Iversen et al. (2014) or Škugor and Deur (2015). Thirdly, the field test could be expanded based on the available detailed data by an analysis of the thermal behavior and thermal limits of DC fast charging in EV deployment, especially when there is no active cooling of the cells. Last but not least, the EV and battery technology is improving fast. Therefore, similar field tests could be conducted with future EV generations and compared to this early stage set up.

Acknowledgements

The authors thank the German Federal Ministry of Transport and Digital Infrastructure for supporting the research by funding the RheinMobil project [ref. no: 16SBW007A] as part of the Federal Government's Schaufenster initiative. They also thank their industrial and research partners of the RheinMobil project consortium, who contributed support, time, and funding to make the project possible. A special thanks goes to our colleague James Barry for his valuable comments concerning the English language.

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Two-Stage Stochastic Program Optimizing the Total Cost of Ownership of Electric Vehicles in Commercial Fleets

Maximilian Schücking [a*], Patrick Jochem [a]
[a] Institute for Industrial Production (IIP), Karlsruhe Institute of Technology (KIT), Hertzstraße 16, D-76187 Karlsruhe, Germany
* Corresponding author: Phone +49 721 608 44590
E-mail addresses: maximilian.schuecking@partner.kit.edu, jochem@kit.edu

ABSTRACT

The possibility of electric vehicles to technically replace internal combustion engine vehicles and to deliver economic benefits mainly depends on the battery and the charging infrastructure as well as on annual mileage (utilizing the lower variable costs of electric vehicles). Current studies on electric vehicles' total cost of ownership often neglect two important factors that influence the investment decision and operational costs: firstly, the trade-off between battery and charging capacity; secondly the uncertainty in energy consumption. This paper proposes a two-stage stochastic program that minimizes the total cost of ownership of a commercial electric vehicle under uncertain energy consumption and available charging times induced by mobility patterns and outside temperature. The optimization program is solved by sample average approximation based on mobility and temperature scenarios. A hidden Markov model is introduced to predict mobility demand scenarios. Three scenario reduction heuristics are applied to reduce computational effort while keeping a high-quality approximation. The proposed framework is tested in a case study of the home nursing service. The results show the large influence of the uncertain mobility patterns on the optimal solution. In the case study, the total cost of ownership can be reduced by up to 3.9% by including the trade-off between battery and charging capacity. The introduction of variable energy prices can lower energy costs by 31.6% but does not influence the investment decision in this case study. Overall, this study provides valuable insights for real applications to determine the techno-economic optimal electric vehicle and charging infrastructure configuration.

Keywords:
Battery electric vehicle; Total cost of ownership; Stochastic programming; Hidden Markov model; Scenario reduction

1. Introduction

Almost a quarter of all greenhouse gas emissions in Europe are caused by transport, which is also the main contributor to local air pollution in cities [1]. These two negative impacts have become a dominating topic in public and political discussions. The introduction of electric vehicles (EVs) is propagated as one promising way to decrease local and global emissions from road transport [2,3]. However, the current market success of EVs is developing slowly.

Due to their characteristics, commercial applications have the potential to overcome the three main remaining techno-economic disadvantages of EVs in comparison to internal combustion engine vehicles (ICEVs). These are their limited range, the duration of recharging, and the higher purchase price. Research on commercial transport has shown that the range of current EV models is suitable for most tours and that lower variable costs for operation might outbalance the higher purchase prices of EVs [4,5]. Therefore, commercial transport, which results in higher annual mileage than privately owned vehicles, is considered a promising introductory market since it also has more predictable regular mobility patterns and faster turnover rates [4,6,7]. Its share in the registration of new passenger cars is substantial; in Germany it amounts to approximately 65% [8].

Due to the limited range and duration of recharging, a detailed analysis of the underlying mobility patterns is required when assessing the substitution potential of EVs. Mobility patterns have a strong impact on energy consumption as well as on the timeslots available for charging. Hence, they have a strong effect on the investment decision concerning the required battery capacity and the charging capacity of the electric vehicle supply equipment (EVSE) as well as the operational costs. Next to the mobility patterns, the outside temperature can also significantly influence the actual energy consumption. Both are subject to uncertainties [9–11]. These sources of uncertainty should be considered in investment planning. Evaluating the influence of the mobility patterns requires detailed information on individual driving tours. However, for most commercial vehicle operations, only little information is available and data on complete driving patterns in high time resolutions are scares. To the best of the authors' knowledge, the existing literature lacks a comprehensive methodical framework for jointly optimizing the investment decision and operational costs of an EV while considering the empirical uncertainties of energy consumption and available charging times during operation based on limited time-series data.

This paper attempts to fill this gap by proposing a two-stage stochastic program in combination with a detailed technical EV model which ensures the full technical substitutability in the investment decision while minimizing the total cost of ownership (TCO) of the vehicle and charging infrastructure. The stochastic program is solved by sample average approximation (SAA). A hidden Markov model (HMM) is introduced to generate the required stochastic input parameters based on limited empirical time series data. To reduce computational effort while keeping a good approximation of the optimal value, a newly developed adaptation of an existing scenario reduction heuristic is proposed. This is tested in a case study of the home nursing service. With 13,300 providers, over 350,000 employees, and around 700,000 patients needing home care, it is an important and common use case in Germany [12].

1.1 Related work

In the literature, the optimization of the technical configuration and TCO of EVs in commercial fleets has been rarely addressed, so far. In the smart home context, several studies assessed the EV investment for private customers [e.g. 13,14]. Table 1 compares different studies that focus on commercial fleets. The generalized research focus of these studies is the competitiveness of different vehicle technologies based on fleet size and vehicle routing optimization. Hiermann et al. [15] specifically focus on the methodical advancements of these optimization approaches to include specific EV characteristics such as charging times.

All papers listed in Table 1 consider EV investment as part of the optimization, as can be seen in line 2. Most of them also evaluate the effect of different battery capacities (line 3). They do so either by comparing different available EV models [16,18] or by introducing a finite number of exemplary vehicles [15,17]. All of these papers consider battery capacity as an exogenous parameter and not an endogenous decision variable. Assumed that the previously deployed ICEVs are fully substituted, an exogenous given battery capacity may only lead by chance to a cost minimal EV investment choice or require the individual assessment of all possible parameter values. Furthermore, only Davis & Figliozzi [16] include battery aging in their analysis by evaluating different replacement scenarios (line 4). However, they do not consider battery aging in their model as a constraint that decreases the actually available battery capacity during utilization.

Most of the studies consider the vehicle and the required EVSE investment, as shown in line 5. They do so either indirectly by including costs for public charging [15] or directly through the investment of own charging or battery swapping stations [17–19]. As part of the investment decision, two papers compare fast charging and swapping stations (line 6). None of the studies compares the effect of variable charging capacities directly. Four papers consider the required charging time as can be seen in line 7. They do so in a simplified way by assuming a constant charging power and completed charging (i.e. a state of charge (SOC) of 100%) at the end of each charging process). However, partially recharging during empirical operations is often observed and might provide a significantly more economical solution. None of the studies investigate the optimization potential that focuses on the trade-off between the investment in battery and charging capacity (line 8).

	Davis & Figliozzi 2013 [16]	**Hiermann et al. 2016** [15]	**Kuppusamy et al. 2017** [17]	**Lebeau et al. 2015** [18]	**Sathaye 2014** [19]	**Our contribution**
(1) Commercial application	Delivery trucks	Delivery trucks	Taxi fleet	Delivery vehicles	Taxi fleet	Home nursing service
(2) EV investment	✓	✓	✓	✓	✓	✓
(3) Variable battery capacity	(✓)	(✓)	(✓)	(✓)		✓
(4) Battery aging model	(✓)					(✓)
(5) EVSE investment		(✓)	✓	✓	✓	✓
(6) Variable charging capacity			(✓)		(✓)	✓
(7) Flexible state of charge (SOC) model		(✓)	(✓)	(✓)	(✓)	✓
(8) Trade-off between investment in battery and charging capacity						✓
(9) Detailed energy consumption model	✓			✓		✓
(10) Empirical mobility patterns	(✓)			(✓)		✓
(11) Impact of uncertainty (mobility patterns & outside temperature)						✓

Table 1 *Outline of previous research on configuration and cost optimization of EVs in commercial applications (ratings in brackets mean that the aspect is only considered to a limited extent)*

Two papers consider detailed technical energy consumption for the EVs (line 9), but only rely on a limited empirical data base (line 10). The other papers assume constant consumption levels. Davis & Figliozzi [16] estimate the energy consumption based on driving cycles and a detailed vehicle dynamics model. Lebeau et al. [18] specifically expand the new methodical approach by Hiermann et al. [15] by an energy consumption model. The authors identify this as the central missing component. Therefore, they add a linear regression model based on the input data from one vehicle with trip duration and temperature as input variables. Even though research has shown that mobility patterns and outside temperature have a strong influence on energy consumption as well as available charging times and are subject to uncertainty, none of the presented studies consider the impact of this uncertainty on the investment decision and operational costs in their model, as shown in line 11.

Solely focusing on the operation of EVs, the effect of uncertain mobility demand on the optimization potential is a commonly researched topic. [e.g. 20–23]. Since these studies focus on the utilization, the battery and charging capacity are set as exogenous parameters. This allows the use of dynamic programming or optimal control for optimization. These approaches cannot be applied when also considering the investment as part of the optimization. Kley [24] proposes a potential solution by incorporating the dynamic optimization into a TCO model for privately owned EVs. This study evaluates the TCO for different battery and charging capacity scenarios, which are again set as exogenous parameters. Jointly optimizing investment and cost of operations under uncertainty requires an alternate methodical approach.

Two-stage stochastic programs are commonly applied in the context of one-time investment decisions [25,26]. The method is based on the fundamental assumption that the decision itself has no influence on the sources of uncertainty [27]. SAA has been established as a standard way to approximate the expected cost function by a finitely discrete set of scenarios, that reflect the observed uncertainty [28,29]. The stochastic program is transformed into a deterministic equivalent with the scenarios representing possible realizations in the decision-making horizon. The complex nature of the underlying uncertainty distribution can require the inclusion of many scenarios. Here, scenario reduction, in which the original set of scenarios is approximated with a smaller representative subset, can be used to limit the computational burden while keeping a high quality of the solution [30]. This approach of a stochastic program with SAA and scenario reduction can be applied to jointly optimize the investment decision and operational costs while taking the uncertain energy consumption into account and without risking exaggerated computing times.

A subsequent methodical challenge lies in the generation of the required stochastic mobility patterns as input scenarios for the stochastic program. For the generation of stochastic driving patterns different temporal distributions, e.g. Weibull, Gamma, and log-normal distribution, are put forward and compared in the literature with inconclusive results [31–33]. Moreover, for vehicle dynamics, the Markov property has been validated [34] and Markov chains are applied to model driving cycles on empirical driving patterns [35,36]. However, using Markov chains for modeling driving patterns requires a fine temporal data resolution of speed and acceleration values. This information is rarely available in real-world commercial applications.

Hidden Markov models (HMMs) can be applied when only limited time-series information is available. Examples of application areas are natural phenomena [37,38], financial markets [39,40], or predictive maintenance [41,42]. An HMM is a white box method which has the advantage of a clear mathematical structure and has proved its value in modeling dynamic systems under uncertainty [43]. HMMs can outperform exponential, Weibull, log-normal, and exponential mixture models [38,44]. An HMM has been applied to model simple EV driving patterns by Iversen et al. [45]. To the authors' knowledge, this methodology has never been applied to model commercial driving tours.

1.2 Contributions and structure of this study

As illustrated in the literature review and Table 1, to the best of the authors' knowledge, there is a gap in the current literature: The body of literature lacks a comprehensive methodical framework for optimizing investment choice and operational costs when introducing EVs in commercial applications that also considers detailed technical EV characteristics and the uncertain actual energy consumption and available charging times during operation.

The study at hand attempts to fill this gap by presenting a two-stage stochastic program, which allows optimizing both the investment decision (first-stage) and expected operational cost (second-stage) for commercial EVs under different sources of uncertainty. The investment decision includes the trade-off between battery and charging capacity. The stochastic program builds on a detailed technical EV model containing energy consumption, charging load-curves, and battery aging. Based on the literature, the mobility patterns and outside temperature are included as key sources of uncertainty for the actual energy consumption and available charging times. Amongst others, detailed information on mobility patterns is required as input to the technical EV model. However, based on their practical experience, the authors assume that only limited information on mobility patterns, e.g. from a logbook, is available in everyday commercial mobility applications. Therefore, an HMM is introduced as an approach for generating mobility scenarios. Furthermore, the paper presents a new scenario reduction heuristic to facilitate a more efficient approximation of the optimal TCO value. All things considered, several methodical approaches and small advancements are newly combined into a comprehensive TCO optimization framework.

This framework is applied to a home nursing service case study. Despite being a common mobility application, the home nursing service, as are other services, is rarely in the focus of transportation research [46,47].

In conclusion, the major contributions of this paper are:

1. Developing an overall investment and operations choice formula, which considers battery capacity, charging capacity, as well as uncertain energy consumption and available charging times under the constraints of a detailed technical EV model.
2. Predicting the stochastic mobility demand patterns based on limited empirical time-series data by training and using an HMM for scenario generation.
3. Comparing three scenario reduction heuristics, one of which is a newly developed advancement, to identify the one that most efficiently approximates the optimal value of the two-stage stochastic model.
4. Applying the newly developed approach to a home nursing service case study, which, despite being a common mobility application, has received little research attention.

The remainder of this paper is structured as follows: Section 2 proposes the two-stage stochastic TCO program, introduces the HMM used for scenario generation, and describes the three applied scenario reduction heuristics. Section 3 outlines the set-up of the case study. Section 4 presents the results as well as their discussion and critical appraisal. Section 5 concludes the paper with a summary and an outlook for future work.

2. Two-stage stochastic program with scenario generation

The techno-economic optimization of the EV investment and operation is based on a TCO approach. TCO goes beyond the initial price to understand the true cost of buying a particular good or service [48]. It is commonly used for EV assessment to ponder the higher purchase price against the savings in operational costs in comparison to ICEV. Implementing the framework provided by Götze and Weber [49] the target group of this study are commercial fleet operators and the techno-economic assessment follows a cost-based approach. In this study, only battery electric vehicles are considered. Fig. 1 provides an overview of the model and data input.

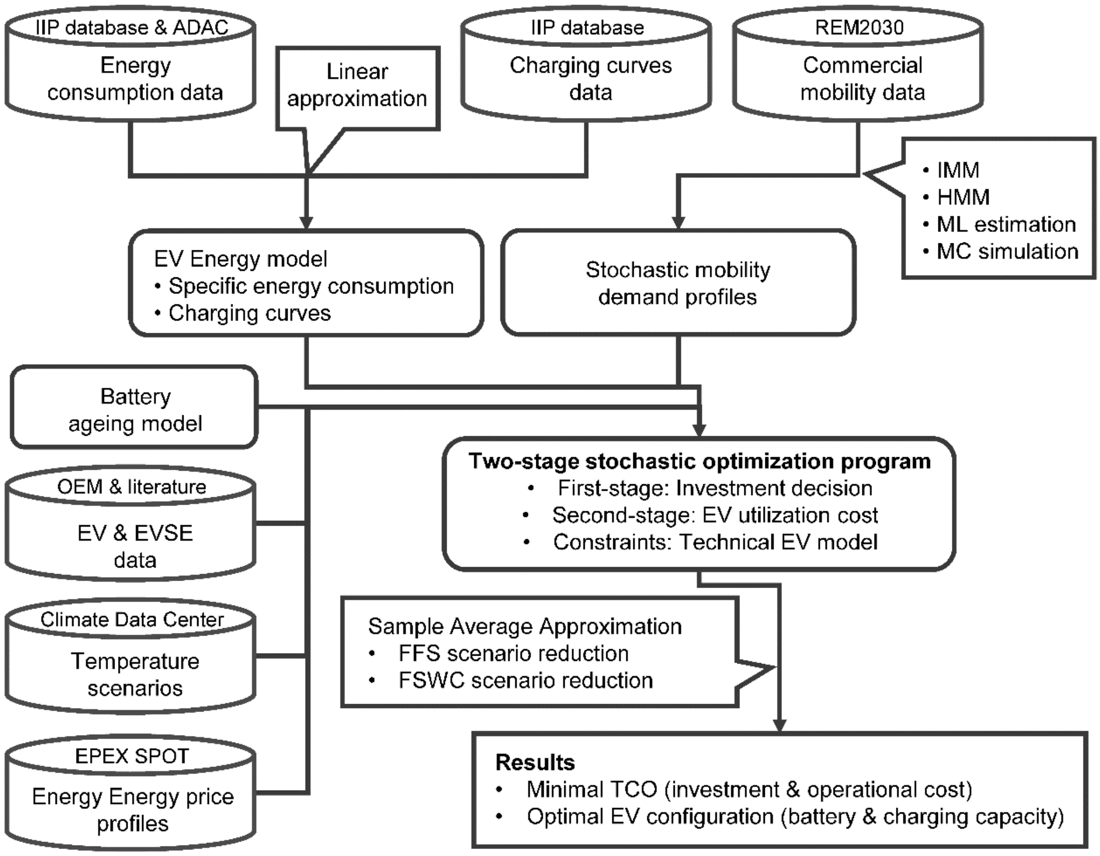

Fig. 1 Structural overview of the proposed techno-economic optimization model

2.1 Two-stage stochastic program

This paper proposes a two-stage stochastic program with multi-periodic costs to account for the uncertainty in the actual energy demand during the one-time investment decision. This approach allows optimizing the TCO by jointly minimizing the costs of the first-stage decision (investment in EV and EVSE) and the expected costs of the second-stage decisions (vehicle usage costs). The SAA method is applied to approximate the expected costs of the second-stage decisions. In the SAA method, a random finite sample of the stochastic input parameters is generated based on the underlying probability distribution. In the case at hand, this sample consists of mobility and temperature scenario sets. These scenarios are used to approximate the expected objective function value of the second-stage costs. For the probability of occurrence of the individual scenarios, a uniform probability distribution is assumed. As a result, the stochastic program is transformed into a deterministic equivalent specified by the sample. Applying deterministic optimization techniques can then solve the problem.

2.1.1 Objective function

Battery and charging capacity are set as the two key technical investment choices. When minimizing the TCO on condition that the mobility requirements will fully be met, the investments in battery and charging capacity form a trade-off. A large battery capacity enables many tours on one charge; a high charging capacity allows for faster recharges between the tours and hence, a smaller battery can be sufficient. The gross battery capacity $BCAP^G$ is set as the first-stage decision variable. For each of the charging capacity alternatives c, the model is solved individually to avoid quadratic constraints in the piecewise linear approximated flexible load curves. The second-stage decision variables charging power $P^{crg}_{t,s^{mob},s^{temp}}$ and state of charge $SOC^{bat}_{t,s^{mob},s^{temp}}$ pertain to the charging decisions during operations in each period t under the realization of the scenarios for mobility demand s^{mob} and ambient temperature s^{temp}, which are considered stochastically independent.

Indices	
T	set of time periods in the planning horizon
A	set of years in the planning horizon
C	set of EVSE types distinguished by charging capacity
S^{mob}	set of mobility demand scenarios
S^{temp}	set of temperature scenarios
Deterministic parameters	
$INV^{EV}_{a_0c}$	one-time EV and EVSE investment [€]
INV^{V}	EV net purchasing price without battery [€]
INV^{EVSE}_{c}	EVSE net purchasing price of charging station type c [€]
$INST^{EVSE}_{c}$	net installation cost of EVSE charging station type $c \in C$ [€]
$INV^{bat}_{a_0}$	net purchasing price battery [€]
pr^{bat}_{a}	specific net battery price on a system level in year $a \in A$ [€/kWh]
$RV^{EVSE}_{a,c}$	residual value of the EVSE in year $a \in A$ [€]
c^{batref}_{a}	net battery refurbishment cost in year $a \in A$ [€/kWh]
$f^{batSL}_{0.7}$	factor battery second-life value level of the current market price
$\alpha, \beta_1, \beta_2, \beta_3$	regression parameters of the residual value (α constant, β_1 age, β_2 monthly distance, β_3 purchase price)
i	interest rate
d	time resolution (duration of one period) $[h]$
A^{EVSEd}	EVSE depreciation time [a]
pr^{el}_{t}	electricity price in period $t \in T$ [€/kWh]
c^{EVma}	EV maintenance cost [€/km]
c^{EVtax}	EV annual tax [€]
c^{EVins}	EV annual insurance cost [€]
f^{EVSEma}	factor indicating the annual EVSE maintenance cost as a proportion of the purchase price
P^{maxcrg}_{c}	charging capacity of EVSE type $\in C$ [kW]
RP_c	remaining battery capacity that sets of charging capacity reduction of EVSE type $c \in C$ [kWh]
f^{EVgn}	factor battery net of gross capacity available for charging and discharging
η^{crg}	overall charging efficiency from the grid to battery
EC^{el}	EV specific energy consumption depending on $BCAP^{G}, DS^{spd}_{t,s^{mob}}$ and $Temp^{amb}_{t,\boldsymbol{s^{temp}}}$ [kWh/km]
w^{batcap}	factor for warranted battery capacity at the end of the first-life
$w^{batdist}$	warranted distance before the end of the first-life [km]
$w^{battime}$	warranted time before the end of the first-life [a]
$\hat{p}_{jk}(t)$	maximum-likelihood estimator of the transition probabilities of the discrete inhomogeneous Markov model
$n_{jk}(t)$	number of historic observations for starting a tour at time $t \in T$
B	number of parameters in the hidden Markov model
H	number of hidden states in the hidden Markov model
O	number of observations in the hidden Markov model
L	log-likelihood of the training data for a specific hidden Markov model
q_m	number of key first-stage decision combinations in the FSWC heuristic
q	target number of scenarios in the FSWC heuristic
pr^{const}	net electricity wholesale price in the base case [€/kWh]
$pr^{EPEX\ SPOT}_{\emptyset,2014}$	annual average of the electricity wholesale price [€/kWh]
$pr^{EPEX\ SPOT}_{t,2014}$	hourly electricity wholesale price at time $t \in T$ [€/kWh]
M	number of scenarios generated by Monte-Carlo simulation
δ	risk level assessing Monte-Carlo simulation confidence
ε	accuracy of estimated mean from Monte-Carlo simulation results

Functions	
$C^{op}(s^{mob}, s^{temp})$	total operational costs depending on the mobility s^{mob} and temperature scenario s^{temp} [€]
$RV_{a,c}^{EV}(s^{mob})$	total residual value of EV and EVSE in year $a \in A$ depending on the mobility scenario s^{mob} [€]
$RV_{a}^{V}(s^{mob})$	residual value of the vehicle without battery in year $a \in A$ depending on the mobility scenario s^{mob} [€]
$RV_{a}^{bat}(s^{mob})$	residual value of the battery in year $a \in A$ depending on the mobility scenario s^{mob} [€]
$DIST(s^{mob})$	total mileage traveled depending on the mobility scenario s^{mob} [km]
$w_{a}^{ucap}(s^{mob})$	battery state of health in year $a \in A$ depending on the mobility scenario s^{mob}
$C^{EVEN}(s^{mob}, s^{temp})$	energy cost depending on the mobility s^{mob} and temperature scenario s^{temp} [€]
$C^{EVMA}(s^{mob})$	EV maintenance cost depending on the mobility scenario s^{mob} [€]
C^{EVTI}	fixed annual costs for insurance and taxes [€]
C^{EVSEMA}	fixed annual for EVSE maintenance [€]
$EC^{el}\left(DS_{t,s^{mob}}^{spd}, \mathrm{BCAP^G}, Temp_{t,s^{temp}}^{amb}\right)$	electric energy consumption depending on driving speed $DS_{t,s^{mob}}^{spd}$, battery capacity $\mathrm{BCAP^G}$ and outside temperature $Temp_{t,s^{temp}}^{amb}$ [kWh/km]
$o_{kj}^{[1]} \coloneqq o(\omega_k, \omega_j)$	Kantorovich distance between the second-stage costs of two scenarios k and j used for scenario selection in the FSWC_O heuristic
Stochastic parameters	
$DS_{t,s^{mob}}^{crg}$	EV charging state in mobility scenario $s^{mob} \in S^{mob}$ in period $t \in T$
$DS_{t,s^{mob}}^{drv}$	EV driving state in mobility scenario $s^{mob} \in S^{mob}$ in period $t \in T$
$DS_{t,s^{mob}}^{spd}$	EV average speed in mobility scenario $s^{mob} \in S^{mob}$ in period $t \in T$
$p_{s^{mob}}$	probability that scenario s^{mob} occurs
$Temp_{t,s^{temp}}^{amb}$	ambient temperature in temperature scenario $s^{temp} \in S^{temp}$ in period $t \in T$ [°C]
$p_{s^{temp}}$	probability that scenario s^{temp} occurs
Decision variables	
$BCAP^G$	first-stage variable representing the gross battery capacity of the EV, integer [kWh]
$P_{t,s^{mob},s^{temp}}^{crg}$	second-stage variable representing the charging power in period $t \in T$ under the mobility scenario $s^{mob} \in S^{mob}$ and temperature scenario $s^{temp} \in S^{temp}$, continuous [kW]
$SOC_{t,s^{mob},s^{temp}}^{bat}$	second-stage variable representing the state of charge (SOC) in period $t \in T$ under the mobility scenario $s^{mob} \in S^{mob}$ and temperature scenario $s^{temp} \in S^{temp}$, continuous [kWh]

***Table 2** Nomenclature*

The objective function represents the TCO with the investment $INV_{a_0c}^{EV}$, as well as the expected operational costs $C^{op}(s^{mob}, s^{temp})$, and residual value $RV_{a,c}^{EV}(s^{mob})$. By applying SAA, the objective function is written as sum of the investment, as first-stage decision, and the expected second-stage costs as the calculated average of all scenarios.

$$\min_{c \in C} INV_{a_0c}^{EV} + \sum_{s^{mob} \in S^{mob},\, s^{temp} \in S^{temp}} p_{s^{mob}}\, p_{s^{temp}} \left(C^{op}(s^{mob}, s^{temp}) - RV_{a,c}^{EV}(s^{mob})\right) \tag{1}$$

For the one-time investment, the net purchase prices for the vehicle (without the battery) INV^V, the battery $INV_{a_0}^{bat}$, the EVSE INV_c^{EVSE}, and the net costs for installation $INST_c^{EVSE}$ are considered.

$$INV_{a_0c}^{EV} = INV^V + INV_{a_0}^{bat} + INV_c^{EVSE} + INST_c^{EVSE} \tag{2}$$

The price of the vehicle INV^{V} is set fixed. The battery price $INV_{a_0}^{bat}$ depends on the market price for battery capacity on system level $pr_{a_0}^{bat}$ in the year the investment is made.

$$INV_{a_0}^{bat} = pr_{a_0}^{bat} BCAP^{G} \tag{3}$$

The investment and installation costs of the EVSE $INST_{c}^{EVSE}$ are fixed and depend on the selected type c.

The EV and EVSE in this analysis are sold at the end of the planning horizon. Hence, their residual values must also be taken into account.

$$RV_{a,c}^{EV}(s^{mob}) = RV_{a}^{V}(s^{mob}) + RV_{a}^{bat}(s^{mob}) + RV_{a,c}^{EVSE} \tag{4}$$

The residual values of the vehicle and the battery depend on the intensity of use over time and therefore the respective mobility scenario s^{mob}. The intensity of use is represented by the total mileage traveled $DIST(s^{mob})$ which itself depends on the mobility demand $DS_{t,s^{mob}}^{spd}$ in the respective scenario s^{mob} and the time resolution d.

$$DIST(s^{mob}) = \sum_{t \in T} DS_{t,s^{mob}}^{spd}\ d \tag{5}$$

The calculation of the vehicle's residual value $RV_{a}^{V}(s^{mob})$ is based on the linear regression formula developed by Linz, Dexheimer, & Kathe [50] also applied for EVs in Plötz et al. [6] where readers are referred to for detailed information concerning the model.

$$RV_{a}^{V}(s^{mob}) = \frac{e^{\alpha} e^{\beta_1 12 a} e^{\frac{\beta_2}{12} \frac{DIST(s^{mob})}{a_{end}}} {INV^{V}}^{\beta_3}}{(1+i)^{a}} \tag{6}$$

The residual value of the battery $RV_{a}^{bat}(s^{mob})$ is estimated based on the battery ageing in terms of the remaining capacity in year a.

$$RV_{a}^{bat}(s^{mob}) = \frac{\left[\left(\left(\frac{f_{0.7}^{batSL} - w^{batcap}}{1 - w^{batcap}}\right) + \left(\frac{1 - f_{0.7}^{batSL}}{1 - w^{batcap}}\right) w^{ucap}(s^{mob})\right) pr_{a}^{bat} - c_{a}^{batref}\right] BCAP^{G}}{(1+i)^{a}} \tag{7}$$

Fischhaber, Regett, Schuster, & Hesse [51] have developed a model in which the residual value of the battery $RV_{a}^{bat}(s^{mob})$ in year a depends on the state of health (SOH) $w_{a}^{ucap}(s^{mob})$ and its second-life use-value. At the end of the first life w^{batcap} the resale value after refurbishment c_{a}^{batref} lies only at a factor $f_{0.7}^{batSL}$ of the current price for a new battery system.

This study takes a practical approach towards battery aging to limit the complexity and avoid non-linear constraints. Empirical studies show that for C-rates[1] of 1 c or less, which can be expected as the outcome of the presented model, the capacity fade is close to linear [52,53]. The warranties provided by the manufacturers are taken as references to model the worst-case linear decline. The warranties of the manufacturers usually guarantee utilization, e.g. 150,000 km, and durability, e.g. 8 years. To account for both limitations, the battery degradation factor in this study $w^{ucap}(s^{mob})$ is calculated as the minimum two terms: First, the total mileage in the mobility scenario in relation to the maximum warranted distance; second, the investment period in relation to the warranted durability.

$$w_{a}^{ucap}(s^{mob}) = min\left\{\frac{w^{batdist} - \left(DIST(s^{mob})\right)}{w^{batdist}}, \frac{w^{battime} - a_{end}}{w^{battime}}\right\} \tag{8}$$

---

[1] The C-rate stands for the ratio of the applied (dis-)charging current to the capacity of the battery, e.g. for a battery a capacity of 40 Ah a charging current of 80 A means a C-rate of 2.

For residual values of EVSE type c in year a, $RV_{a,c}^{EVSE}$ there are currently no well-founded models. Therefore, following the legal depreciation time a linear loss of value independent of the intensity of use is assumed.

$$RV_{c,a}^{EVSE} = \frac{INV_{c,a_0}^{EVSE}\left(1-\frac{a}{A^{EVSEd}}\right)}{(1+i)^a} \quad (9)$$

The costs of operation are divided into fixed and variable costs with the variable costs $C^{EVEN}(s^{mob}, s^{temp})$ and $C^{EVMA}(s^{mob})$ depending on the assumed mobility demand s^{mob} and ambient temperature s^{temp} scenario.

$$C^{op}(s^{mob}, s^{temp}) = C^{EVEN}(s^{mob}, s^{temp}) + C^{EVMA}(s^{mob}) + C^{EVTI} + C^{EVSEMA} \quad (10)$$

Fixed are the annual costs for insurance and taxes

$$C^{EVTI} = \sum_{a \in A} \frac{c^{EVtax} + c^{EVins}}{(1+i)^a} \quad (11)$$

as well as EVSE maintenance for each year a of operation.

$$C^{EVSEMA} = \sum_{a \in A} \frac{INV_c^{EVSE} f^{EVSEma}}{(1+i)^a} \quad (12)$$

The energy and EV maintenance costs are variable. The energy costs depend on the total energy charged during operation, the electricity price pr_t^{el} in period t, and the chosen time resolution d.

$$C^{EVEN}(s^{mob}, s^{temp}) = \sum_{t \in T} P_{t,s^{mob},s^{temp}}^{crg}\, pr_t^{el} d \quad (13)$$

EV maintenance costs are set variable only depending on the distance traveled $DIST(s^{mob})$ in the specific mobility demand scenario s^{mob}.

$$C^{EVMA}(s^{mob}) = DIST(s^{mob})\, c^{EVma} \quad (14)$$

2.1.2 Constraints

The technical model of the EV sets the constraints for the stochastic program. In the following, the focus lies on the energy model. The non-linear progressions of the energy consumption and charging curves are piecewise linearly approximated (see Section 5.1 and Appendix C). This approach leads to higher quality results than the commonly assumed fixed maximum capacity while the overall problem remains linear [54]. The thermal behavior of the battery is neglected.

The mobility scenarios determine when the EV can be charged. No public charging is included as risk mitigation. Currently, only limited public charging stations are available. Therefore, in the opinion of the authors, commercial applications, in which mobility is an essential part of the service, should not be dependent on the accessibility of public charging stations. Hence, the vehicle is only available for charging when parking on company grounds (the binary charging parameter $DS_{t,s^{mob}}^{crg} = 1$ and the binary driving parameter $DS_{t,s^{mob}}^{drv} = 0$).

$$P_{t,s^{mob},s^{temp}}^{crg} = 0,\ \forall\, t \in T, s^{mob} \in S^{mob}, s^{temp} \in S^{temp} | DS_{t,s^{mob}}^{crg} = 0 \quad (15)$$

Four typically used AC charging types distinguished by their charging capacity are compared in this paper: Mode 2 with 2.2 kW from a domestic socket, Mode 3 with 3.7, 11, and 22 kW (IEC61851-1). The battery charging curve is piecewise approximated by two linear parts. Exemplary recorded curves can be found in Schücking et al. [55] or Landau et al. [56]. Starting from an empty battery a constant maximum power P_c^{maxcrg} can be utilized.

$$P^{crg}_{t,s^{mob},s^{temp}} \leq P^{maxcrg}_{c}, \forall\, t \in T, s^{mob} \in S^{mob}, s^{temp} \in S^{temp} \tag{16}$$

After reaching a certain threshold, in this study defined by the remaining battery capacity to charge, the charging capacity is reduced depending on the SOC $SOC^{bat}_{t,s^{mob},s^{temp}}$.

$$P^{crg}_{t,s^{mob},s^{temp}} \leq SOC^{bat}_{t,s^{mob},s^{temp}} \left(-\frac{P^{maxcrg}_{c}}{RP_c}\right) + \frac{w^{ucap}(s^{mob}) f^{EVgn} BCAP^{G} P^{maxcrg}_{c}}{RP_c}, \forall t \in T, s^{mob} \in S^{mob}, s^{temp} \in S^{temp} \tag{17}$$

The reduction depends on the SOH $w^{ucap}(s^{mob})$ and the available net capacity f^{EVgn}. The point of reduction RP_c varies between the different types of EVSE. In this study, no vehicle-to-grid services such as providing energy back to the grid or other ancillary services are included (Appendix C1).

In the energy model, it is important to distinguish the different measurement points for assessing energy consumption. From the technical point of view the tank-to-wheel (TTW) energy consumption is relevant. From an economic point of view, the grid-to-wheel efficiency (GTW) must be considered. The losses due to transformation and resistances that occur between the grid and the battery are included in the charging efficiency factor η^{crg} [57].

The discrete energy model is set by the SOC in period $t+1$ which equals the SOC in period t plus the energy charged minus the energy consumed through driving calculated by the average speed $DS^{spd}_{t,s^{mob}}$ and the specific TTW energy consumption EC^{el} (Appendix C2).

$$SOC^{bat}_{t+1,s^{mob},s^{temp}} = SOC^{bat}_{t,s^{mob},s^{temp}} + \left[\left(P^{crg}_{t,s^{mob},s^{temp}} \eta^{crg}\right) - DS^{spd}_{t,s^{mob}} EC^{el}\left(DS^{spd}_{t,s^{mob}}, BCAP^{G}, Temp^{amb}_{t,s^{temp}}\right)\right] d$$
$$\forall t \in T, s^{mob} \in S^{mob}, s^{temp} \in S^{temp} \tag{18}$$

For the TTW energy consumption EC^{el} the average speed $DS^{spd}_{t,s^{mob}}$ (drag), the additional battery weight (rolling resistance) and the ambient temperatures $Temp^{amb}_{\boldsymbol{t,s^{temp}}}$ (auxiliary load) are considered as individual influence factors. The SOC can never exceed the maximum available capacity

$$SOC^{bat}_{t,s^{mob},s^{temp}} \leq w^{ucap}(s^{mob}) f^{GN} BCAP^{G}, \forall t \in T, s^{mob} \in S^{mob}, s^{temp} \in S^{temp} \tag{19}$$

and must always be positive.

$$SOC^{bat}_{t,s^{mob},s^{temp}} \geq 0\ \forall t \in T, \forall s^{mob} \in S^{mob}, s^{temp} \in S^{temp} \tag{20}$$

Furthermore, the SOC level after purchase (period t_0) and when the EV is sold at the end of the time (period t_{end}) are set to be the same.

$$SOC^{bat}_{t_0,s^{mob},s^{temp}} = SOC^{bat}_{t_{end},s^{mob},s^{temp}}, \forall s^{mob} \in S^{mob}, s^{temp} \in S^{temp} \tag{21}$$

2.2 Scenario generation with a hidden Markov model

The mobility demand scenarios are one core input to the SAA. They consist of different tours taken by the EV over a fixed period. A tour starts with leaving the company grounds and ends with the return. It can consist of several trips and intermediate stops, which makes it a complex structure to predict. The key parameters required by the optimization model are the starting time of the tour as well as the parameters of the individual trips and stops during the tour.

The stochastic model used to generate the scenarios from the historical data and forecast the future mobility demand consists of three parts: an inhomogeneous Markov model to predict the starting point of the tours, a multinomial HMM to generate the individual tours, and a set of conditional normal distributions to estimate the mean speed per trip depending on the duration.

Since the probability of starting a tour is dependent on the time of day in line with previous studies, a discrete inhomogeneous Markov model is used to account for the temporal variance of the transition probabilities [45]. The maximum-likelihood estimator of the transition probabilities $\hat{p}_{jk}(t)$ for visible states S, can be calculated based on the historic observations $n_{jk}(t)$ at time t.

$$\hat{p}_{jk}(t) = \frac{n_{jk}(t)}{\sum_{l=1}^{N} n_{jl}(t)}, \forall j, k \in S \tag{22}$$

HMMs are finite mixture models. They consist of two parts: an unobserved parameter process and an observed state-dependent process (Appendix A). The unobserved parameter process satisfies the Markov property and can, therefore, be applied to driving cycle modulation. HMMs can be trained on historical data in supervised learning. The most common approach to find the estimates of the model parameters is the Baum-Welch algorithm [58]. This paper applies a strategy version for this algorithm based on Biernacki, Celeux, & Govaert [59] with several runs and different random starting parameters (Appendix A). This approach does not guarantee a global optimum but reduces the risk of getting stuck in a local one [60].

Different evaluation criteria are used to identify the best suitable HMM. The number of hidden states cannot be deduced from the data. An ex-post evaluation is necessary. With each additional hidden state, the model fit indicated by the log-likelihood increases. However, so does the number of parameters. In the case of the multinomial-HMM, the number of parameters B is calculated by $B = H + H^2 + H \cdot O$ where H is the number of hidden states and O is the number of observations. To avoid an overcomplex model two commonly used evaluation metrics are applied. The Akaike information criterion (AIC) [61]

$$AIC = -2 \log L + 2B \tag{23}$$

and the Bayes information criterion (BIC) [62].

$$BIC = -2 \log L + B \log O \tag{24}$$

Both provide relative model quality estimates, where L is the log-likelihood of the training data. The HMM with the lowest values is the best fitting model.

As an additional selection criterion k-fold cross-validation is used. It is a standard practice in supervised statistical learning to ensure out-of-sample predictive performance [63]. k-fold cross-validation is applicable to HMMs [64]. In this paper, 4-fold cross-validation is chosen. In each run ¾ of data are taken for training while ¼ is left out for testing.

The last part of the stochastic driving profile generation is the estimation of each trip's mean speed. For driving profiles, the mean speed increases with the total driving distance of the trip [65]. Accordingly, speed and trip duration cannot be considered independent. For different intervals of duration, separate normal distributions are assumed based on the historical data with the statistical value as maximum likelihood estimators for μ and σ.

2.3 Scenario reduction heuristics

The complex nature of the underlying uncertainty distribution often requires many scenarios for the SAA. Since the approximated deterministic model is solved considering all scenarios simultaneously, this can lead to a significant computational burden. The most common approach to limiting the computational burden while keeping a high quality of the solution is to approximate the original set of scenarios with a smaller representative subset. Fast forward selection (FFS) is a commonly applied scenario reduction heuristic that relies on the probability metrics of the stochastic input parameters when generating the representative subset [30,66].

Over the years, FFS has faced some criticism for its sole focus on the input parameters and their failure to consider the individual scenario's impacts on the first-stage decision and second-stage cost. The literature proposes different advancements that build on FFS but cluster the scenarios according to key first-stage decision variables or consider the individual scenario's impact on the optimum value [67–69].

Adding to this line of research, three different scenario reduction heuristics are compared in the following: FFS heuristic (Appendix B) introduced by Heitsch & Römisch [30] as well as two versions of forward selection in wait-and-see-clusters (FSWC) heuristic proposed by Feng & Ryan [67].

The FSWC heuristic differs from FFS by including the key first-stage decision variables in the scenario reduction process by implementing the following four steps:

- Step 1:
  For each mobility scenario, the deterministic subprogram is solved, and the key first-stage decision variables are recorded.
- Step 2:
  The scenarios are clustered by their first-stage decision variables. If the number of first-stage decision variable combinations q_m is equal to or smaller than the target number of scenarios q step 3 can be skipped.
- Step 3:
  The number of groups q_m is reduced by clustering them into q clusters. Instead of the k-means clustering algorithm [70] used by Feng & Ryan [67] the improved k-means++ [71] method is applied in this paper to create the clusters q.
- Step 4:
  For each of the clusters, one representative scenario is selected by using FFS. The probabilities of the unselected scenarios in the cluster are added to the probability of the selected one.

In the presented framework the battery and charging capacity are used for clustering.

As an additional approach, this paper proposes a new advancement of the original FSWC algorithm (in the following called FSWC_S). The new version (in the following called FSWC_O), also considers the overall output performance of the individual scenarios. In step 4, instead of selecting the representative scenario for each cluster based on the Kantorovich distance between their probability distributions, the second-stage costs of the individual optimization runs are used, represented by $o_{kj}^{[1]} \coloneqq o(\omega_k, \omega_j)$. The required information is already available through the individual solution of the deterministic subprograms from step 1. Therefore, no additional effort is required in comparison to FSWC_S. The motivation behind this advancement is to provide a potentially more efficient way of approximating the optimum value of the presented two-stage stochastic model. This can be achieved by having even smaller scenario subsets delivering a high-quality solution and therefore reducing the computational time of the overall program.

3. Data and case study design

The stochastic program is implemented for the home nursing service use case: Nurses drive around in small vehicles to attend to care-dependent people in their homes. Its technical and organizational requirements can be met by the properties of EVs. Mobility is essential to the operations and the mobility cost is the second-highest cost item after labor. The fleets usually consist of EVs from the mini or small segment. The tours show a high frequency of starts and stops with an annual mileage of 15,000 km in urban and 20,000 km in rural environments. Due to the frequent short trips, combustion engines are especially inefficient leading to high fuel consumption and maintenance costs. Previous research has identified it as one of the most promising commercial use cases for early EV introduction [4,5].

Technical and financial EV and EVSE properties, electricity prices, mobility demand, and temperature are the data input to the model. Whenever possible literature values are validated with current market information or directly taken from manufacturers or leasing companies (Table 3). Also, direct data from operations, e.g. charging infrastructure maintenance, electricity prices, insurance, and warranties are used.

The estimation of the specific energy consumption in dependence of the mean speed per trip is split into three components: the energy consumed by propulsion, the additional energy consumption due to the battery weight, and the energy required by the auxiliaries depending on the outside temperature (Appendix C1). The resulting, here piecewise linearly approximated, specific energy consumption curve in Fig. 2 shows the distinctive progression that can also be found in empirical studies [e.g. 72–74].

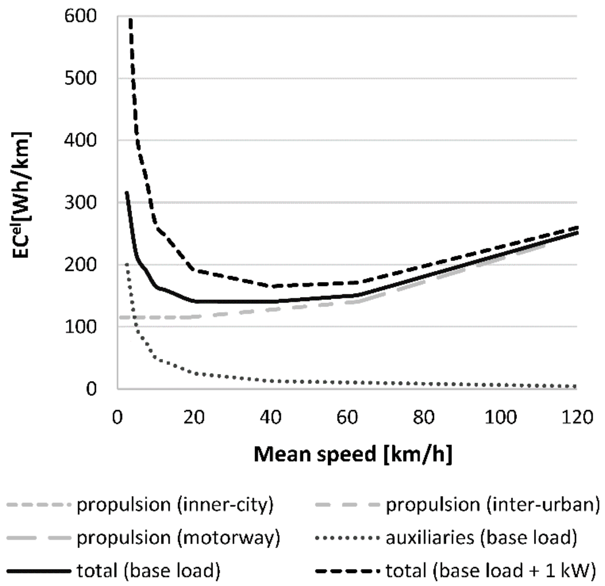

Fig. 2 *Linear approximation of the EV specific energy consumption depending on the average speed and auxiliary demand (Appendix C1, Source: ADAC)*

Parameter	Value	Explanation & source
a_0	2017	year of investment
INV^V	20,000 €	the mean EV net purchase price with basic configuration and no battery (mini and small car segment) [75]
pr_{2017}^{bat}	210 €/kWh	the net battery price on a system level, mean value from the literature [76,77]; validated with current EV purchase prices [78]
pr_{2020}^{bat}	185 €/kWh	the net battery price on a system level, mean value from the literature [76,77]
$f_{0.7}^{batSL}$	0.5	the reselling price of the battery at the end of life will be around 50% of the current market price for a new comparable battery [51]
c_a^{batref}	50 €/kWh	estimation of the battery refurbishment cost based on the mean value from review by [51] assumed to be independent of a
α	0,97948	a constant from the regression model by [50]
β_1	$-1.437 \cdot 10^{-2}$	the age factor from the regression model by [50]
β_2	$-1.17 \cdot 10^{-4}$	the mileage factor from the regression model by [50]
β_3	0.91569	the purchase price factor from the regression model by [50]
a_{end}	3 a	assumption of EV usage time due to fast technological advances, 3.8 years is the current average for commercial vehicles [6]
d	1 min	time resolution of the model
i	5.02%	the mean value of interest rates in Germany over the last 10 years [79]
T^{EVSEd}	8 a	assumption based on comparable technical equipment, no reliable empirical data available or legal amortization period defined in Germany
pr_t^{el}	0.20 €/kWh	net price for electricity (assumed constant, since this is currently the case for most home nursing service providers in Germany) (EPEX SPOT)
c^{EVma}	0.024 €/km	the mean value of EV maintenance costs from the literature [80–82]
c^{EVtax}	0 €/a	EV are exempted from taxes and tolls in Germany
c^{EVins}	450 €	assumption for EV insurance based on interviews (IIP database)
f^{EVSEma}	0.10	assumption for EVSE maintenynce based on interviews with installation companies (IIP database)
f^{EVgn}	0.87	the mean current value for the gross to net battery capacity ratio estimated based on information provided by manufacturers of current EV models
η^{crg}	0.85	the mean value of charging efficiency based on own measurements and review [56,57]
w^{batcap}	0.70	the mean current value of warrantied battery capacity communicated by the manufactures of current EV models
$w^{batdist}$	160,000 km	the mean current value of warrantied battery lifetime milieage communicated by the manufactures of current EV models
$w^{battime}$	8 a	the mean current value of warrantied battery life communicated by the manufactures of current EV models
ρ^{bat}	95 Wh/kg	the energy density of current Li-ion batteries [81]
c_{rr}	0.0088	the rolling resistance coefficient mean value for tires on the road surface [81]
g	9.81 N/kg	the gravitational constant

***Table 3** Overview of the technical and economic input parameters for the case study*

Table 4 provides an overview of the four EVSE alternatives that are compared in this study. The progression of the piecewise linear charging load-curves can be seen in Fig. 3 (Appendix C2). The net purchase prices INV_c^{EVSE} for the EVSE are current mean market values. For the 2.2 kW, investment and installation costs are assumed to be zero since it only requires a separately protected standard power socket.

P_c^{maxcrg}	**2.2 kW**	**3.7 kW**	**11 kW**	**22 kW**
RP_c	1 kWh	1 kWh	3.5 kWh	7 kWh
INV_c^{EVSE}	0 €	600 €	1,200 €	1,800 €
$INST_c^{EVSE}$	0 €	100 €	200 €	300 €

Table 4 *Technical and economic input parameters for the different EVSE alternatives (Sources: IIP database)*

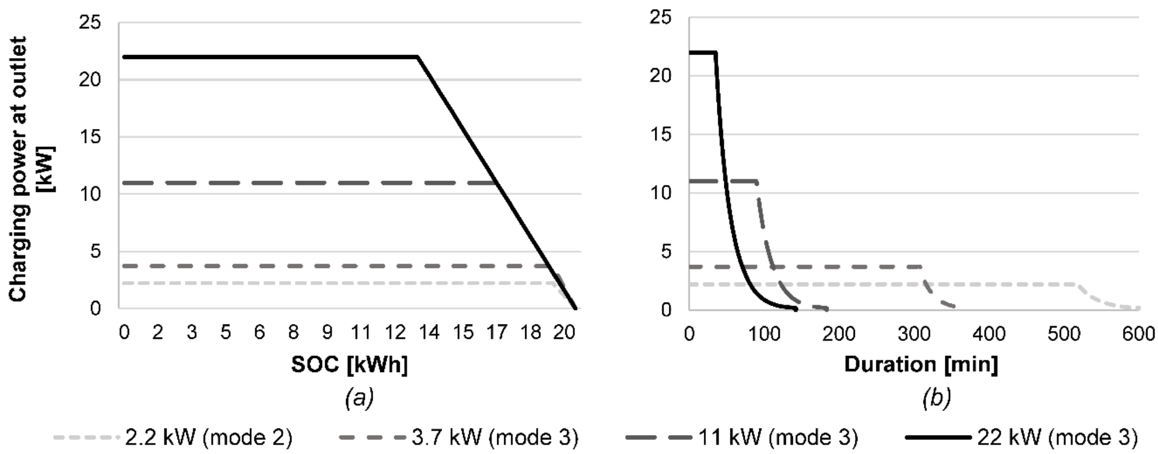

Fig. 3 *Maximum available charging power for the EVSE alternatives depending on SOC (a) and duration (b) (Appendix C2, Source: IIP database)*

The data input to train the mobility demand model is taken from the regional eco mobility 2030 (REM2030) project [83]. The empirical data consists of 91,422 single trips from 630 commercial ICEVs that were deployed by various companies from different economic segments over an average period of three weeks. For each trip the time of departure, arrival, the distance traveled, and the distance to the company are recorded. Also, metadata concerning the vehicles and companies is available [83]. This case study is based on ICEV data under the assumption that the mobility profiles will not change when EVs are introduced since they are determined by the customer and user demand.

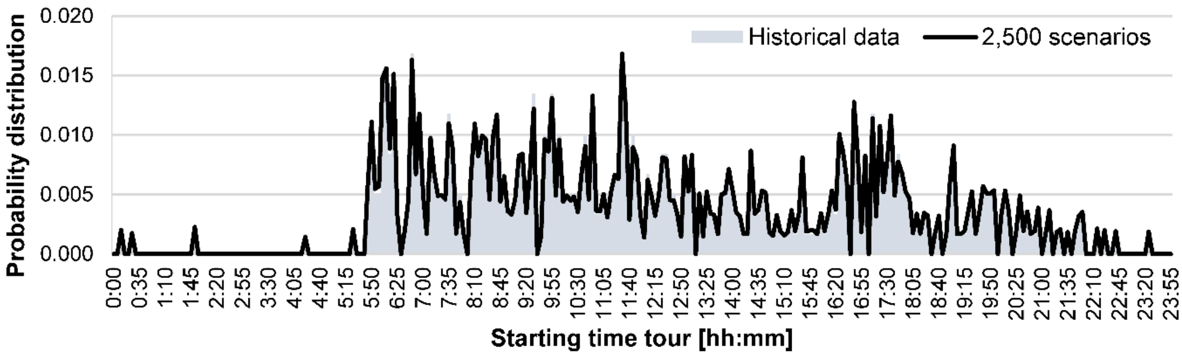

Fig. 4 *Distribution of the tour starting times for the home nursing service case study (Source: REM2030* [83]*)*

For this case study, one home nursing service company with ten vehicles and 1,698 logged trips is selected. The minimum of recorded trips per vehicle is 17 and the maximum 299. The demand for home-nursing service is independent of the weekday. The relative frequency of starting tours shows three high peaks throughout the day, indicating that in the morning, around noon, and in the late afternoon, there is a higher probability for starting a tour (Fig. 4).

The proposed model requires tours consisting of one or more cohesive, individual trips as input. Therefore, it is necessary to cluster the single recorded trips into tours that start and end at the company. The tours are created based on assumptions about the driving profiles. Unfortunately, the times at the company are not given in the data set. As a workaround, it is assumed that the vehicle has returned to the company if the waiting time between two trips is larger than 30 minutes. This approach has been approved by operators. Based on this approach 594 tour profiles are created. Since around 70% of all of the trips are shorter than 10 minutes with over 25% being shorter than 5 minutes a time resolution d of one minute is required to allow a detailed energy consumption assessment.

Temperature data for five large German cities from 1981 to 2016 provided by the Climate Data Center (CDC) is taken as data input for the temperature scenarios [84]. From readings at these five measurement points over 25 years, an average year with 52 weeks and hourly values is calculated as the set of temperature scenarios.

To analyze the effect of variable electricity prices on the battery and charging capacity investment decision as well as on the operational costs, flexible tariffs are introduced. In the base case, the net price for electricity pr_t^{el} is assumed to be constant. For the flexible tariffs, hourly electricity prices for Germany from 2014 at the European Power Exchange (EPEX SPOT) are taken and separated into 52 weekly scenarios. To assess the sensitivity of the optimal results to a flexible tariff, the weeks with the minimal, median, and maximal variation are selected (Table 5). The EPEX SPOT lists wholesale prices. Hence, additional charges must be considered. The final net price pr_t^{el} is calculated by subtracting the annual average wholesale price $pr_{\emptyset,2014}^{EPEX\,SPOT}$ from the net price in the base case pr_t^{const} and adding the hourly wholesale price $pr_{t,2014}^{EPEX\,SPOT}$.

$$pr_t^{el} = pr_t^{const} - pr_{\emptyset,2014}^{EPEX\,SPOT} + pr_{t,2014}^{EPEX\,SPOT} \tag{26}$$

Scenario	Mean pr_t^{el}	Minimum pr_t^{el}	Maximum pr_t^{el}
Constant	0.200 €/kWh	0.200 €/kWh	0.200 €/kWh
Flexible minimum	0.181 €/kWh	0.201 €/kWh	0.222 €/kWh
Flexible median	0.173 €/kWh	0.203 €/kWh	0.248 €/kWh
Flexible maximum	0.136 €/kWh	0.187 €/kWh	0.218 €/kWh

***Table 5** Overview of the assessed electricity price scenarios (Source: EEX)*

4. Case Study Results

The following section presents and discusses the results regarding the applied framework and implications for commercial applications.

4.1 Mobility scenario generation

As input to the framework, the empirical tour profiles are coded with the three introduced parameters $DS_{t,s^{mob}}^{crg}$,$DS_{t,s^{mob}}^{drv}$, and $DS_{t,s^{mob}}^{spd}$ which indicate the current status of the EV at any given point in time (Table 6).

Vehicle status	$DS_{t,s^{mob}}^{crg}$	$DS_{t,s^{mob}}^{drv}$	$DS_{t,s^{mob}}^{spd}$
EV is parked on company grounds and can be charged	1	0	0
EV is parked during a tour and cannot be charged	0	0	0
EV is driving	0	1	>0

***Table 6** Overview of the three different vehicle states that are used to model the mobility scenarios*

HMMs with different numbers of hidden states are trained to identify the best fitting model with the tour profiles assumed to be independent of the time of day. Four separate training and evaluation sets were created from the 594 empirical tours. The model training was implemented in Python using the *Annaconda* environment and the *hmmlearn* package with the functions *fit* to train the model, *score* to calculate the likelihood, and *predict* to decode the hidden states using the Viterbi algorithm. The training was run on a Win Server 2016 (x64) system with a 2x Intel Xeon 5430, 2.66GHz CPU, and 24 GB 4 Core RAM.

Hidden states	**2**	**3**	**4**	**5**	**6**	**7**	**8**
Score	-10,166.78	-9,833.68	-9,769.73	-9,735.75	-9,723.50	-9,722.33	-9,717.96
AIC	20,353.56	19,703.35	19,595.45	19,551.51	19,554.99	19,584.65	19,611.91
BIC	20,435.84	19,851.44	19,825.81	19,880.59	19,999.25	20.160.55	20,335.90
4-fold score	-2,759.53	-2,497.78	-2,486.18	-2,463.14	-2,467.39	-2,460.60	-2,460.56

Table 7 *Model evaluation results for the HMMs with an increasing number of hidden states*

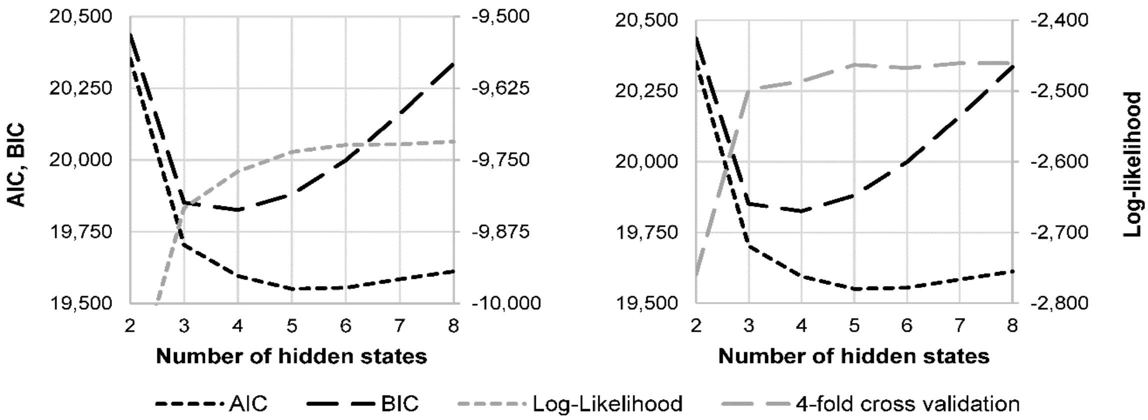

Fig. 5 *AIC, BIC, log-likelihood, 4-fold cross-validation values of the HMMs with an increasing number of hidden states*

The results of the model evaluation indicate that an HMM with either four or five hidden states has the best fit (Table 7 & Fig. 5). The BIC favors four hidden states, the AIC five. The 4-fold cross-validation as an indication for out-of-sample performance also favors the HMM with five hidden states. Further, increasing the number of hidden states delivers no significant gain in predictability (Table 7 & Fig. 5). Hence, the HMM with five hidden states is selected (Appendix B). The comparison of the empirical data and the scenarios created underlines the quality of the model (Fig. 4 & Fig. 6).

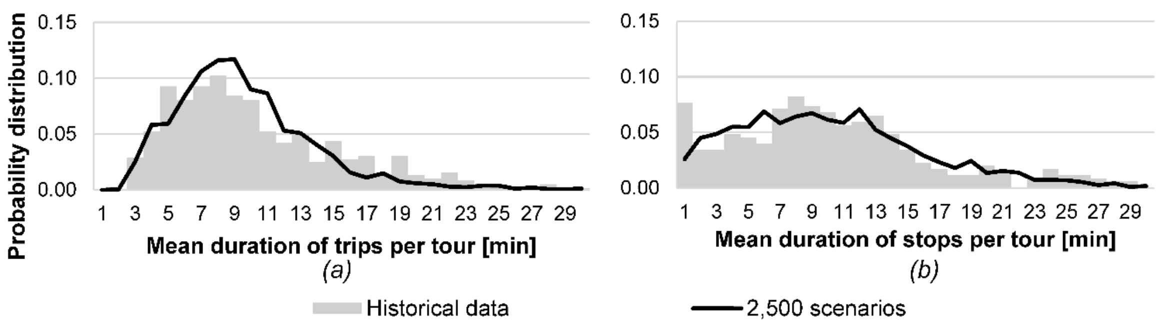

Fig. 6 *Comparison of the historical data and the scenarios generated by the HMM*

For estimation of the mean speed values in dependence of the individual trip duration, the empiric values are separated into five classes. For each class, a normal distribution is assumed based on the ML estimation of μ and σ (Table 8). The goodness of fit is assessed with the Kolmogorov-Smirnoff (KS) test.

With the stochastic model, 2,500 scenarios of one-week mobility demand in one-minute time resolution were generated by Monte-Carlo simulation. The high number of scenarios M is required to ensure with 95% confidence (risk level δ = 0.05) that the estimated mean varies 5% (accuracy ε) or less from the original values for the four tour characteristics: number of trips per tour, mean duration of trips per tour, number of stops per tour, and mean duration of stops [85].

$$M \geq \Phi^{-1}(1-\delta)^2 \frac{\sigma^2}{\varepsilon^2} \tag{27}$$

	0-5 min	6-10 min	11-15 min	16-20 min	>20 min
$\boldsymbol{\mu}$	14.91	22.36	35.56	41.91	50.72
$\boldsymbol{\sigma}$	8.42	11.04	13.95	13.34	15.58
KS test					
$\boldsymbol{\sqrt{r}L_n^{norm}}$	$\sqrt{63}L_n^{norm} = 0.57$	$\sqrt{205}L_n^{norm} = 0.81$	$\sqrt{198}L_n^{norm} = 0.68$	$\sqrt{63}L_n^{norm} = 0.57$	$\sqrt{63}L_n^{norm} = 0.67$
$\boldsymbol{l_{n;\,0,95}^{norm}}$	$l_{>30;\,0,95}^{norm} = 0.89$	$l_{>30;\,0,95}^{norm} = 0.89$	$l_{>30;\,0,95}^{norm} = 0.89$	$l_{>30;\,0,95}^{norm} = 0.89$	$l_{>30;\,0,95}^{norm} = 0.89$
Normal distribution	Cannot be rejected	Cannot be rejected	Cannot be rejected	Cannot be rejected	Cannot be rejected

Table 8 *Results of the ML estimation for the normal distribution parameters of the average speed depending on trip duration and goodness of fit assessment*

4.2 Subsets for scenario reduction

All scenario reduction algorithms were implemented in Python and run on a Win Server 2016 (x64) system with a 2x Intel Xeon 5430, 2.66GHz CPU, and 24 GB 4 Core RAM. Scenario subsets containing from 5 to 25 scenarios are created with each heuristic. In step 2 of the FSWC, the 2,500 individual sub-problem solutions can be clustered into 70 different combinations of optimal battery and charging capacity. Fig. 7 provides an overview of the relative frequency of the battery and charging capacity combinations as well as examples of clusters created out of the 70 combinations by the k-means++ algorithm in step 3.

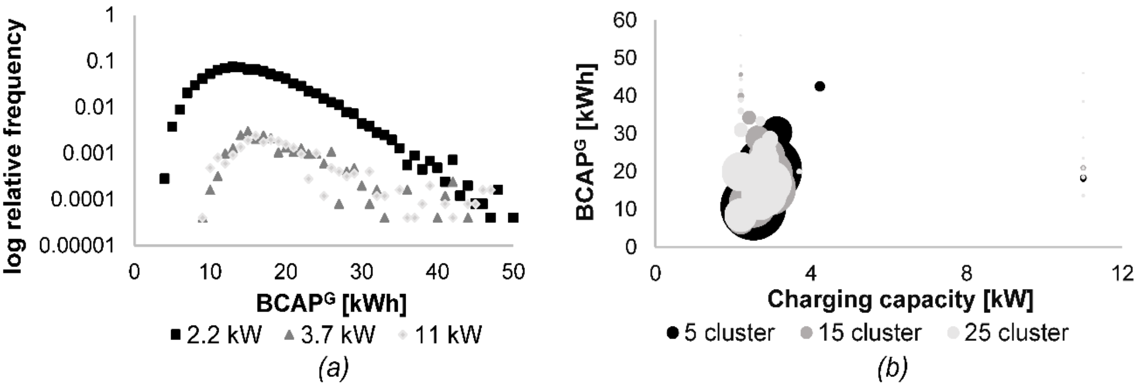

Fig. 7 *Solutions of the individually optimized subprograms (a) and exemplary clusters created by the k-means++ algorithm (b)*

4.3 Optimization

The optimization model is solved for scenario subsets of different sizes whose composition is determined by the three reduction heuristics. The program sizes for the different subsets can be found in Table 9. The optimization is implemented in Python 3.63, solved with the Gurobi solver (7.5.2), and run on a Win Server 2016 (x64) system with a 2x Intel Xeon 5430, 2.66GHz CPU, and 24 GB 4 Core RAM.

S^{mob}	No. of lines	No. of columns	No. of non-zeros	No. of continuous variables	No. of integer variables
5	3,528,002	1,512,014	5,608,024	1,512,013	1
10	7,056,002	3,024,014	11,208,684	3,024,013	1
15	10,584,002	4,536,014	16,937,014	4,536,013	1
20	14,112,002	6,048,014	22,739,234	6,048,013	1
25	17,640,002	7,560,014	28,520,874	7,560,013	1

Table 9 *Program size dependent on the number of mobility demand scenarios (S^{temp} = 10)*

4.3.1 Scenario reduction – mobility scenarios

The progression of the optimal value shows distinctive differences between the scenario reduction approaches. The optimal value is highly sensitive to the composition of scenarios selected. In comparison, both FSWC approaches require fewer scenarios than FFS to reach a stable approximated solution in the observed range (Fig. 8a). Furthermore, the stabilization level of the optimal value differs for all three algorithms. For smaller subsets, the optimal choice of charging capacities varies. From subsets containing 15 selected by FSWC and 20 by FFS onwards, 11 kW becomes the consistent cost-minimal choice. Detailed numerical results for all charging capacity alternatives can be found in Appendix D1.

The effects of increasing scenario subset sizes on the optimal gross battery capacity choice also shows distinctive differences between the three scenario reduction heuristics (Fig. 8b). With FFS the battery capacity increase is monotone. In each step, new mobility scenarios are added with some increasing the required optimal battery capacity. For scenario subsets selected by FSWC, the progress of the optimal battery and charging capacity configuration is more volatile. As new clusters are formed in each step, the composition of the most representative scenarios does not build on the selection in the smaller subsets. Like the optimal value and charging capacity, the optimal choice for battery capacity stabilizes with larger subset sizes. A small difference of 1 kWh remains between the optimal choice based on FSWC and FFS (Table D.1). This small discrepancy cannot explain the observed gap between the optimal TCO values generated by the three heuristics.

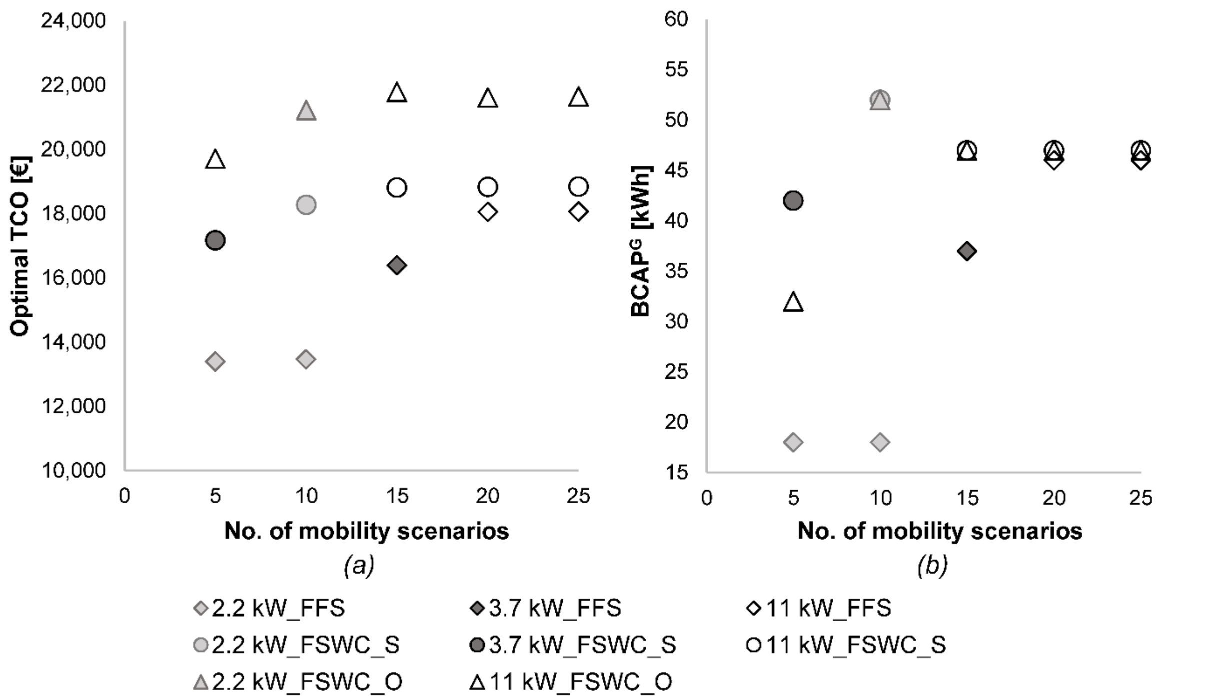

Fig. 8 *Optimal TCO values (a) and gross battery capacities (b) with an increasing number of mobility demand scenarios for the three reduction heuristics FFS, FSWC_S & FSWC_O (S^{temp} = 10)*

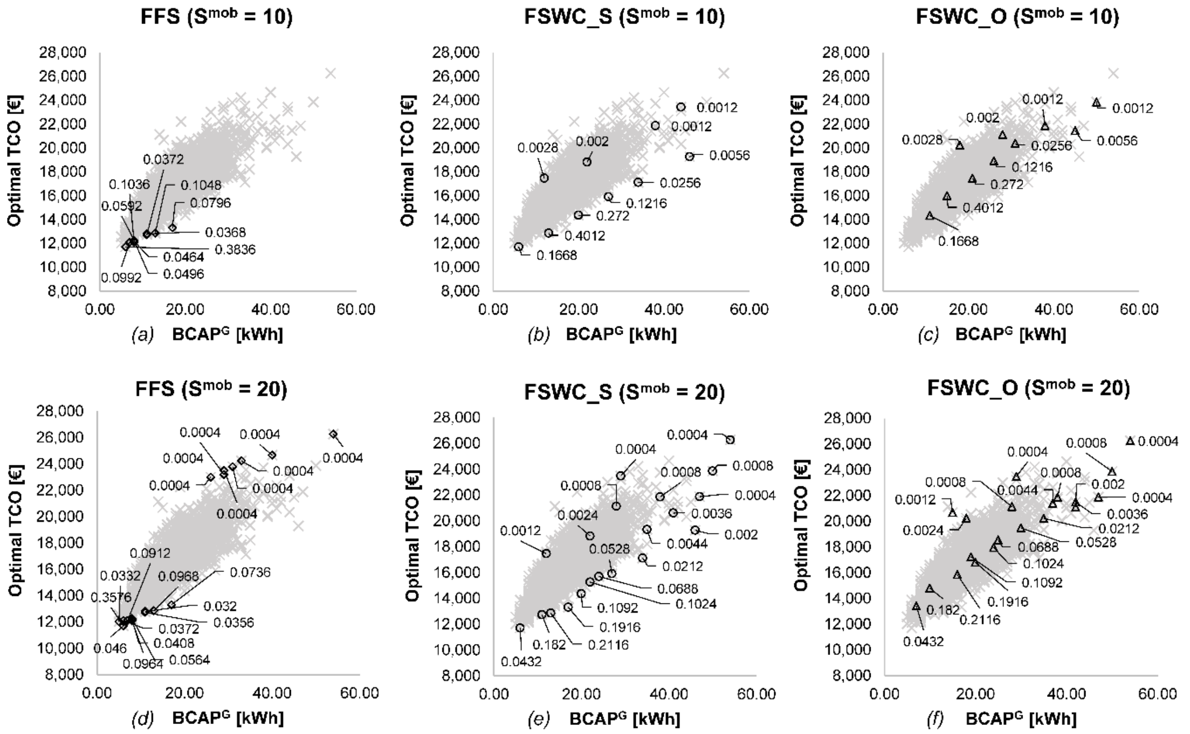

***Fig. 9** Distribution of the optimal TCO values and battery capacity choices for the 2,500 individual subproblem solutions with the allocated probabilities compared for all three scenario reduction heuristics (S^{mob} = 10 or 20; S^{temp} = 10)*

As is illustrated by Fig. 9, the gap can be explained by the second-stage cost distribution of the selected scenarios and their allocated probabilities. For the subset consisting of ten scenarios, FFS only selects scenarios that require a comparably low battery capacity. The optimal TCO values of the selected scenarios are at the lower boundary of the possible optimal TCO values for these configurations. In the subset of 20, also scenarios with individual solutions that have a large optimal battery capacity and comparatively high TCO values are included. However, they show rather low probabilities (0.0004). The scenario selection through FSWC_S and FSWC_O shows a more even distribution, but also distinctive differences (Fig. 9). The effect of selecting the representative scenario for each cluster and attributing the probabilities based on the second-stage costs as a measure for output performance, as it is done in the FSWC_O approach, becomes clearly visible.

4.3.2 Scenario reduction – temperature scenarios

The effect on the optimal TCO value and battery capacity for an increasing number of temperature scenarios differs notably from the mobility scenarios. The comparison of the subsets with an increasing number of scenarios selected by the FFS algorithm shows a fairly stable progression (Fig. 10). The charging capacity of 11 kW is always the cost-minimal choice. The optimal TCO value rises only slightly with the inclusion of more temperature scenarios. The outside temperature has only a small effect on the gross battery capacity, which rises from 45 to 47 kWh for the optimal TCO solution. Numerical results for the individual charging capacity alternatives can be found in Appendix D2.

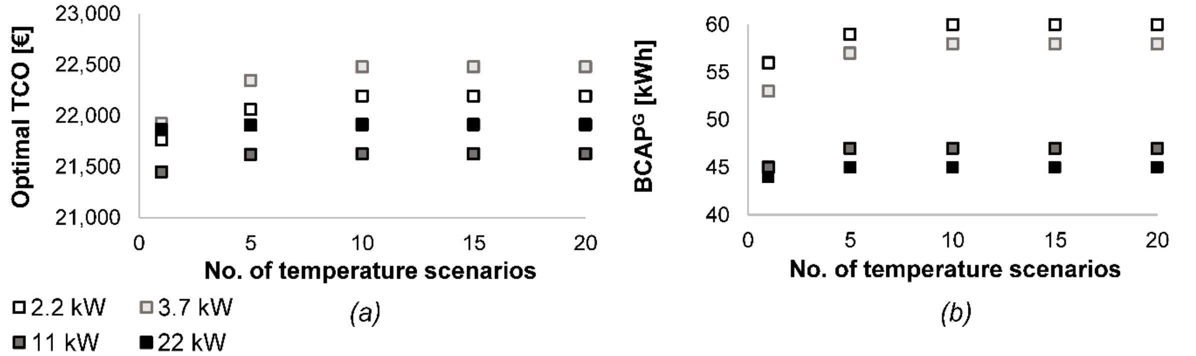

Fig. 10 *Optimal TCO values (a) and gross battery capacity (b) with an increasing number of temperature scenarios (FFS, S^{mob} = 15)*

4.3.3 Evaluation of the stochastic approach and the applied heuristics

The comparison of the optimal TCO values resulting from the different scenario reduction heuristics shows that the newly proposed FSWC_O delivers the best approximation for our case study. The relative error to the solution for all 2,500 scenarios (z_{2500}*) is 1.3% (Table 10). Hence, this solution is taken for the evaluation of the stochastic approach based on the expected value of perfect information (EVPI). The EVPI is calculated by the difference of the expected value of all individual subproblem solutions (EX_{2500}) and the optimal stochastic solution ($z_S{}^{mob*}$). It represents the amount one would be willing to pay for perfect foresight [25]. In this case study, the EVPI is 4,956 € (Table 10). The proportionally high value is owed to the large influence of the uncertain mobility patterns on the optimal investment decision. This underlines the importance of considering the uncertain energy demand in the investment decision even for the relatively regular mobility patterns of the home nursing service. The effect will arguably be even stronger for commercial use cases that show a higher variance in their mobility patterns.

	FFS	FSWC_S	FSWC_O
S^{mob}	25	25	25
$z_S{}^{mob*}$	18,071 €	18,847 €	21,656 €
P_c^{maxcrg}	11 kW	11 kW	11 kW
$BCAP^G$	46 kWh	47 kWh	47 kWh
z_{2500}*	21,382 €	21,382 €	21,382 €
error	18.3%	13.5%	1.3%
EX_{2500}	16,700 €	16,700 €	16,700 €
EVPI			4,956 €

Table 10 *Overview of the solution quality for the different scenario reduction heuristics and the EVPI*

Due to the different process steps required for the applied scenario reduction heuristics, a clear statement concerning their computational efficiency is challenging. Taking only the final optimization into account, FSWC_O delivers the relatively best approximation. For a detailed comparison of the upstream process steps and potential benefit of parallelized subproblem optimization, the reader is referred to Feng & Ryan [67]. However, the results of the case-study show a clear advantage of the newly proposed FSWC_O compared to the FSWC_S. For both heuristics, the upstream process steps require the same computational time and resources. The second-stage costs taken for the selection of the most representative scenario in FSWC_O are already calculated for the individual subproblems in FSWC_S. Since the quality of the approximated solution is significantly higher for the same subset sizes, in this case study FSWC_O outperforms FSWC_S (Table 10). A qualitative advantage of both FSWC versions over FFS is the transparency throughout the reduction process through the inclusion of the key first-stage decisions. Especially in the context of real applications, this can be an advantage.

4.4 Technological and economic implications for commercial mobility applications

The results of the case study provide interesting insights for commercial fleet operators to determine the techno-economic optimal EV and EVSE system configuration and TCO under uncertain energy consumption. The evaluation of the stochastic approach points to the importance of considering the uncertainty in the investment decision through joint optimization of the investment and expected operational costs. Based on the optimal choice of a gross battery capacity of 47 kWh and charging capacity of 11 kW, home nursing service fleet operators can scan the market to identify small EV models, with a suitable endowment. For example, the current version of the Renault ZOE Z.E. 50 with a gross battery capacity of 52 kWh and up to 22 kW charging capacity would meet the identified requirements.

The potential total cost savings enabled by the inclusion of the battery and charging capacity trade-off in the evaluation framework are notable (Table D.1). For FSWC_O (s^{mob} = 25, s^{temp} = 10) the optimal 11 kW solution reduces the TCO in comparison to the optimal 22 kW configuration by 1.3% (286 €). The cost advantage in comparison to the optimal 2.2 kW and 3.7 kW configurations are 2.6% (566 €) and 3.9% (852 €) respectively (Table D.1). When excluding the cost items, that are independent of the investment choice, e.g. the loss of value for the EV excluding the battery (Eq. 6), the proportional cost advantage increases to 3.2%, 6.3%, and 9.4% respectively. Hence, the results support the argumentation to consider different battery and charging capacity configurations in the investment decision.

The utilization of variable electricity prices combined with an optimal charging scheduling bears the potential for further TCO reductions. As can be seen in Fig. 11, charging EVs in low-price periods can reduce the second-stage cost through load shifting into periods with lower electricity prices. For the optimal 11 kW solution, the total energy costs over the investment period are 2,213 €. Under the assumption that the maximal volatile electricity price scenario would occur daily throughout the investment period, these costs could be reduced by 696 € (i.e. by 31.6%). Even though these effects are relatively small in relation to the overall TCO, variable electricity prices could also influence the optimal investment decision. However, in this case study, the introduction of flexible tariffs does not influence the optimal configuration of 47 kWh battery and 11 kW charging capacity in any of the assumed scenarios (Fig. 11). For other mobility applications, a faster charging option or a larger battery capacity allowing to use low-price periods more efficiently might influence the optimal trade-off between battery and charging capacity.

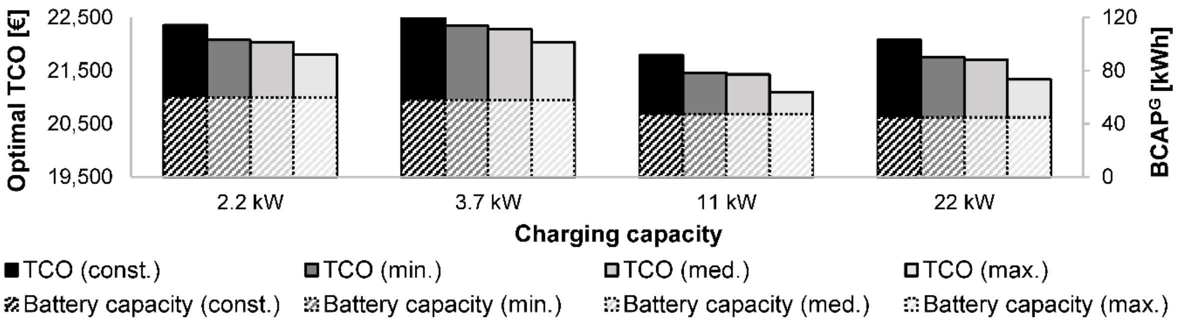

Fig. 11 *Optimal values and battery capacities for the different electricity price scenarios (FSWC_O, S^{mob} = 25; S^{temp} = 10)*

A detailed look into the upstream process steps of the FSWC heuristic provides additional insights that can potentially be beneficial in the investment decision. For the home nursing service case study only few mobility scenarios require battery capacities over 30 kWh or an 11 kW EVSE, when solved individually (Fig. 7 & Fig. 9). This is also reflected in the probabilities allocated to the selected scenarios (Table D.3). All scenarios, which when solved individually, require a battery capacity of less than or equal to 30 kWh, have a cumulative probability of 0.9576; all scenarios, which when solved individually, have a cost-minimal charging capacity of 11 kW, have a cumulative probability of only 0.0076. Hence, the transparency gained through the individual subproblem solution and scenario clustering helps to identify outlier scenarios. This may lead to a reconsideration of a full technical substitution as a condition for the introduction of EVs. In this case study, the willingness to exclude a small proportion of the mobility demand might lead to a system configuration with a significantly lower TCO.

Besides commercial fleet operators, the proposed framework may also be helpful for other user groups. For example, manufacturers of EV and EVSE can use it to draw conclusions on which vehicle configurations are required by commercial customers. Also, policymakers can apply the framework to evaluate the techno-economic substitution potential of EVs in widespread commercial applications. With the commercial vehicle market being an important introductory market, targeted subsidies for the identified mobility applications could notably accelerate the market introduction of EVs.

4.5 Critical appraisal

The suggested optimization approach and presented results are subject to various limitations that require consideration. Some limitations result from the lack of data. Also, simplifications are made to reduce the model complexity. For the overall framework, the key assumptions are that the vehicle must be able to fully cover all tours and the EV has its dedicated EVSE. As the basis for further optimization, both assumptions could be removed when considering a mixed commercial fleet. The abstraction of unrestricted battery capacity is chosen to identify the ideal configuration as a decision-making base for the investment. Currently, manufacturers offer two or three battery capacity choices for their current vehicle models, at best. Furthermore, the study neglects other sources of uncertainty that can influence energy consumption, e.g. the individual driving behavior, as well as the TCO, e.g. the development of electricity or battery prices. For the technical EV model, the key simplifications are the piecewise linear approximations of energy consumption, charging curves, and battery aging. Finally, based on this study, no general statements can be made about the criteria for selecting the appropriate scenario reduction heuristic. FFS worked well for the temperature scenarios; FSWC worked significantly better for the mobility scenarios. A possible explanation for this discrepancy might be the chosen modulation of the driving states based on the three parameters (Table 6). Overall, it can be stated that for the mobility scenarios in this case study, a similarity between two scenarios in the input distribution does not correlate to a similarity in the output of the model, i.e. optimal investment choice and second-stage costs. Hence, relying on the output performance instead of on the stochastic input parameters for scenario selection delivers a better approximation.

5. Conclusion and future work

This paper proposes a comprehensive methodical framework for optimizing the investment choice and operational costs when introducing electric vehicles in commercial fleets. It considers detailed technical electric vehicle characteristics and the uncertain actual energy consumption and available charging times during operation. A two-stage stochastic program that minimizes the costs of the first stage (investment decision) and the second stage (vehicle usage costs) builds the core of the framework. The proposed approach specifically focuses on the trade-off between the electric vehicle's battery and charging capacity in the investment decision as well as on the influence that mobility demand patterns and outside temperature have on energy consumption and available charging times. The stochastic program is solved by sample average approximation. The mobility demand patterns, as part of the stochastic input parameters, are generated by a multinomial-hidden Markov model based on limited empirical time series data. To reduce the computational effort while keeping a good approximation, a newly developed adaptation of an existing scenario reduction heuristic is proposed. The overall framework is applied to a home nursing service case study.

The results of the case study show that the proposed framework is a well-suited approach to address the identified gap in the literature. The results illustrate the impact that mobility patterns and outside temperature as sources of uncertainty can have on the investment decision and therefore underline the importance of the stochastic approach. In the case study, allowing different battery and charging capacities in the investment decision can reduce the total cost of ownership. The influence of the mobility patterns on the investment decision is notably higher than the one of the outside temperatures. In the presented case, the introduction of variable electricity prices does not influence the optimal investment decision. Nevertheless, variable prices can lead to a lower total cost of ownership by enabling load-shifting into low price periods. Regarding the methodology applied, the newly proposed scenario reduction heuristic improves the quality of the approximated solution by including the overall output performance in the selection process with no additional computation effort. Additionally, the scenario clustering based on the optimal investment decision for their individual subproblems increases the transparency and provides valuable insights that can be beneficial in the investment decision. Moreover, the case study demonstrates that a hidden Markov model is well suited to generate stochastic commercial mobility patterns based on limited empirical time series data. In its entirety, the case analysis validates that the proposed framework can directly be applied by commercial fleet operators to determine the optimal electric vehicle and charging station configuration required for the substitution of an internal engine combustion vehicle and to minimize the related total cost of ownership.

Future work is needed to address the shortcomings of the presented framework and related open issues. The precision of the optimization model could be improved by considering the non-linearity of the technical constraints. Also, the hidden Markov model could be extended into an inhomogeneous model. Especially for use cases, where the tours differ in their characteristics throughout the day and between weekdays, an inhomogeneous approach would increase the predictability. Furthermore, the model could be applied to other mobility use cases to assess their potential and the suitability of the model. Also, additional sources of uncertainty could be included. Finally, future research could extend the optimization focus. One obvious extension would be to combine the model with a fleet size and routing optimization approach. This would make it possible to further optimize costs by utilizing the flexibility of different electric vehicle and charging infrastructure configurations or sharing common charging infrastructure between electric vehicles.

Funding Source

This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors.

Appendix A
Hidden Markov model

Hidden Markov models (HMMs) are finite mixture models. They consist of two parts: an unobserved parameter process and an observed state-dependent process. The unobserved parameter process satisfies the Markov property.

$$Pr\left(Z_t|\mathbf{Z}^{(t-1)}\right) = \Pr(Z_t|Z_{t-1}), \forall t \in T \quad \text{(A.1)}$$

It can only be observed through the state-dependent process $\{X_t: t \in 1,2,\ldots\}$ which is solely dependent on the current hidden state Z_t.

$$Pr\left(X_t|\mathbf{X}^{(t-1)}, \mathbf{Z}^{(t)}\right) = \Pr(X_t|Z_t), \forall t \in T \quad \text{(A.2)}$$

In contrast to independent mixture models, there is a temporal dependency. The current hidden state Z_t and therefore the state-dependent process hinges on the previous state Z_{t-1}.

$$p_i(x) = \Pr\,(X_t = x|Z_t = i)\ \forall t \in T \quad \text{(A.3)}$$

$p_i(x)$ is the probability mass function of X_t when the HMM is in a hidden state i at time t. In line with Zucchini et al. [44] three additional properties of the HMM are assumed: temporal homogeneity, stationarity of the Markov chain, and conditional independence. A multinomial HMM can be defined by $(\boldsymbol{A}, \boldsymbol{B}, \pi)$: $\boldsymbol{A}$ is the matrix of the transmission probabilities between the hidden states, $\boldsymbol{B}$ is the matrix of state emission probabilities, and π is the vector of the initial state distribution.

The Baum-Welch algorithm used for training the HMM is a specific form of the EM algorithm which is generally applicable to finite mixture models [86] and makes use of the conditional independence assumption [39]. The likelihood of the estimated parameters increases monotone with every iteration. Depending on the initial parameters the progress can be slow, and it is never clear whether a local or a global optimum has been reached.

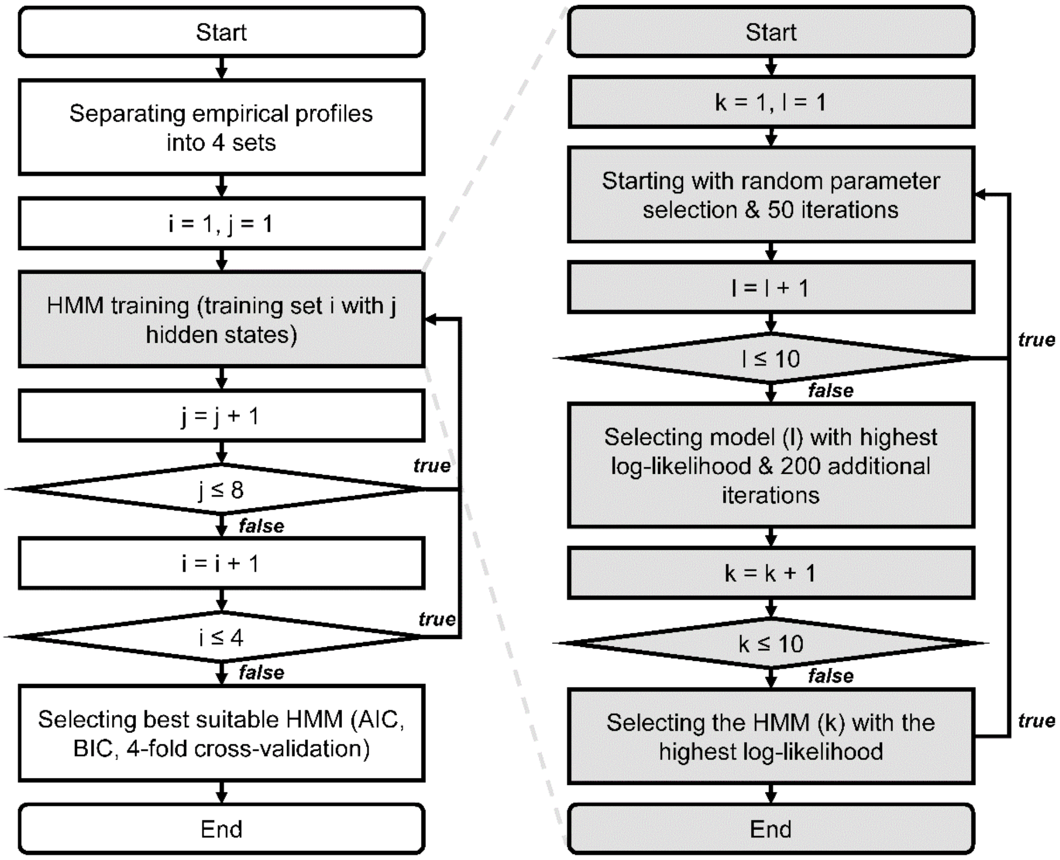

Fig A.1 *Implementation strategy of the Baum Welch algorithm in the case study (based on Biernacki et al.* [59]*)*

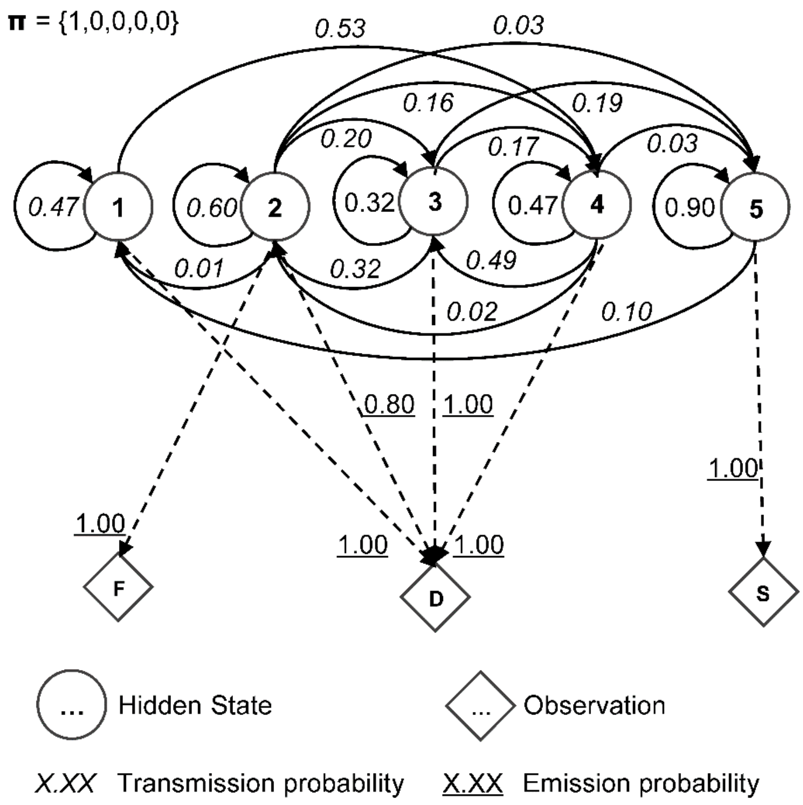

Fig. A.2 *The relationship of hidden states and observations in the multinomial HMM (case study example)*

Appendix B
Fast Forward Selection (FFS) heuristic

The fast forward selection (FFS) heuristic stepwise selects the scenario from the set of unselected scenarios that has the shortest (updated) Kantorovich distance to the remaining scenarios and is, therefore, the most representative one. The distance between the scenarios is measured with $c(\omega_i, \omega_j)$ which is the sum of a norm of all the distances at any point t in T between the scenarios. The Euclidean norm is used to measure the distance. N is the target number of scenarios. FFS proceeds as follows:

- Step 1:
  The distance $c_{kj}^{[1]} \coloneqq c\left(\omega_k, \omega_j\right)$ between all scenario pairs $k, j = 1, \dots, N$ is calculated.
  The weighted distance $z_l^{[1]} \coloneqq \sum_{j \neq l} p_j c_{jl}^{[1]}$ of each scenario $l = 1, \dots, N$ to the rest is computed.
  Scenario $s_1 = \arg\min_{l=1,\dots,N} z_l^{[1]}$ is selected and $J^{[1]} = 1, \dots, N \backslash s_1$ is set.
- Step i:
  1. The scenario pair distance $c_{kj}^{[i]} = \min\left[c_{kj}^{[i-1]}, c_{kj_{i-1}}^{[i-1]}\right]$ is updated for all unselected scenarios $k, j \in J^{[i-1]}$ with the minimum of the original pair distance and the distance to the scenario selected in $i - 1$.
  2. The updated weighted distance $z_l^{[i]} \coloneqq \sum_{j \in J^{[i-1]} \backslash i} p_j c_{jl}^{[i]}$ of each unselected scenario $l \in J^{[i-1]}$ to the rest is computed.
  3. Scenario $s_i = \arg\min_{l \in J^{[i-1]}} z_l^{[i]}$ is selected and $J^{[i]} = J^{[i-1]} \backslash s_i$ is set.

Step i is repeated until the target number of selected scenarios is reached. To the probability p_j of each selected scenario $j \in J'$ the sum of the probabilities p_i of the unselected scenarios closest to it is added, at the end.

$$q_j = p_j + \sum_{i \in L(j)} p_i \ , \forall j \in J' \quad \text{(B.1)}$$

$$L(j) \coloneqq \ \{i \in J \backslash J', j = j(i)\}, \ j(i) = \arg\min_{j \in J'} c_j^{[1]} \ , i \in J \backslash J' \quad \text{(B.2)}$$

Appendix C1
Electric vehicle energy consumption model

The energy consumption is split into three parts: propelling the electric vehicle (EV), additional energy consumption through battery weight, and the auxiliaries' demand.

$$EC^{el}\left(DS_{t,s^{mob}}^{spd}, \boldsymbol{BCAP^G}, Temp_{t,s^{temp}}^{amb}\right) = EC^{prop}\left(DS_{t,s^{mob}}^{spd}\right) + EC^{wght}\left(\boldsymbol{BCAP^G}\right) + EC^{aux}\left(Temp_{t,s^{temp}}^{amb}\right) \quad \text{(C.1)}$$

A detailed description of forces, resistances, and efficiencies in a dynamic driving model and a discussion of the external influences on energy consumption can be found in the literature [81,87].

Drive cycle	Mean speed
Inner-city (NEDC, phase 1 & WLTP phase 1)	18.5 km/h
Inter-urban (NEDC, phase 2 & WLTP phases 2-4)	63 km/h
Motorway (ADAC BAB)	114 km/h

Table C.1 *Drive cycle characteristics of ADAC measurement*

The data for the piecewise linear approximation of the energy required for propelling the EV forward is based on real-world measurements taken by the German automobile club ADAC. This study relies on real-world data since the values stated by the manufacturers are measured under laboratory conditions. Different points of measurement are required to approximate the energy consumption depending on the mean driving speed. Table ***C.1*** lists the combinations of phases from three driving cycles used by the ADAC for their measurements of inner-city, inter-urban, and motorway consumption [88]. For each of the measurement points the mean speed of different EVs from the mini and small segment was deducted from the applied driving cycles. The force required to overcome the drag resistance is proportional to the square of the speed. To avoid quadratic constraints, it was piecewise linearly approximated by the parameters m_{spd} and b_{spd} (Table C.2).

$$EC^{prop}\left(DS^{spd}_{t,s^{mob}}\right) = m_{spd}DS^{spd}_{t,s^{mob}} + b_{spd} \tag{C.2}$$

$\boldsymbol{DS^{spd}_{t,s^{mob}}}$	**(0,18.5]**	**(18.5,63]**	**(63, …)**
m_{spd}	0	0.5693	1.863
b_{spd}	115.45	104.92	23.43

Table C.2 *Parameters for the piecewise linear approximation of energy consumption for propulsion*

The additional energy required to overcome the increased rolling resistance due to the battery weight is calculated with the energy density ρ^{bat}, the rolling resistance coefficient c_{rr}, and the gravitational constant g.

$$EC^{wght}(\boldsymbol{BCAP^G}) = \frac{\boldsymbol{BCAP^G}}{\rho^{bat}}c_{rr}g \tag{C.3}$$

The specific mean energy consumption increases by 0.2524 Wh/km for each additional kWh of capacity, which fits the around 3% increase per 100 kg additional weight [89]. Higher weight also increases the vehicle inertia which leads to higher losses in recuperation. This is neglected in this study since the increases are small and difficult to assess.

The specific energy consumption of the auxiliaries is highly sensitive to the speed of the EV $DS^{spd}_{t,s^{mob}}$ since the power demand of the auxiliaries is assumed to be constant. At a constant load, the specific energy consumption increases at a slower speed. For the auxiliaries, a baseload of 500 W is set. This value is based on empiric measurements and literature values [81]. The specific energy consumption is piecewise linearly approximated by five separate functions (Table C.3).

$$EC^{aux}\left(DS^{spd}_{t,s^{mob}}, Temp^{amb}_{t,s^{temp}}\right) = \left(m_{temp}DS^{spd}_{t,s^{mob}} + b_{temp}\right)f_{temp}\left(Temp^{amb}_{t,s^{temp}}\right) \tag{C.4}$$

$\mathbf{DS^{spd}_{t,s^{mob}}}$	**(0,5]**	**(5,10]**	**(10,20]**	**(20,40]**	**(40, …)**
m_{temp}	-40	-10	-2.5	-0.625	-5/48
b_{temp}	300	150	75	37.5	50/3

Table C.3 *Parameters for the piecewise linear approximation energy consumption of the auxiliaries*

Heating and cooling the passenger cabin requires additional power. In this study four levels of additional power demand factor f_{temp} to heat or cool the cabin are set depending on the ambient temperature (Table C.4). Other temperature dependencies such as increased losses due to higher battery inner-resistance or lower recuperation power are neglected in this study. Therefore, the ambient temperature from the temperature scenarios $Temp^{amb}_{t,s^{temp}}$ is taken as variable input to the energy consumption function.

$\boldsymbol{Temp^{amb}_{t,s^{temp}}}$	**(…,0)**	**[0,10)**	**[10,15)**	**[15,25)**	**[25,30)**	**[30, …)**
f_{temp}	4	3	2	1	2	3

Table C.4 *Factor for the auxiliaries' intensity of use dependent on the outside temperature*

Appendix C2

Electric vehicle charging load-curves

The input data for the charging curves comes from own empirical measurements (IIP database). The maximum charging power P_c^{maxcrg} and the reduction points RP_c for different EVs for single-phased 2.2 kW and 3.7 kW charging were recorded with an external energy measurement device directly at the power outlet. The three-phased 11 kW (16 A, 400 V) and 22 kW (32 A, 400 V) charging curves were taken from the EV battery management system data. Hence, the charging losses in the on-board charging unit must be considered when calculating their maximum power at the grid level. The recorded curves are validated by other empirical results from the literature [56]. Due to the modeling choice of the flexible battery capacity, the linear increase in charging power as a result of the increase in battery voltage at a constant current level had to be neglected.

Appendix D1

	s^{mob}	5		10		15		20		25	
	c	zs^{mob*}	$BCAP^G$	zs^{mob*}	$BCAP^G$	zs^{mob*}	$BCAP^G$	zs^{mob*}	$BCAP^G$	zs^{mob*}	$BCAP^G$
FFS	2.2	13,392	18	13,460	18	16,721	44	18,220	56	18,237	56
	3.7	13,931	18	13,999	18	16,389	37	18,511	54	18,527	54
	11	14,471	18	14,539	18	16,929	37	18,055	46	18,071	46
	22	15,011	18	15,078	18	17,468	37	18,470	45	18,486	45
FSWC_S	2.2	17,252	47	18,281	52	19,360	60	19,383	60	19,390	60
	3.7	17,169	42	18,446	49	19,650	58	19,673	58	19,680	58
	11	17,459	40	18.361	44	18,816	47	18,839	47	18,846	47
	22	17,999	40	18,901	44	19,106	45	19,128	45	19,136	45
FSWC_O	2.2	20,149	44	21,227	52	22,193	60	22,192	60	22,222	60
	3.7	20,309	41	21,513	50	22,479	58	22,478	58	22,508	58
	11	19,710	32	21,673	47	21,627	47	21,626	47	21,656	47
	22	19,997	30	21,580	42	21,913	45	21,912	45	21,942	45

***Table D.1** Optimal values and battery capacities for the three scenario reduction heuristics and four different charging capacities (the cost-minimal decision set for each subset size is highlighted; FFS with $s^{temp} = 10$)*

Appendix D2

	s^{temp}	5		10		15		20	
	c [kW]	zs^{mob*}	$BCAP^G$	zs^{mob*}	$BCAP^G$	zs^{mob*}	$BCAP^G$	zs^{mob*}	$BCAP^G$
FFS	2.2	22,060	59	22,192	60	22,193	60	22,193	60
	3.7	22,346	57	22,479	58	22,479	58	22,479	58
	11	21,620	47	21,626	47	21,627	47	21,627	47
	22	21,907	45	21,913	45	21,913	45	21,913	45

***Table D.2** Optimal values and battery capacities for the FFS scenario reduction heuristic and four different charging capacities (the cost-minimal decision set for each subset size is highlighted; FSWC_O with $s^{mob} = 15$)*

Appendix D3

Scenario No.	zs^{mob*}	***BCAP^G***	c	Probability
37	20,014	33	2.2	0.0200
55	21,863	38	11	0.0008
76	19,520	29	2.2	0.0280
114	15,050	12	2.2	0.1100
238	21,130	28	11	0.0008
542	21,724	35	11	0.0016
774	20,321	44	2.2	0.0012
1004	18,856	25	2.2	0.0568
1036	18,826	22	11	0.0008
1102	23,867	50	2.2	0.0008
1171	21,882	47	11	0.0004
1175	20,677	15	11	0.0012
1214	20,241	18	11	0.0016
1310	20,441	34	2.2	0.0100
1404	16,710	16	2.2	0.1920
1439	14,140	9	2.2	0.1084
1497	17,328	21	2.2	0.1452
1593	21,370	40	2.2	0.0028
1627	18,143	23	2.2	0.0912
1763	26,263	54	11	0.0004
1867	15,854	16	2.2	0.2116
1928	21,395	37	2.2	0.0044
1978	19,745	20	3.7	0.0028
2019	12,719	6	2.2	0.0068
2393	23,490	29	2.2	0.0004
			Cumulative probability of scenarios with 2.2 kW	0.9896
			Cumulative probability of scenarios with 3.7 kW	0.0028
			Cumulative probability of scenarios with 11 kW	0.0076
			Cumulative probability of scenarios with ≤ 30 kWh	0.9576
			Cumulative probability of scenarios with ≤ 40 kWh	0.9972

Table D.3 *Optimal solutions for the individual mobility scenarios and the associated probabilities for the SAA (FSWC_O with* $s^{mob} = 15$*, FFS with* $s^{temp} = 10$*)*

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Journal of Cleaner Production 142 (2017) 263–278

Contents lists available at ScienceDirect

Journal of Cleaner Production

journal homepage: www.elsevier.com/locate/jclepro

Empirical carbon dioxide emissions of electric vehicles in a French-German commuter fleet test

Axel Ensslen [a,*], Maximilian Schücking [a], Patrick Jochem [a], Henning Steffens [a], Wolf Fichtner [a], Olaf Wollersheim [b], Kevin Stella [b]

[a] Chair of Energy Economics, French-German Institute for Environmental Research (DFIU), Karlsruhe Institute of Technology (KIT), Hertzstraße 16, Karlsruhe, 76187, Germany
[b] Project Competence E (PCE), Karlsruhe Institute of Technology (KIT), Hermann-von-Helmholtz-Platz 1, Eggenstein – Leopoldshafen, 76344, Germany

ARTICLE INFO

Article history:
Received 10 November 2015
Received in revised form
14 June 2016
Accepted 15 June 2016
Available online 23 June 2016

Keywords:
CO_2 emissions
Electric vehicle
Commuting
France
Germany

ABSTRACT

According to many governments electric vehicles are seen as an efficient mean to mitigate carbon dioxide emissions in the transport sector. However, the energy charged causes carbon dioxide emissions in the energy sector. This study demonstrates results from measuring time-dependent electricity consumption of electric vehicles during driving and charging. The electric vehicles were used in a French-German commuter scenario between March and August 2013. The electric vehicles ran a total distance of 38,365 km. 639 individual charging events were recorded. Vehicle specific data on electricity consumption are matched to disaggregated electricity generation data with time-dependent national electricity generation mixes and corresponding carbon dioxide emissions with an hourly time resolution. Carbon dioxide emission reduction potentials of different charging strategies are identified. As carbon dioxide emission intensities change over time according to the electric power systems, specific smart charging services are a convincing strategy to reduce electric vehicle specific carbon dioxide emissions. Our results indicate that charging in France causes only about ten percent of the carbon dioxide emissions compared to Germany, where the carbon intensity is more diverse.

1. Introduction

Electric vehicles (EV) are considered as an eco-innovation that has the potential to reduce environmental problems caused by the transportation sector (Jochem et al., 2016; Lane and Potter, 2007; Rezvani et al., 2015). The potential for CO_2 emission reductions depends on the CO_2 emissions generated for charging the EV compared to the emissions from conventional Internal Combmagnitude in different countries (Doucette and McCulloch, 2011; Faria et al., 2013; Nordelöf et al., 2014). For example CO_2 emission intensities of electricity generation largely differ between France and Germany (Fig. 1) due to severe differences in the underlying electricity generation mixes (ENTSOE-E, 2014). Heavy fluctuations of electricity fed-in by photovoltaic and wind turbines can be observed in Germany whereas the high share of nuclear power effect corresponding CO_2 emission intensities in France.

Quantifying CO_2 emission reduction potentials of EV are of particular interest with regards to European greenhouse gas emissions reduction targets. However, this task remains challenging like ongoing discussions on the appropriateness of standardized driving cycles to measure CO_2 emissions of EV and ICEV show.

The objective of this paper is to contribute to this discussion by quantifying CO_2 emission reduction potentials of EV used for commuting in the French-German cross-border context based on time-dependent empirical EV energy consumption data as well as data on CO_2 emissions of the national power plant portfolios.

2. Literature review on EV specific CO_2 emissions

Literature discussing CO_2 emission reduction potentials of EV deployment usually compares the calculated values to other potentially substituted vehicle technologies. Most do so by comparing them to an identical or similar ICEV model (Doucette and McCulloch, 2011; Faria et al., 2013). Others set them in reference to regulatory limits (e.g. Euro VI) or fleet targets for ICEV

* Corresponding author.
E-mail addresses: axel.ensslen@kit.edu (A. Ensslen), maximilian.schuecking@kit.edu (M. Schücking), patrick.jochem@kit.edu (P. Jochem), henningsteffens@gmx.de (H. Steffens), wolf.fichtner@kit.edu (W. Fichtner), olaf.wollersheim@kit.edu (O. Wollersheim), kevin.stella@kit.edu (K. Stella).

http://dx.doi.org/10.1016/j.jclepro.2016.06.087
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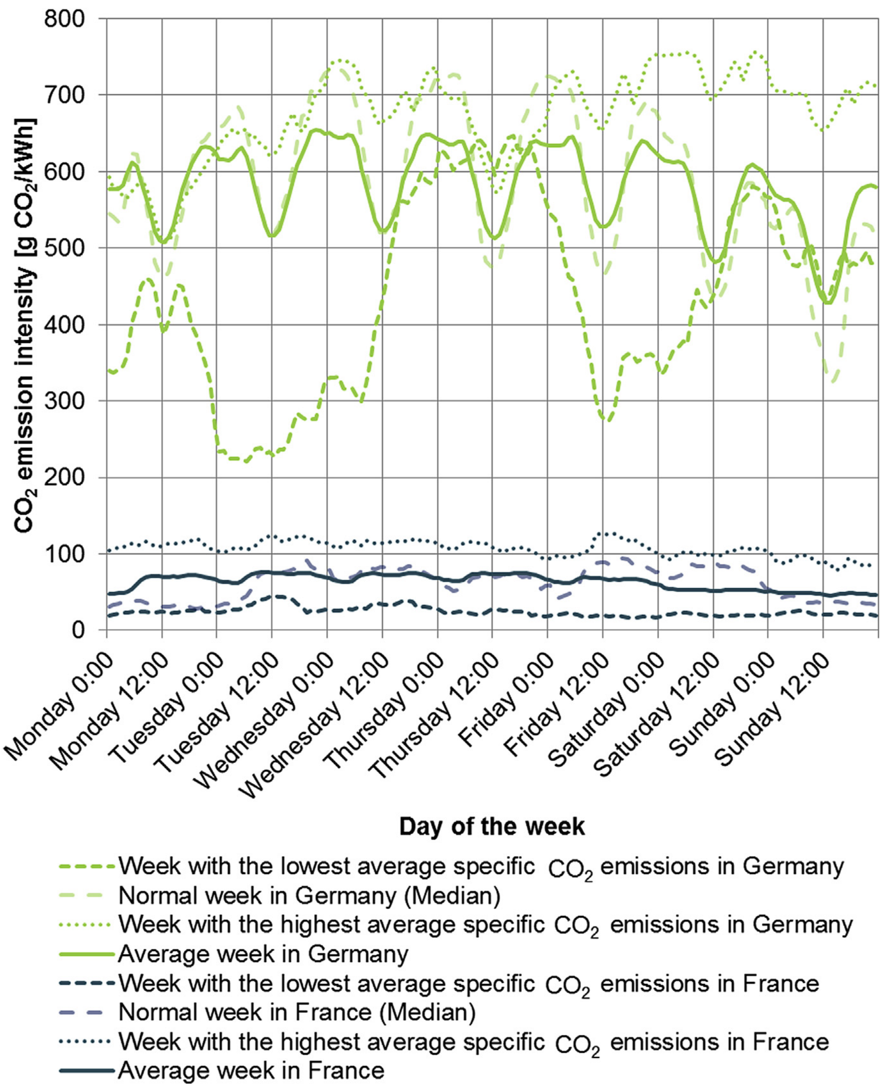

Fig. 1. CO_2 emission intensities of electricity generation in France and Germany in 2013. (Sources: EEX Transparency, 2015; RTE, 2014).

(Donateo et al., 2014, 2015; Jochem et al., 2015). Some illustrate the potential by calculating the point of ecological break-even in dependence of driven mileage (Bickert et al., 2015). Yet others expand the basis for comparison to other new technologies such as hybrid electric vehicles (HEV), plug-in hybrid electric vehicles (PHEV), or fuel cell electric vehicles (FCEV) (Campanari et al., 2009; Ma et al., 2012; McCarthy and Yang, 2010; Sharma et al., 2012).

Most outcomes of previous studies indicate some kind of reduction potential. A significant dependence on the carbon intensity of electricity generation can be found. A high share of low-carbon energies in the energy mix, such as renewables or nuclear power, significantly favors the EV emission values (Faria et al., 2013). To lower the CO_2 emissions, especially for a carbon intensive energy mix such as Germany, a change towards renewable energies is needed (Bickert et al., 2015) or the implementation of specific low carbon charging strategies, such as load shifting (Jochem et al., 2015; Robinson et al., 2013).

However, these results are not consistent as they highly depend on the method and setting of the research. Table A1 in the Appendix provides an exemplary overview of different studies focusing on emissions of EV. The results of these studies are divers, because they differ in the following dimensions: region, system boundaries, specific energy consumption, definition of emission intensity (i.e. time resolution, average or marginal), and type of pollutants.

The system boundaries have two main sub-dimensions: the product life cycle and process chain of energy production. A life cycle assessment (LCA) of EV usually considers all emissions of their production process and all upstream materials used, the emission caused by operation, and the emissions caused by their recycling and disposal (e.g. Bickert et al., 2015; Hawkins et al., 2013; Muneer et al., 2015). Other studies focus only on the emissions caused during operation neglecting the upstream and downstream.

The second dimension considers the extent to that the value chain of the energy carrier (i.e. fuel or electricity) is considered. For EV the literature distinguishes between four different perspectives: tank-to-wheel (TTW), grid-to-wheel (GTW), plant-to-wheel (PTW) and well-to-wheel (WTW) (Fig. 2).

TTW as the most limited only considers the efficiency of the energy conversion stored in the battery. Additionally to the TTW perspective, GTW considers efficiency losses from the grid into the battery. PTW additionally considers the losses in the process of energy generation, transport and conversion. WTW as the most holistic approach considers all the energy consumption (and emissions) from resource depletion, electricity generation, transport, conversion, and vehicle usage. While energy conversion for generating electricity to run EV takes place in power plants (PTW)

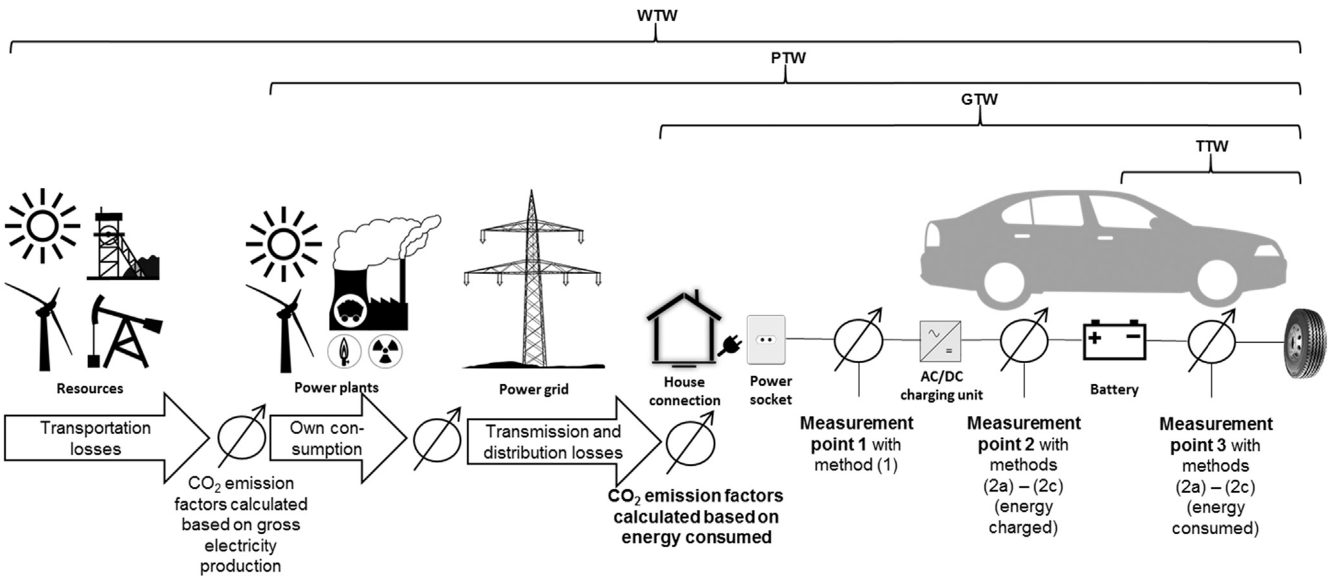

Fig. 2. Energy measurement points and methods in the energy supply chain for charging EV.

with the major parts of efficiency losses, fuel combustion, corresponding energy conversion and efficiency losses for ICEV occur in internal combustion engines (TTW). Therefore concerning the emissions caused by energy supply TTW for ICEV is adequately represented by PTW of EV.

In this context it is also important to distinguish whether empirically measured energy consumption values are taken or values based on standardized driving cycles, such as the New European Driving Cycle (NEDC), as basis for emission assessment. Like the consumption values of ICEV depending on the conditions of deployment (driving profiles, driver behavior, and the auxiliaries, etc.) the real energy consumption values can significantly differ from the ones based on standardized driving cycles (Donateo et al., 2014; Muneer et al., 2015; Rangaraju et al., 2015). Nevertheless, most studies do not consider real driving profiles.

The considered time resolution and time duration of the investigation varies significantly between studies and shows a significant impact on the results. Some only take average values for one year of a specific energy mix (e.g. Campanari et al., 2009; Doucette and McCulloch, 2011) others take smaller distinctions looking at different seasons, monthly averages or even use disaggregated data with a 30 min time resolution (e.g. Donateo et al., 2014; Rangaraju et al., 2015; Robinson et al., 2013). Some studies do not focus on the average emissions of the energy mix, but focus only on the marginal emissions that are caused by the additional demand of EV, which are mostly carbon-intensive plants (Jochem et al., 2015; Ma et al., 2012; McCarthy and Yang, 2010), which consequently leads to higher CO_2 emission values. Due to different energy mixes depending on various factors such as local resources, climate, and energy policy, it is important to clearly distinguish regional boundaries in which the emissions are investigated. Especially the different energy mixes and their volatility can have a significant impact on the EV emissions Doucette and McCulloch, 2011; Faria et al., 2013; Ma et al., 2012). For example average CO_2 emissions from electricity generation in 2013 in the neighboring countries, Germany and France, illustrate these differences evidently: 486 g/kWh in Germany and 64 g/kWh in France (IEA, 2015).

The importance of clearly distinguishing between the different approaches to assess emissions from EV is illustrated by Jochem et al. (2015) for the example of Germany. EV specific PTW CO_2 emissions are measured based on four methods including (i) the annual average electricity generation mix, (ii) the time-dependent average electricity generation mix, (iii) the marginal electricity generation mix and (iv) balancing zero emissions (e.g. by the European Emission Trading System). As vehicle driving and parking is not equally distributed over the day in general (Kaschub et al., 2011; Ketelaer et al., 2014) and the European carbon pricing mechanism seems to be inefficient (Koch et al., 2014), quantifying EV specific CO_2 emissions with methods (ii) or (iii) considering time-dependent energy mixes seems appropriate, when charging under a high volatile energy emission factor (cf. Fig. 1).

There seems to be a research gap in the current literature concerning charging-dependent PTW CO_2 emissions of EV based on empirical, disaggregated, time-dependent data series of the energy mix charged in real world usage scenarios in order to derive CO_2 reduction potentials for different countries. Due to the various potential ways to set the system boundaries and measure the energy consumption, there is no direct comparability of the different studies and their proposed reduction potentials among themselves. The studies that are comparing the CO_2 emissions of EV in different countries do so, due to the lack of empirical data, mainly based on standardized driving cycles or exemplary recorded trips. In order to fill this gap in the literature a long-term fleet test of EV deployed in a common and real cross-border mobility profile between two countries with distinctively different energy mixes is required.

Therefore, we present a French-German commuter fleet test as a case study. The driving profiles of commuters are characterized by a deterministic, repetitive, and therefore predictable mobility demand on fixed routes. Hence, commuting is widely considered an ideal application for substituting ICEV with EV (e.g. Tomić and Kempton, 2007). According to the Association of European Border Regions (2012) the French-German Pamina region is notably characterized by a high degree of cross-border labor mobility with large-scale cross-border cooperation. About 16,000 workers daily cross the French-German border in the Pamina region for commuting purposes, which underlines the validity presented results.

In order to achieve the paper's objective of quantifying the time-dependent real CO_2 emission reduction potentials of EV in the French-German cross-border context we raise the following research questions:

(i) How much energy was charged and consumed by the EV on the individual trips during the fleet test and how much does this amount depend on the chosen measurement points or assessment method (e.g. GTW, TTW, NEDC)?

(ii) What are the CO_2 emissions caused by the EV considering the time-dependent national PTW CO_2 emissions and the different assessment methods?

(iii) How high are the real CO_2 emission reduction potentials of different EV use cases based on the previous results?

3. Methods and data

Section 3.1 describes the French-German e-mobility commuter case study. Section 3.2 presents the methods applied (Section 3.2.1) and data used (Section 3.2.2) to measure EV specific energy charged and consumed. Section 3.3 provides an overview on the methods applied (Section 3.3.1) and data used (Section 3.3.2) to measure charging-dependent CO_2 emissions of EV.

3.1. Case study description

The fleet test to answer the proposed research questions was a French German cross-border e-mobility project carried out between 2013 and 2015 (Stella et al., 2015). EV were used by cross-border shift workers to commute between their homes in Alsace (France) and their workplace in Karlsruhe (Germany) in fixed car-pooling groups (Table 1). Hence, the time of use changed according to their rolling shift schedule: the workers arrived 30 min before the start of their eight hour shift at 6 am, 2 pm, or 10 pm respectively. After their shift they immediately started their journey back home, which usually lasted between one and 1.5 h. The average commuting distance of 75 km one-way was too long to travel two ways on one battery charge. Therefore, the EV were directly recharged during the eight hours of work as well as at home, usually immediately after arrival. Out of the six EV used by the shift workers during the project data of three e-Wolf Delta 2 is analyzed in this study.

3.2. Measuring EV specific energy charged and consumed

Different methods to quantify the energy charged and consumed by EV are applied. The first approach calculates the energy charged during the charging events based on an exemplary charging curve (Fig. 3) measured at measurement point 1 (Fig. 2) during a charging event. The second approach quantifies the energy charged (measurement point 2, Fig. 2) and consumed (measurement point 3, Fig. 2) based on data from EV on-board data loggers. The third approach calculates the energy consumed during the charging events based on standard energy consumption (NEDC). Furthermore, information on the case study are provided including important meta-information of the data used.

3.2.1. Assessment methods

To calculate the time-dependent CO_2 emissions, it is essential not only to know the total amount of energy charged, but also the changes of charging power during the charging process. The amount of energy charged during one charging event or discharged during a journey can be calculated via the integral of the product of current and voltage over time. As recording frequency of the on-board data logger measuring the charging power, the voltage and current was rather low, three different approaches are used to approximate the energy charged and consumed by the EV.

One possibility to calculate the energy charged during the charging processes relies on one exemplary charging curve recorded for the conventional AC charging process from 0% to 100% state of charge (SOC) (1). Voltage and current were measured at measurement point 1 within the energy supply chain presented in Fig. 2. This approach is used to quantify the GTW charging energy of the three EV under investigation. Fig. 3 indicates that the charging power was set by the on-board charging unit of the EV, which lay at a maximum of 2.544 kW significantly lower than the allowed 3.6 kW for the European domestic Schuko socket outlets (CEE 7/7). For the charging process two different phases can be distinguished: almost directly after the start and for the main part of the process the effective charging power remained almost constant at 2.544 kW; after around 8.75 h the charging power started to decrease stepwise until it reaches zero at 10.75 h. This simply reflects the constant current constant voltage charging regime used by almost all lithium ion battery chargers. This regime starts with constant current until a preset cell voltage level is reached. At this time, the charger switches to constant voltage charging, which requires a current derating until a predefined minimum current level, where the charging process is finished (Kaschub et al., 2013).

Our approach of modelling EV charging processes is based on Kaschub et al. (2013), but is using a battery voltage limit of 685 V as an indicator for the point of power reduction. Until this voltage level, the battery is charged at constant power (i.e. 2.544 kW) (Formula 1). Then an approximated linear charging power reduction begins (Formula 2 and Fig. 3).

$$w_{q,1,constant} = 2.544 \cdot \Delta t_{q,1,constant} [kWh] \quad (1)$$

$$w_{q,1,reduction} = \frac{1}{2} \cdot 2.544 \cdot \Delta t_{q,1,reduction} [kWh] \quad (2)$$

The energy needed during charging event q in this approach is calculated by:

$$w_{q,1} = w_{q,1,constant} + w_{q,1,reduction} \quad (3)$$

For each individual charging process the energy charged was calculated based on these considerations.

A second possibility to calculate the energy charged during the charging processes is based on the data recorded by the EV on-board data logger (2a). It calculates the energy consumed and recuperated during the journeys as well as the energy charged and the timely distribution by multiplying the battery voltage, the battery current and the interval from the actual data point to the previous (Formula 4).

Table 1
Characteristics of shift worker commuting in the project.

User group	Employees in shift production
User per EV	Fixed group of 5–7 people
Usage frequency	7 days per week before and after shift changeovers
Average one-way distance	75 km
Average annual mileage	36,000 km
Average speed	55–60 km/h
Type of EV	3 e-Wolf Delta 2
Charging locations	At home and at work
Charging infrastructure	12 standard outlets (230 V, max. 16 A, max. 3.7 kW)

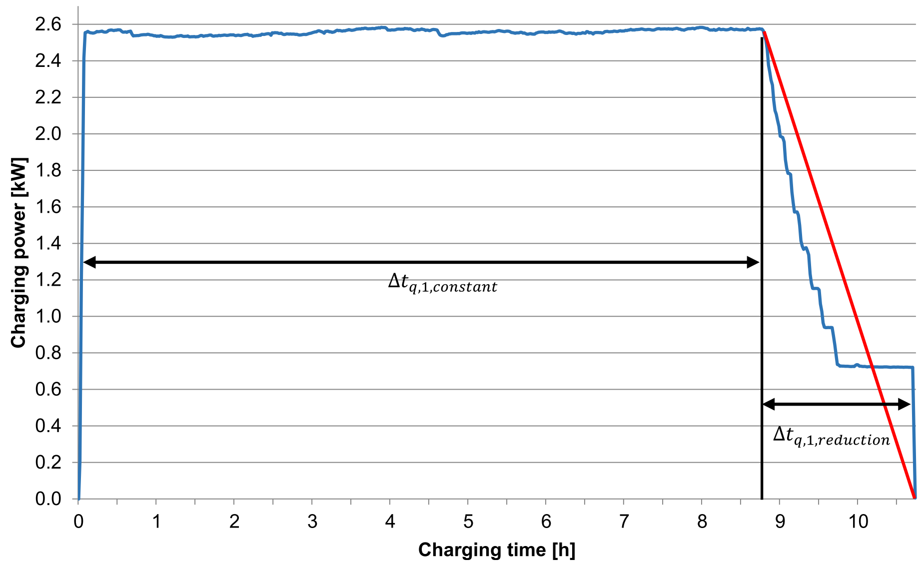

Fig. 3. Recorded charging curve of project EV (e-Wolf Delta 2) at domestic power outlet.

$$w_{q,2a} = \sum_{\substack{t_{Logger} \\ \in T_{Logger,q}}} U_{t_{Logger}} \cdot I_{t_{Logger}} \cdot \Delta t_{\ Logger} \tag{4}$$

This approach is used to measure the energy charged at battery entrance without considering the losses of the AC/DC charging unit (measurement point 2, Fig. 2) and the energy consumed at the battery outlet (measurement point 3, Fig. 2).

The frequency of only one data point every 20 s while driving and five to ten minutes while charging still lead to a significant degree of inaccuracy. So additionally this study compares two rolling means for the values of battery voltage and current taking into account three (2b) and five measured values (2c). As the switch between charging and driving is promptly, equalizing over a high number of values is not sensible. Therefore, the first rolling mean only includes the preceding and the following data point (2b); the second rolling mean includes the two predecessors and followers of each data point (2c).

The third possibility to calculate the energy charged during the charging processes is widely applied in literature and takes the standard energy consumption based on the NEDC (3). The NEDC does not consider the losses during charging processes, although this has been suggested by UNECE (2005). For our vehicle the manufacturer states 187 Wh/km as specific energy consumption (Table 2). Accordingly the energy consumption on the journeys was estimated under the assumption that this was the exact energy consumption for each journey and therefore had to be recharged after the arrival.

As the energy charged calculated by (1) is based on data measured directly at the socket outlet (GTW), no additional losses for transmitting energy from the power socket to the wheel need to be considered. On the other hand (2a), (2b), (2c), and (3) are all based on the energy charged and consumed at battery level. Therefore, the charging efficiency from the grid to the battery additionally needs to be taken into account.

3.2.2. Data used

The EV used in the project, i.e. the e-Wolf Delta 2 (an EV reconstruction based on the chassis of Nissan NV200), and the installed charging infrastructure were chosen according to the technological, user, and research requirements. For the accompanying research it was important to gain detailed access to the vehicle and its battery data. Technical data of the e-Wolf Delta 2 are presented in Table 2.

Table 2
Technological data of the EV (e-Wolf Delta 2).

Technical data	e-Wolf Delta 2
Number of seats	7
HV-Battery capacity	24.2 kWh
HV-Battery voltage (max.)	720 V
Number of cells	168
Cell technology	Li-ion NMC
Battery weight	250 kg
Energy consumption (NEDC)	187 Wh/km
Maximum range (NEDC)	154 km
Performance	60 kW
Peak performance	90 kW
Heating	Bio-Diesel
Vehicle mass (empty)	1666 kg
AC charging power	2.5 kW (nominal)
AC plug type	Type 2 (EN 62196–2)
AC charging mode	Mode 1 (IEC 61851)
Data logger	On-board CAN and GPS Logger

Only conventional charging (Mode 1, according IEC 61851) was used. Therefore, standard outlets (230 V) with a maximum current of 16 A were installed at the workers' homes as well as at the plant.

To allow a detailed assessment of the energy consumption and charging processes the e-Wolf Delta 2 were equipped with special data loggers (VIKMOTE VX 20, Vikingegaarden). Details on the data collected are presented in Stella et al. (2015).

The charging events were identified and distinguished based on the data recorded by the EV data logger. Whenever the ignition was switched off, indicated by a LV-circuit of zero, and a current speed of zero the start of a charging event was set.

Over the timeframe of this study, from March to August 2014, the three EV travelled about 38,365 km, 18,612 in France and 19,753 in Germany. 639 charging events were recorded, 299 in France and 340 in Germany. 565 transnational commuting trips were identified, 283 to France and 282 to Germany.

As expected, in Germany the charging events usually started before the shifts of the commuters started at 6:00, 14:00 and 22:00. In France the charging events mostly started between one and two hours after work when the commuters had returned back home (Fig. 4). The active charging hours are well distributed over the days with peaks before shift changeovers in Germany and after shift changeovers in France.

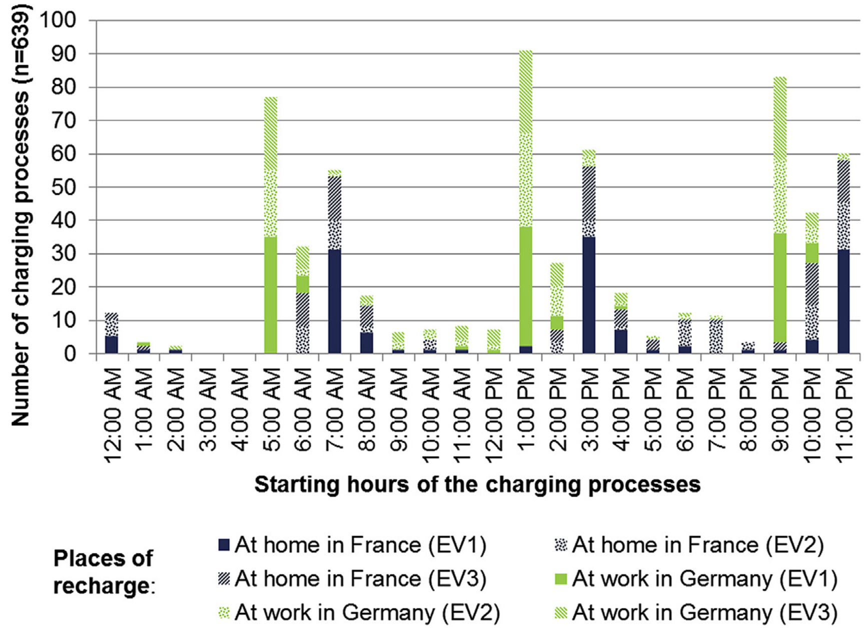

Fig. 4. Timely distribution of starting hours of the charging events.

3.3. Measuring charging-dependent CO_2 emissions

As CO_2 emission intensities of electricity generation show large seasonal as well as hourly variations (Fig. 1), particularly in Germany, usage of a time-dependent mix to assess CO_2 emissions of EV is appropriate (Jochem et al., 2015). Therefore (ii) the time-dependent average electricity generation mix or (iii) the marginal electricity generation mix could be used. Since the EV were used for commuting and usually showed a very low SOC at arrival they had to be directly charged after they were plugged in to ensure that sufficient energy could be charged during the available time. This represents a highly inelastic manner and is very similar to other electrical appliances. Consequently it seems not to be justified to take the EV as the marginal consumer. Hence, using (iii) the marginal electricity generation mix seems not to be appropriate for our evaluation. Consequently we focus on the (ii) hourly average CO_2 emission mix of the electricity generated.

3.3.1. Method

The energy charged w_q during a charging event q with duration of T_q (cf. Formula 3 and Formula 4) is mapped to the time-dependent and country specific CO_2 emission factors of electricity generated ($f_{i,t}$) in order to quantify the CO_2 emissions of a charging event $c_{q,i}$ (Formula 5).

$$c_{q,i} = \frac{\sum_{t\in T_q} f_{i,t}\cdot \Delta t}{T_q}\cdot w_q, \qquad \forall i, \forall q \tag{5}$$

The time-dependent CO_2 emission factors of country i during hour t ($f_{i,t}$) are calculated based on the time-dependent shares of the energy generated by sources j of power generation in hour t ($e_{i,j,t}$) multiplied with the appropriate specific CO_2 emission factors of the different energy sources $k_{i,j}$ (cf. Formula 6).

$$f_{i,t} = \sum_{j\in J} e_{i,j,t}\cdot k_{i,j}, \qquad \forall i, \forall t \tag{6}$$

$e_{i,j',t} = \frac{E_{i,j',t}}{\sum_{j\in J} E_{i,j,t}}$ represents the share of electricity generated in country i by one energy source j' during hour t with $E_{i,j,t}$ representing the electricity generated by energy source j in country i during hour t with

$t \in T = \{1;\ldots;T\}$: Hourly time intervals from March 2013–August 2013.
$i \in I = \{France; Germany\} = \{F; G\}$: Countries considered.
$j, j' \in J = \{Lignite;\ Hard\ coal; Natural\ gas; Oil;\ Nuclear; Pump\ storage; Run-of-river\ hydro;\ Wind; Photovoltaics;\ Bioenergy,\ Waste\ and\ others\}$: Power plant technologies.

Additionally, knowing all $c_{q,i}$ as well as the overall distances travelled by the EV during the period considered, the average specific CO_2 emissions of the project EV as well as country specific average CO_2 emissions for exclusively charging in one of the countries can be calculated.

3.3.2. Data

The emission factors in Table 3 represent the emission factors of the energy at power outlet level. As only PTW CO_2 emissions and not the life cycle emissions, i.e. no WTW perspective, are considered within this study, specific emission factors for nuclear power, hydro power, wind, and photovoltaics are zero (Table 3). For the German case the total CO_2 emission values from electricity generation divided by the total electricity consumption in the year 2012 including losses for transmission and distribution are used to calculate $k_{i,j}$ (Icha, 2014). For France only data on electricity generation by source is available (RTE, 2015). In order to include CO_2 emissions for efficiency losses of electricity transmission and distribution the values are calculated based on 6% losses provided by the major French distribution system operator (ERDF, 2009) and the 2.5% losses provided by the French transmission grid operator (RTE, 2016). Corresponding efficiency losses are in line with other studies, e.g. Donateo et al. (2015) calculated with about 7% losses and Robinson et al. (2013) with 9.1% losses. In order to calculate French electricity consumption based on gross electricity generation in accordance to Icha (2014), power plant's self-consumption of 24 TWh in 2013 (INSEE, 2014) as well as electricity produced from pump storage of 7 TWh in 2013 (INSEE, 2014) are taken into account. Corresponding efficiency losses consequently amount to 13.3%.[1] These efficiency losses are comparable to those in Germany, which amounted to about 11.6% in 2012 (Icha, 2014). In

[1] $100\% - (100\% - 2.5\%)\,(100\% - 6\%)\left(\frac{575\ TWh - 7\ TWh - 24\ TWh}{575\ TWh}\right) = 13.3\%$.

Table 3
Specific emission factors depending on the sources of energy in France (RTE, 2015) and Germany (Icha, 2014).

Energy source (j)		Specific emission factors $k_{i,j}$ $\left(\frac{gCO_2}{kWh}\right)$		
		France (F)		Germany (G)
		$k_{F,j}^{PROD}$	$k_{F,j}^{CONS} = k_{F,j}^{PROD} \cdot \vartheta$	$k_{G,j}^{CONS}$
Lignite		956	1102.5	1159.7
Hard coal				904.8
Gas	Combustion turbine	593	683.9	376.8
	Co-generation	350	403.6	
	CCG	359	414.0	
	Other gases	552	636.6	
Oil	Combustion turbine	777	896.1	571.4
	Co-generation	459	529.4	
	Other fuels	783	903.0	
Nuclear		0	0	0
Pump storage hydro		0	0	0
Run-of-river hydro		0	0	0
Wind		0	0	0
Photovoltaics		0	0	0
Bioenergy waste and others		983	1133.7	328.1

Legend:
Remark: CO_2 emissions for electricity generation and distribution are considered; CO_2 emissions for fuel provision and power plant construction are not considered.
Combustion turbine: Also known as gas turbine.
Co-generation: Generates electricity and useful heat at the same time.
CCG: Combined Cycle Gas – Combination of thermodynamic cycles to improve turbine efficiency.
Other gases: E.g. steam turbines or gas engines.
Other fuels: E.g. steam turbines and diesel engines.
Bioenergy, waste and others: Specific CO_2 emissions of biomass, biogas and waste are assumed to be at the same level in France. For Germany specific CO_2 emissions of biomass are assumed to be zero. Waste and other energy sources are at different levels leading to differences observed for specific CO_2 emissions of bioenergy, waste and others between France and Germany.
PROD: Calculations based on gross electricity generation.
CONS: Calculations including efficiency losses.

order to calculate the specific CO_2 emissions of France based on electricity consumption $k_{F,j}^{CONS}$ we multiplied the specific CO_2 emissions based on gross electricity generation $k_{F,j}^{PROD}$ with $\vartheta = 1.153$[2] (Table 3). The additional losses are included in the GTW energy consumption assessment.

The datasets concerning hourly electricity generation by different energy sources for the year 2013 originate from RTE for France (RTE, 2015) and from the EEX Transparency Platform for Germany (EEX Transparency, 2015).

4. Results

In Section 4.1 the energy charged and consumed by the considered EV are presented. In Section 4.2 the results concerning corresponding charging-dependent CO_2 emissions are given.

4.1. EV specific energy charged and consumed

The battery efficiency and the charging efficiency of the EV deployed were calculated by comparing the measured energy values at three different points as presented in Fig. 2. The energy losses in the battery depend on various factors, e.g. the cell chemistry, the assembly and connection between the cells, and the cell temperature. To calculate an average value of the battery efficiency for all three EV the ratio of the total amount of energy consumed at battery level (measurement point 3, Fig. 2) and total amount of energy charged at battery level (measurement point 2, Fig. 2) was calculated for (2a), (2b), and (2c). The corresponding results are presented in Table A2 in the Appendix. Since the measured battery efficiency of the second EV (EV2) were greater than one and showed other additional irregularities (later in the project it was discovered that one cell of the battery pack was damaged), the values were excluded for calculating charging efficiency. The empiric average charging efficiency between the sockets and the batteries of EV1 and EV3 amounted to 0.924.

Comparing GTW and NEDC energy of the three project EV, on average norm consumption (18.7 kWh/100 km) was exceeded by 42% (Table 4). Considering the charging processes only taking place in France (Germany), on average norm consumption was exceeded by about 49% (36%). Neglecting the losses in the AC/DC charging unit (measurement point 2, Fig. 2) efficiency losses compared to NEDC amount to about 32%, i.e. 39% for the charging processes taking place in France and 26% for the charging processes taking place in Germany. Additionally neglecting the losses in the battery (measurement point 3, Fig. 2) results in efficiency losses of about 30% compared to NEDC, i.e. 34% for the trips from Germany to France and 26% for the trips from France to Germany.

Next to the overall surplus compared to NEDC values the results show that the energy consumption is on average significantly higher on the home trips from Germany to France (Table 4 and Fig. 5). These findings are supported by highly significant independent sample t-test results (Student, 1908) with medium effects (Cohen's d ranges between 0.55 and 0.69, Table 4). These results are of particular interest, as they indicate that external factors influenced electricity consumption of the EV on their home trips significantly. However, no significant differences between the variations of energy consumption on the trips to work and back home could be observed. According to Table 4 standard deviations of trip specific energy charged and consumed per kilometer do not differ significantly. This is supported by insignificant Levene–test results (Levene, 1960) which are also presented in Table 4.

4.2. Charging-dependent CO_2 emissions

The average CO_2 emissions during the charging processes of the project EV in France and Germany are presented in Fig. 6. According to these results average CO_2 emission factors of the charging events vary

[2] $\vartheta = 1/(1-13.3\%) = 1.153$.

Table 4
Total energy charged and consumed by the project EV.

Activity	Parking and charging						Driving, consuming and recuperating					
Assessment method	Method (1)			Average of the methods (2a), (2b) & (2c)			Average of the methods (2a), (2b) & (2c)			Method 3 (NEDC)		
	Measurement point 1			Measurement point 2			Measurement point 3			–		
Place of recharge/Trip destination	Total	F	G	Total	F	G	Total	F	G	Total	F	G
Total energy [kWh]	10,195.6	5182.7	5012.9	9456.7	4818.9	4637.7	9320.7	4674.6	4646.1	7174.3	3480.4	3693.8
Overall surplus of total energy compared to calculations based on NEDC [%]	42.1%	48.9%	35.7%	31.8%	38.5%	25.6%	29.9%	34.3%	25.8%	–		
Average trip specific energy per kilometer [kWh/km]	0.267	0.279	0.254	0.248	0.259	0.237	0.244	0.251	0.236			
Standard deviation of trip specific energy per kilometer [kWh/km]	0.044	0.048	0.034	0.043	0.044	0.038	0.024	0.023	0.023			
t-Test results	$t(563) = 7.26$, $p < .001$, $d = 0.61$			$t(563) = 6.55$, $p < .001$, $d = 0.55$			$t(563) = 8.21$, $p < .001$, $d = 0.69$					
Levene-test results	$F(1; 564) = 0.092$, $p = .76$			$F(1; 564) = 0.182$, $p = .67$			$F(1; 564) = 0.559$, $p = .46$					

considerably, particularly in Germany. The standard deviations of average CO_2 emissions during the charging processes ($SD_{c_{q,F}}$ and $SD_{c_{q,G}}$) and Levene's test (Levene, 1960) show that the variations of the distributions differ at a highly significant level ($SD_{c_{q,F}}$=30.6; $SD_{c_{q,G}}$ = 91.2; F[1;637] = 201.9, p < .001). Obvious differences observed concerning arithmetic averages $M_{c_{q,F}}$ and $M_{c_{q,G}}$ are supported by highly significant t-test (Student, 1908) results with strong effect sizes (Cohen, 1988) (t[423.2] = 97.3, p < .001, d = 7.5). These findings are further supported by aggregated results presented in Table 5.

On average PTW CO_2 emissions of charging the project EV from March until August 2013 exceeded CO_2 emissions calculated based on norm consumption by about 37% (measurement point 1, Fig. 2). Not taking into account efficiency losses in the battery and for charging still results in a surplus of PTW CO_2 emissions of about 27% (measurement points 2 and 3, Fig. 2).

Two major reasons for the discrepancies between real CO_2 emissions and CO_2 emissions calculated based on NEDC can be distinguished in (i) differences between the specific NEDC consumption and real consumption and (ii) differences between TTW and GTW. As NEDC consumption is also measured at measurement point 3 (Fig. 2) the first reasons for the discrepancies between the CO_2 emissions calculated based on NDEC and real consumption can be quantified. This amounts to about 27% for all trips considered, to about 34% for the trips from Germany to France and to about 26% for the trips from France to Germany (Table 5). However, this analysis neglects the losses occurring in the converter and the battery. Additionally incorporating the losses between measurement point 1 and measurement point 3 (Fig. 2) permits accounting for GTW consumption in order to quantify the empirical, time-dependent PTW CO_2 emissions, as efficiency losses between electricity generation and measurement point 1 (Fig. 2) are considered in the specific emission factors used.

Empirical specific GTW energy charged amount to about 0.27 kWh/km (Table 4, measurement point 1) and results in average specific transnational PTW CO_2 emissions of about 83.7 g CO_2/km. Specific CO_2 emissions derived from norm consumption are on average only at a level of 60.9 g CO_2/km (Table 5). During the evaluation period of six months about 3.2 tons of CO_2 were emitted. As the major part of the electricity generated in France is based on "carbon-free" nuclear power, specific PTW CO_2 emissions are substantially lower for the EV (16.4 g CO_2/km in France compared to 147.1 g CO_2/km for Germany). A detailed EV specific overview on charging-dependent CO_2 emissions is provided in Table A3.

5. Discussion

Section 5.1 discusses the results concerning EV specific energy consumption, Section 5.2 the results concerning CO_2 emissions and Section 5.3 corresponding potentials to reduce CO_2 emissions.

5.1. *Energy consumption*

When putting the emission values into a broader context concerning the energy charged two distinctive outcomes have to be discussed: firstly, the higher energy consumption in comparison to the NEDC values and secondly, the higher average energy consumed on the commuters' way home. The higher energy need of about 42% is not the result of a single factor, but can rather be

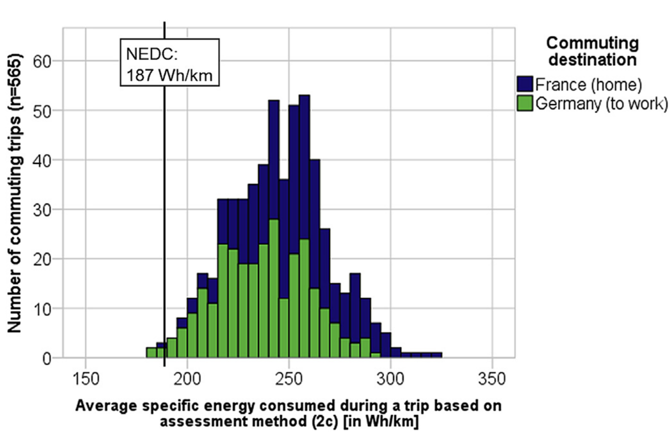

Fig. 5. Distributions of the specific energy consumed (measurement point 3, Fig. 2) during the bi-national commuting trips by the 3 project EV.

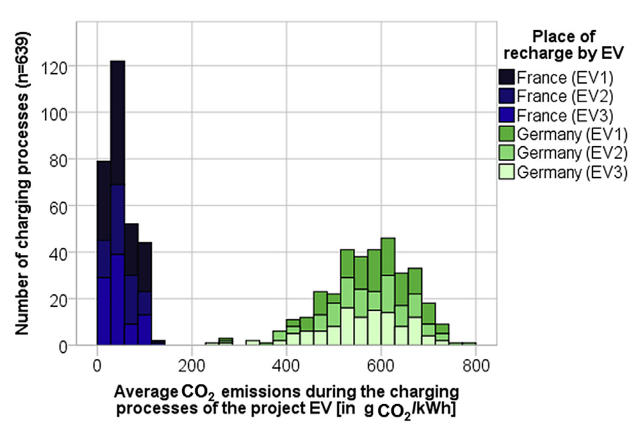

Fig. 6. Distribution of the average CO_2 emissions during the charging processes of the project.

Table 5
Total and average CO_2 emissions of project EV.

Activity	Parking and charging						Driving, consuming and recuperating					
Assessment method	Method (1)			Average of the methods (2a), (2b) & (2c)			Average of the methods (2a), (2b) & (2c)			Method 3 (NEDC)		
	Measurement point 1			Measurement point 2			Measurement point 3			–		
Place of recharge/Trip destination	Total	F	G	Total	F	G	Total	F	G	Total	F	G
Total CO_2 emissions [kg]	3209.6	304.8	2904.8	2976.9	283.7	2693.2	2957.0	275.1	2681.8	2338.0	205.3	2132.8
Overall average time-dependent specific CO_2 emissions (in g CO_2/km)	83.7	16.4	147.1	77.6	15.2	136.3	77.1	14.8	135.8	60.9	11.0	108.0
Overall surplus of average time-dependent specific CO_2 emissions compared to calculations based on NDEC [%]	37.3%	48.5%	36.2%	27.3%	38.2%	26.3%	26.5%	34.0%	25.7%	0%		

explained by a combination of different factors.

First of all, the charging efficiency is considered in the GTW energy calculated based on method (1) (Table A2), which the NEDC does not take into account. The calculated average value of 0.924 is supported by the technical data of the e-Wolf Delta 2 components, e.g. the on-board AC/DC charging unit itself has an efficiency of up to 0.95, according to the manufacturer; and the calculated battery efficiency lies between 0.976 and 0.984. It is slightly higher than the charging efficiency that has been stated in previous studies with a value around 0.9 (e.g. Campanari et al., 2009; Eaves and Eaves, 2004; Van Vliet et al., 2011), which might be due to other battery types, on-board AC/DC charging units or other electrical components (Thomas, 2009). Additionally, our period of investigation was mainly during summertime, when due to the mild temperatures less energy is lost due to the battery's internal resistance, than in winter.

When we compare our results to a recent commercial German vehicle test of EV (ADAC, 2015) with 11 EV, results of our empiric additional energy consumption compared to the NEDC values are comparable. The commercial test provides deviations from +17.1% up to +49.7%, with an average of +34.7% (standard deviation 11%). This test also includes the new Nissan eNV200, which is very similar to the project vehicles Delta 2 (the car bodies are identical). The project vehicles consume (based on the GTW approach) on average 17% (26.6 kWh/100 km) more than the Nissan eNV200 in the commercial test. Furthermore the results provided by Hacker et al. (2009) indicated an additional empirical energy demand measured by the GTW approach of 25% up to 70% compared to NEDC values.

Additionally to efficiency losses during the charging process, two further influencing factors leading to an increased energy demand were identified: route profiles and average payload. In this specific usage scenario the EV travel high distances on motorways and (flat) country roads (share of motorways 49.5% and country roads 46.4%) and have only a very low share of inner-city usage (4.1%) – which is not optimal for EV. This leads to comparably energy intensive high speed profiles with average speeds between 55 km/h and 60 km/h (Stella et al., 2015), where a higher amount of energy is lost to drag, whereas the driving cycle used by ADAC (2015) only covers a short motorway phase. The last, but probably most severe argument is the payload. As commuters use the EV to carpool in order to travel as cheap as possible to work, usually 5 to 7 people travel in one EV.

The difference in specific higher energy consumption (~7% surplus) between the trips from France to Germany and back from Germany to France is arguably the result of three conditions: (i) the shift workers might try to get home as quick as possible after work resulting in higher average speeds or higher driving dynamics. Furthermore, (ii) the users' homes are located at higher altitudes. Finally (iii) the average wind direction in this area is south-west, which is opposing the usual commuting direction when driving home and therefore increasing the drag losses.

Additionally, the data quality and uncertainties in the energy consumption measurement should be addressed. In terms of generalization it should be kept in mind that only the energy charged of three EV was measured. Even more limiting is the fact that EV2 showed some irregular behavior in its data due to damaged individual battery cells. Also the precision of the measurement of the energy consumed and recuperated is limited due to the 20 s time resolution of data points taken during a trip. As the recuperation phases are often shorter, these phases might be underrepresented due to the sampling frequency. Within this work the ratio of energy recuperated and energy consumed lies between 10% and 15%. This should be considered as lower bound. Furthermore, the assessment of energy charged in the GTW approach with method (1) at measurement point 1 (Fig. 2) is based on one exemplary charging curve. Charging behavior might vary considerably based on different parameters, particularly outdoor temperatures.

5.2. CO_2 emissions

The calculated EV emissions based on the French and German energy mix reveal significant differences between the two countries. Therefore, different reduction potentials are derived from the comparisons to comparable ICEV. Assuming that the project vehicles would only be charged in Germany results in average time-dependent PTW CO_2 emissions of about 147.1 g CO_2/km. This is about 36% above the CO_2 emissions calculated based on the norm consumption of the EV (Table 5) and can be explained by the comparably high energy consumption mainly due to the specific driving profiles and the high occupancy rates. Although the CO_2 emissions calculated by ADAC (2015) are based on a WTW assessment, the average PTW CO_2 emissions according to our results still exceed the CO_2 emissions calculated for Nissan eNV200 by about 15%. Comparing CO_2 emissions according to norm consumption of a conventional Nissan NV200 also having an identical chassis (128 g CO_2/km) with the CO_2 emissions calculated based on the norm energy consumption of the project EV (11 g CO_2/km in France and 108 g CO_2/km in Germany) leads to the conclusion that EV usage in France (Germany) is – with regard to CO_2 – more environmentally friendly than usage of comparable ICEV. CO_2 emission reduction potentials in France (Germany) consequently amount to 91.4%[3] (15.6%[4]). However, additional efficiency losses in the batteries and the AC/DC charging unit (charging efficiency, Section 4.1) increases the amount of energy needed for charging. This consequently also increases CO_2 emissions and results in reduction potentials compared to ICEV of about 90.7%[5] in France and 8.7%[6] in Germany.

[3] (128 gCO_2/km – 11 gCO_2/km)/128 gCO_2/km.
[4] (128 gCO_2/km – 108 gCO_2/km)/128 gCO_2/km.
[5] (128 gCO_2/km – (11 gCO_2/km/0.924))/128 gCO_2/km.
[6] (128 gCO_2/km – (108 gCO_2/km/0.924))/128 gCO_2/km.

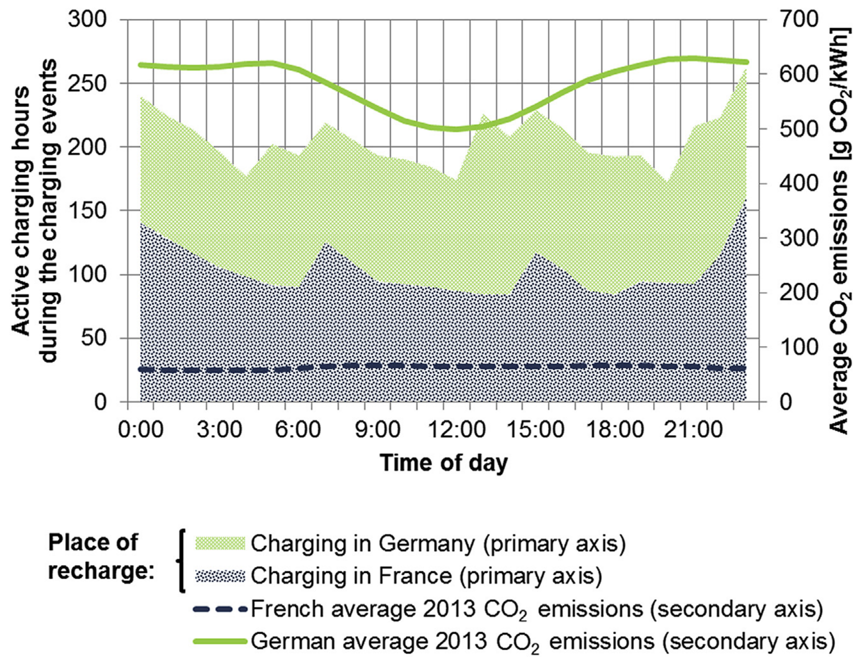

Fig. 7. Cumulated active charging hours of the project vehicles.

Table 6
Estimates on CO_2 emission reduction potentials and strategies.

Use cases	Number of commuters	Strategies to reduce CO_2 emissions	CO_2 emission reduction potential per electric kilometer travelled
French-German transnational commuters in the Pamina region	~16,000 (Association of European Border Regions, 2012)	Shifting charging activities to France, if possible. If commuters need to charge in Germany, shifting load into periods with high shares of fluctuating renewable energy sources.	Assuming that energy consumption is equal on the way to work and back and the EV are charged as often in Germany as in France, CO_2 emissions can be almost halved. Load shifting, so EV are charged as much as possible in France, would permit to further reduce CO_2 emissions of EV charging.
German commuters using EV instead of cars	66% of the German workforce, i.e. ~27 million (Wingerter, 2014)	Load shifting into periods with high shares of fluctuating renewable energy sources.	The high volatility of CO_2 emission intensities of the German electricity generation mix results in highly volatile CO_2 emission reduction potentials. According to Fig. 7 load shifting into afternoon hours could decrease CO_2 emission intensities of EV charging by about 100 gCO_2/kWh on average.
French commuters using EV instead of cars	About 73% of the French commuters use cars, i.e. 18.6 million (INSEE, 2009)	Emissions are always at comparably low levels, so charging when convenient is possible. Alternatively usage of self-generated renewable energy could be an option.	About 10 times less CO_2 emissions are generated if EV are used instead of ICEV.

PTW CO_2 emissions for charging EV in France are consequently about 10 times lower than CO_2 emissions of comparable ICEV and about 10 times lower than charging in Germany. These results underline the effects of the different electricity generation mixes in France and Germany on operational, charging and time-dependent CO_2 emissions of EV.

It needs to be critically mentioned, that the disaggregated data on electricity generation used for the calculations differs between France and Germany. Notably electricity generation by source is classified differently and specific CO_2 emissions in the two countries differ (Table 3). Nevertheless, almost all of the specific CO_2 emissions provided for operating the power plants are within the range of Turconi et al. (2013). Furthermore, differences between official German statistics on annual electricity generation by source and the averages calculated based on the hourly disaggregated data provided by the EEX Transparency Platform (EEX Transparency, 2015) were observed. In comparison to the AGEB (2015) the shares of lignite (~9 percentage points (pp)) and nuclear power (~7 pp) are heavily and the shares of electricity generated by wind (~3 pp) and photovoltaic (~2 pp) are slightly overrepresented, while on the other hand gas (~8 pp), biomass, waste and others (~11 pp) are heavily underrepresented. Furthermore, we did not consider electricity exchange between countries (which is currently increasing). In the border region this electricity exchange is strongly influencing the regional electricity generation mix. For other uncertainties, such as regional specific grid losses or power generation mixes (such as local electricity use from photovoltaics), there is to our knowledge currently no reliable data available and therefore could not be used. Depending on the region the time-dependent local energy mix could potentially vary significantly from the national one (UBA, 2016). Further limitations include that only CO_2 emissions were considered. Other environmental indicators were neglected in this analysis.

5.3. CO_2 emissions reduction potentials and strategies

Focusing on our results, we observed that if EV would have been charged exclusively in Germany, specific CO_2 emissions according to NEDC of the EV would have still been slightly lower than for a comparable ICEV (Section 5.2). Consequently, according to our findings the upcoming European fleet target of 95 g CO_2/km in 2022 would not be achieved by the project EV when real power plant emissions would be considered. For Italy, Donateo et al. (2014) are more optimistic about the potentials of EV to reach the fleet targets. However, as the German electricity generation is in a considerable decarbonization process, the 95 g CO_2/km target might be achieved in 2022 – even with our calculation method.

The time-dependent CO_2 emissions assessed for 2013 and the CO_2 emissions calculated based on national average CO_2 emissions are about at the same level. This is surprising, as time-dependent CO_2 emissions fluctuate heavily during the day, particularly in Germany. However, this can be explained by the usage scenario within this particular project, as the commuters are shift workers with a 24 h rotating shift schedule. The EV were in constant deployment and charged rather slow (Mode 1). Consequently, charging times are well distributed over the hours of a day (Fig. 7). For commuters not working in a rotating shift schedule the outcome would be different.

Our results implicate that CO_2 emission reduction potentials of EV could be used by charging them during windy and sunny hours in Germany. From an environmental perspective, the time the charging processes take place is much more important in Germany than in France, as time-dependent CO_2 emissions in France remain relatively stable on a low level (Fig. 1). The findings are supportive to Faria et al. (2013) who showed that CO_2 emission reduction potentials of EV are high for France. Additionally Faria et al. (2013) showed that the reduction potential in Portugal varies significantly depending on the month and time of day.

Therefore, particularly for Germany, we suggest introducing controlled Mode 3 (IEC 61851) charging with comparably higher charging powers up to 44 kW and the possibility to shift load into periods with comparably low time-dependent CO_2 emissions. This however would require smart services controlling the charging events so the batteries are fully charged at the end of the shifts. In this context the potentially harmful effects of higher charging powers on battery health as well grid constraints need to be considered.

An overview on strategies and potentials for reducing CO_2 emissions by substituting ICEV with EV for different commuting use cases in the French-German context is presented in Table 6. Based on our findings the strategy suggestions for the different use cases vary: for transnational EV users commuting between France and Germany we recommend charging their EV in France as much as possible in order to reduce the specific CO_2 emissions. For commuters only commuting within Germany we recommend shifting the load into periods with high shares of renewables, i.e. particularly into afternoon hours, when the sun is shining, or into windy periods. As CO_2 emissions in France are generally on a low and stable level, our results permit to conclude that charging when convenient has no negative impact on CO_2 emissions. Further reduction is only possible when self-generated renewable energies are available. In this case the charging schedule should be adapted accordingly.

6. Conclusions

The energy needed for charging three well-loaded electric vehicles in a French-German fleet test resulted in an average specific consumption surplus above the official values of about 42% on average. Considering time-dependent average French (characterized by a high share of nuclear power) and German (characterized by a high share of fluctuating renewables) electricity generation mixes, time-dependent carbon dioxide emissions for charging electric vehicles are roughly ten times lower in France than in Germany. Recommendations derived from the case study results of focusing on commuting with electric vehicles in a region with a high degree of cross-border labor mobility include that time-dependent plant to wheel carbon dioxide emissions for charging electric vehicles should be considered in future driving test procedures. Furthermore, the findings of this study underline the postulation that hypothetical energy consumptions of the standardized driving cycles should be validated by long-term real-world consumption analysis. Assuming that electric vehicles are not charged equally distributed over the day in general, time-dependent carbon dioxide emissions should be calculated and considered in the currently developed Worldwide Harmonized Light Vehicles Test Procedures. The better specific real world consumption and corresponding carbon dioxide emissions are incorporated in upcoming test procedures, the more attractive it becomes for car manufacturers to build low consuming electric vehicles and provide attractive services supportive to charging electric vehicles, when carbon dioxide emissions are low.

7. Future work

In order to assess charging dependent carbon dioxide emissions precisely, future research could address this problem by comparing the energy consumption of different types of electric vehicles operating on the same routes. For this, the data on energy consumption of the vehicles during driving and charging phases should be recorded in higher sampling rates. This would allow better estimates on energy consumption of electric vehicles. Furthermore, to compare the empirical carbon dioxide emissions of electric vehicles and internal combustion engine vehicles, measuring real fuel consumption of comparable conventional cars operating on the same routes could be investigated. The data on time-dependent carbon dioxide emissions within the two countries could be analyzed in a more detailed manner in order to develop environmentally friendly charging strategies for the two countries. Analyses focusing on the research question how charging processes of electric vehicles used in France and Germany could be scheduled in a carbon dioxide minimizing manner could also be addressed in future works by focusing on EV specific time-dependent marginal carbon dioxide emissions due to the fact that EV are marginal consumers, when they are capable to shift their load. Furthermore, load flow calculations, taking into account the technical constraints of the electric power grid, could be supportive to map energy sources and sinks more precisely in order to derive conclusions about the real carbon dioxide emissions of consumers in different areas.

Acknowledgements

This paper was made possible by the RheinMobil project [ref. no: 16SBW007A]. RheinMobil is funded by the German Federal Ministry of Transport and Digital Infrastructure (BMVI). RheinMobil is part of the Schaufenster initiative in Baden Württemberg „LivingLabBWe mobil“. Furthermore, we thank Sina Mostafavi for reviewing this article to check for spelling and grammar as well as two anonymous reviewers, who improved the paper significantly by giving helpful comments.

Appendix

Table A1
Examples of previous studies discussing EV emissions.

Author	Region	Time of data	System boundaries	Energy consumption	Definition of emission intensity	Type of pollutants	Reduction potential	Recommended measurements and policies
Bickert et al. (2015)	Germany	2013/4 2020 & 2030 (projected)	LCA	NEDC + 20%, 2.7 kW for auxiliaries	Lifetime emissions of different energy sources	CO_2eq	Comparison to ICEV on individual level shows that only a mileage of 2500–5500 km/a is required to reach an ecological life-cycle CO_2 break-even	Expansion of EV in Germany has to go hand in hand with increasing the share of renewable energies, therefore incentives should encourage charging with renewable energies.
Campanari et al. (2009)	Italy	2007	WTW	ECE-EUDC, US06	Average emissions Italian power mix, coal, renewables, natural gas	CO_2	In comparison to ICEV on individual level at higher one-way ranges fuel cell electric vehicles (FCEV) show high CO_2 reduction potential, EV, if not charged with renewables, have almost none	–
Chatzikomis et al. (2014)	Greece	2012	LCA	NEDC, EPA values	Average emission values of electricity mix	CO_2	The potential total environmental impact of different levels of EV diffusion in Greece depends on the energy efficiency of both technologies and the source of electricity	–
Donateo et al. (2014)	Italy	2013	PTW	Measured EV consumption from eight separate charging events	Hourly disaggregated emissions	CO_2, NO_x, CH_4, SO_x, CO, HC, VOC, metals, particles	Comparison to the EU fleet targets and Euro VI limits on individual level shows significant lower emissions for all pollutants, but HC, which is lies at the same level	–
Donateo et al. (2015)	Italy	2013	PTW, LCA	Measured charging energy from 7.700 charging events	Specific emissions from three timeslots per day	CO_2, NO_x, CH_4, CO, particles	Comparison of different EV energy mix, charging habits, vehicle types, and driving conditions to the EU fleet targets and Euro VI limits shows reduction potential for most pollutants	–
Doucette and McCulloch (2011)	USA, France, India, China	2009	TTW	Numerical simulation based on NEDC	The grid average intensity	CO_2	Comparison of different EV types to their ICEV counterparts on individual level shows high reduction potentials for France, medium for USA, and none or even negative for India and China	Countries need to decarbonize their power generation to gain a positive effect from EV introduction.
Faria et al. (2013)	Portugal, Poland, France	2011	WTW, LCA	Measured EV consumption on two different routes	Primary average and monthly distribution of energy among the year for three different energy mixes for three hour time slots	CO_2	Comparison of different EV types to their ICEV counterparts on individual level shows high reduction potentials for France, medium for Portugal and none or even negative for Poland. The reduction potential in Portugal varies significantly depending on the month and time of day, for Poland and France it is almost constant	Two main factors are required to make EV more sustainable from an environmental perspective: eco-driving attitude, and an environmental electricity mix.
	Europe	<2010	LCA					

Hawkins et al. (2013)				Industry performance tests of NEDC. Nissan LEAF: 17.3 kW h/ 100 km	Aggregated environmental impacts of vehicles' global warming potentials and other potential impacts.	CO_2eq, toxicity, acidification, eutrophication	EV powered by the present European electricity mix offer a 10% −24% decrease in global warming potential (GWP) relative to conventional diesel or gasoline vehicles; but supply chain exhibit high toxicity potential.	Reducing vehicle production supply chain impacts and promoting clean electricity sources in decision making regarding electricity infrastructure.
Jochem et al. (2015)	Germany	2030 (projected)	WTW	Assumption: 20 kW h/ 100 km	Hourly electricity mix further regionally disaggregated in order to account for transmission capacities of the electricity grid	CO_2	Comparison of different assessment methods and charging strategies on the total energy consumption and emission to ICEV EU emission targets for 2030 on individual level shows that taking the marginal electricity mix the emissions will be higher than the targets set by the EU	Controlled charging should be supported, consistent methodologies to address key factors affecting EV CO_2 emissions should be developed, and efficient policy instruments to guarantee emission free mobility should be implemented
Ma et al. (2012)	England, California	2015 (projected)	WTW, LCA	Standard driving cycles, auxiliaries, additional load	Annual average energy mix and marginal emission factor	CO_2eq	Comparison of ICEV and hybrid electric vehicle (HEV) to comparable ICEV assessed with average and marginal grid intensity at different driving conditions for England and California shows that depending on the driving style there is no CO_2 emission reduction potential for England and only very little for California	–
McCarthy and Yang (2010)	California	2009	WTW	Simulation based on annual driving data	Marginal emission factor from an hourly dispatch model	CO_2	Comparison of emissions of individual level between EV, ICEV, PHEV, and FCV shows that EV have the lowest specific emissions, more than half of comparable ICEV	–
Muneer et al., 2015	Scotland, Slovenia	2010/1	LCA	Simulation based on driving data	UK and Scottish average annual energy mix and local renewables	CO_2eq	–	Significant investment into renewable energies is required to lower the carbon emissions from EV
Nordelöf et al. (2014)	Worldwide review	1998–2013	WTW, LCA, LCIA	Review: different studies are considered	Review: different studies are considered	CO_2eq, toxicity, acidification, eutrophication	Greenhouse gas emission reduction potentials of EV are heavily dependent on the fossil content of the electricity mix.	Environmental benefits from large-scale deployment of EV depends on parallel improvements of the background energy system.
Rangaraju et al. (2015)	Belgium	2011	WTW, LCA	Measured charging energy	Disaggregated hourly emissions	CO_2eq, NO_x, SO_2, particle	Comparison of EV to ICEV emissions for different pollutants on individual level shows significant savings potential for CO_2eq, NO_x, and SO_2 but nor for particle emissions, also charging strategies and electricity mix influences the savings potential	–
Robinson et al. (2013)	England	2011/2	WTW	Charging profiles of 7.704 charging events over two six month periods	Two half hourly disaggregated emission profiles for winter and summer	CO_2	Comparison of different charging processes shows the effect of carbon content of the electricity mix and season	Smart metering and/or financial incentives are recommended to increase load shifting to of peak times
Sharma et al. (2012)	Australia	2011	LCA (no disposal)	AUDC	Average energy mix	CO_2eq	Comparison of total live cycle emissions of EV, HEV, and ICEV of different types shows that EVs do not always have a comparative environmental advantage	–

Table A2
Total energy charged and consumed by the project EV assessed by different methods (1)–(3) including charging efficiency calculations.

		1 (GTW)			2a			2b			2c			3 (NEDC)		
		Total	France	Germany	Total	France	Germany	Total	France	Germany	Total	France	Germany	Total	France	Germany
EV1	Overall energy charged (measurement points 1 & 2) [kWh]	4361.6	2329.6	2032.0	4124.0	2167.7	1956.3	4100.0	2156.2	1943.8	4079.1	2143.9	1935.2	–		
	Overall energy consumed (measurement point 3/ NEDC assumption) [kWh]	–			3949.5	2075.5	1874.0	3980.6	2091.2	1889.4	3987.3	2094.8	1892.6	3055.6	1534.3	1521.3
	Battery efficiency (2×)	–			0.958	0.957	0.958	0.971	0.970	0.972	0.977	0.977	0.978	–		
	Charging efficiency (excl. battery)	–			0.946	0.930	0.963	0.940	0.926	0.957	0.935	0.920	0.952	–		
	Method 1 (GTW) compared to NEDC (incl. charging efficiency)	–												1.32	1.37	1.21
	Consumption ratio including battery efficiency to NEDC	–			1.313	1.374	1.252	1.324	1.385	1.262	1.326	1.387	1.264	–		
EV2	Overall energy charged (measurement points 1 & 2) [kWh]	2611.1	1261.8	1349.3	2327.4	1162.3	1165.1	2306.6	1153.0	1153.7	2289.6	1145.6	1143.9	–		
	Overall energy consumed (measurement point 3/ NEDC assumption) [kWh]	–			2437.2	1158.0	1279.2	2451.7	1164.0	1287.7	2454.1	1165.8	1288.3	1940.2	896.6	1043.6
	Battery efficiency (2×)	–			1.047	0.996	1.098	1.063	1.010	1.116	1.072	1.018	1.126	–		
	Charging efficiency (excl. battery)	–			0.891	0.921	0.864	0.883	0.914	0.855	0.877	0.908	0.848	–		
	Method 1 (GTW) compared to NEDC (incl. charging efficiency)													1.24	1.30	1.19
	Consumption ratio including battery efficiency to NEDC				1.220	1.254	1.190	1.227	1.261	1.198	1.228	1.263	1.199			
EV3	Overall energy charged (measurement points 1 & 2) [kWh]	3222.9	1591.3	1631.6	3070.0	1519.4	1550.6	3046.1	1508.3	1537.8	3027.2	1500.5	1526.7			
	Overall energy consumed (measurement point 3/ NEDC assumption) [kWh]				2889.2	1419.3	1470.0	2904.9	1426.8	1478.1	2907.7	1428.4	1479.3	2178.5	1049.5	1128.9
	Battery efficiency (2×)	–			0.941	0.934	0.948	0.954	0.946	0.961	0.961	0.952	0.969			
	Charging efficiency (excl. battery)	–			0.953	0.955	0.950	0.945	0.948	0.942	0.939	0.943	0.936			
	Method 1 (GTW) compared to NEDC (incl. charging efficiency)													1.37	1.40	1.34
	Consumption ratio including battery efficiency to NEDC				1.359	1.386	1.335	1.367	1.393	1.342	1.368	1.395	1.343			
Total	Charging (measurement points 1 & 2) [kWh]	10,195.6	5182.7	5012.9	9521.4	4849.3	4672.0	9452.7	4817.4	4635.3	9395.9	4790.1	4605.9			
	Consumption (measurement point 3/NEDC assumption) [kWh]				9275.8	4652.8	4623.1	9337.2	4682.0	4655.2	9349.1	4689.0	4660.1	7174.3	3480.4	3693.8
Average	Charging (measurement points 1 & 2) [kWh/km]	0.266	0.278	0.254	0.248	0.261	0.237	0.246	0.259	0.235	0.245	0.257	0.233			
	Consumption (measurement point 3/NEDC assumption) [kWh/km]				0.242	0.250	0.234	0.243	0.252	0.236	0.244	0.252	0.236	0.187	0.187	0.187
Average consumption above NDEC	Charging (measurement points 1 & 2)	42.1%	48.9%	35.7%	32.7%	39.3%	26.5%	31.8%	38.4%	25.5%	31.0%	37.6%	24.7%			
	Consumption surplus (measurement point 3/ NEDC assumption)				29.3%	33.7%	25.2%	30.1%	34.5%	26.0%	30.3%	34.7%	26.2%	0.0%	0.0%	0.0%

Table A3
Overview on CO_2 emission assessment results.

		Different assessment methods used to assess the energy charged of the project EV in order to calculate CO_2 emissions of project EV														
		Method (1), measurement point 1			Method (2a), measurement points 2 & 3			Method (2b), measurement points 2 & 3			Method (2c), measurement points 2 & 3			3 (NEDC)		
		Total	F	G	Total	F	G	Total	F	G	Total	F	G	Total	F	G
CO_2 emissions of EV1 [kg]	Charging	1318.6	138.0	1180.5	1265.3	127.6	1137.7	1258.2	127.6	1130.6	1251.9	126.2	1125.6	–		
	Consumption	–			1209.7	121.8	1087.9	1219.6	122.7	1096.8	1221.7	123.0	1098.7	973.4	90.4	883.0
Average time-dependent specific CO_2 emissions of EV1 (in g CO_2/km)	Charging	80.7	16.8	145.1	77.4	15.6	139.8	77.0	15.6	139.0	76.6	15.4	138.4	–		
	Consumption	–			74.0	14.8	133.7	74.6	15.0	134.8	74.8	15.0	135.1	59.6	11.0	108.5
CO_2 emissions of EV2 [kg]	Charging	869.2	81.3	788.0	758.9	75.7	683.1	751.7	75.1	676.5	745.6	74.7	670.9	–		
	Consumption	–			814.9	75.5	739.4	820.4	75.9	744.5	820.9	76.0	744.9	662.2	58.7	603.5
Average time-dependent specific CO_2 emissions of EV2 (in g CO_2/km)	Charging	83.8	16.9	141.2	73.1	15.8	122.4	72.4	15.7	121.2	71.9	15.6	120.2	–		
	Consumption	–			78.5	15.7	132.5	79.1	15.8	133.4	79.1	15.9	133.5	63.8	12.2	108.1
CO_2 emissions of EV3 [kg]	Charging	1021.8	85.5	936.3	973.8	81.9	892.0	966.0	81.3	884.7	959.4	80.9	878.5	–		
	Consumption	–			917.7	76.5	841.1	922.7	77.0	845.7	923.5	77.1	846.4	702.4	56.2	646.2
Average time-dependent specific CO_2 emissions of EV3 (in g CO_2/km)	Charging	87.7	15.2	155.1	83.6	14.6	147.7	82.9	14.5	146.5	82.4	14.4	145.5	–		
	Consumption	–			78.8	13.6	139.3	79.2	13.7	140.1	79.3	13.7	140.2	60.3	10.0	107.0
Total CO_2 emissions [kg]	Charging	3209.6	304.8	2904.8	2998.0	285.2	2712.8	2975.9	284.1	2691.8	2956.9	281.8	2675.1	–		
	Consumption	–			2942.3	273.8	2668.5	2962.6	275.6	2687.0	2966.0	276.1	2690.0	2338.0	205.3	2132.8
Surplus of CO_2 emissions compared to calculations based on NEDC [%]	Charging	37.3%	48.5%	36.2%	28.2%	39.0%	27.2%	27.3%	38.4%	26.2%	26.5%	37.3%	25.4%	–		
	Consumption	–			25.8%	33.4%	25.1%	26.7%	34.3%	26.0%	26.9%	34.5%	26.1%	0.0%		
Average time-dependent specific CO_2 emissions (in g CO_2/km)	Charging	83.7	16.4	147.1	78.1	15.3	137.3	77.6	15.3	136.3	77.1	15.1	135.4	–		
	Consumption	–			76.7	14.7	135.1	77.2	14.8	136.0	77.3	14.8	136.2	60.9	11.0	108.0
Surplus of average time-dependent specific CO_2 emissions compared to calculations based on NDEC [%]	Charging	37.3%	48.5%	36.2%	28.2%	39.0%	27.2%	27.3%	38.4%	26.2%	26.5%	37.3%	25.4%	–		
	Consumption	–			25.8%	33.4%	25.1%	26.7%	34.3%	26.0%	26.9%	34.5%	26.1%	0.0%		

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Transportation Research Part D 75 (2019) 87–105

Contents lists available at ScienceDirect

Transportation Research Part D

journal homepage: www.elsevier.com/locate/trd

Utilization effects on battery electric vehicle life-cycle assessment: A case-driven analysis of two commercial mobility applications

Michael Held[a], Maximilian Schücking[b,*]

[a] Fraunhofer Institute for Building Physics (IBP), Department Life Cycle Engineering, Wankelstraße 5, D-70563 Stuttgart, Germany
[b] Institute for Industrial Production (IIP), Karlsruhe Institute of Technology, Hertzstraße 16, D-76187 Karlsruhe, Germany

ARTICLE INFO

Keywords:
Battery electric vehicles
Life-cycle assessment
Commercial mobility use-cases

ABSTRACT

The utilization has a significant effect on the life-cycle assessment (LCA) of battery electric vehicles (BEVs). This article evaluates this effect in detail by presenting a case-driven LCA for BEVs deployed in two commercial mobility applications. The empirical data was recorded over 2.5 years and 450,000 km. The findings of this article indicate that regular and predictable mobility demand patterns in combination with a high vehicle utilization are favorable conditions for an environmentally beneficial deployment of BEVs. These characteristics allow tailoring the battery capacity to the requirements and avoiding an unnecessary offset from production. When charging the vehicles with electricity from renewable energy sources (RESs), the high operating grade utilizes the comparatively lower environmental impacts per kilometer. A high lifetime mileage allows breaking-even to comparable internal combustion engine vehicles (ICEVs) in most investigated impact categories. Since regular and predictable mobility patterns, as well as a high operating grade, are commonly found in commercial applications these are especially suitable for replacing ICEVs with BEVs from an environmental perspective.

1. Introduction

Passenger cars are significant contributors to anthropogenic climate change, local emissions of air pollutants, and are highly dependent on nonrenewable fossil fuels (Helmers and Weiss, 2017). The market for passenger cars is projected to double from around 1 billion today to 2 billion by 2040 (BP, 2018). Without a replacement of fossil fuels as an energy source, this development will lead to a significant increase in emissions from transport.

Battery electric vehicles (BEVs) are propagated as one solution to reduce the greenhouse gas (GHG) and local tailpipe emissions as well as the dependency on fossil fuels (Hawkins et al., 2013a). As a consequence of political measures and technological advances the numbers of BEVs and Plug-in hybrid vehicles (PHEVs) sold worldwide is increasing rapidly with over 1 million new registrations in 2017 surpassing the total number 3.1 million (IEA, 2018). However, the actual environmental benefit from replacing internal combustion engine vehicles (ICEVs) with BEVs is part of an ongoing debate in scientific research.

1.1. Related work

For the holistic assessment of the environmental impact from different vehicle power train technologies, the standardized quantitative Life-Cycle Assessment (LCA) approach has emerged as the dominant methodology. This approach considers the whole

* Corresponding author.
E-mail addresses: michael.held@ibp.fraunhofer.de (M. Held), maximilian.schuecking@partner.kit.edu (M. Schücking).

https://doi.org/10.1016/j.trd.2019.08.005

Available online 28 August 2019

life-cycle from raw material extraction to recycling and disposal and not only the direct tailpipe emissions or indirect emissions from the electricity used for charging (Helmers and Weiss, 2017; Nordelöf et al., 2014). Furthermore, it includes several impact factors, not just the Global Warming Potential (GWP) (Ausberg et al., 2015; Klöpffer, 2014). This approach allows uncovering potential burden-shifting or rebound effects from GWP to other impact categories (Egede et al., 2015; Ellingsen et al., 2014). However, a large number of previous studies focuses on GHG or just CO_2 emissions when assessing the environmental impact of BEVs (Helmers and Weiss, 2017; Nordelöf et al., 2014).[1] Only around a quarter of all publications between 2011 and 2015 include additional environmental impact factors (Helmers and Weiss, 2017). These LCA studies commonly compare the different technologies on individual vehicle level in one or more specific energy markets under the current or future conditions (Bauer et al., 2015; Cox et al., 2018; Hawkins et al., 2013a; Notter et al., 2010; Tagliaferri et al., 2016).

The life-cycle of a vehicle consists of three phases: cradle-to-gate, which includes all upstream processes of raw material extraction, production of materials, and manufacturing, the utilization, and the End-of-Life (EoL) treatment which includes the recycling, recovery, and disposal. In the following, the main influence factors on the environmental impacts of different power train technologies identified by previous studies are presented with emphasis on the utilization phase.

The cradle-to-gate phase causes significant environmental impacts that highly depend on powertrain technology. For BEVs, it is essential to distinguish the vehicle glider, powertrain, and battery (Bauer et al., 2015; Tagliaferri et al., 2016). In comparison to other powertrain alternatives, especially the materials and production processes of the battery cells and packs increase the environmental impact of the BEV from cradle-to-gate (Cerdas et al., 2018; Dunn et al., 2015; Held et al., 2016). Several LCAs for different battery technologies exist in the literature (Ellingsen et al., 2014; Kim et al., 2016; Peters et al., 2012; Sullivan and Gaines, 2012). Detailed inventory information is vital to assess the cradle-to-gate impacts reliably. However, only a few publications provide high-resolution inventories for BEVs and their batteries (Ellingsen et al., 2017). Ellingsen et al. (2014) and Kim et al. (2016) are two prominent examples that offer primary industry data.

For the utilization phase, previous publications have identified two critical influencing factors on the overall environmental impact of BEVs: the energy demand and the source of the energy carrier. In contrast to the upstream supply chain, for the utilization, primary inventory data is broadly available, and energy flows are more straightforward to model.

The energy consumption of passenger cars is highly sensitive to external vehicle characteristics and technological performance (Ellingsen et al., 2014; Hawkins et al., 2013a, 2013b). External factors are the user characteristics, the mobility patterns, the desired temperature in combination with the surrounding conditions, as well as the road and traffic conditions (Egede et al., 2015). Empirical studies have demonstrated the impact of these factors on the energy consumption of BEVs (Helmers et al., 2017; Neubauer and Wood, 2014; Schücking et al., 2016; Wu et al., 2015).

Three approaches can be found in the literature to estimate the energy consumption of different powertrain technologies: values stated by the manufacturers, detailed technical models, and empirical values. Most studies rely on the standardized energy consumption values since they facilitate an easy comparison between different powertrain technologies (Ellingsen, 2016; Hawkins et al., 2013a, 2013b; Tagliaferri et al., 2016). However, empirical studies have shown that the real-world values for all powertrain technologies can notably differ from the ones measured on standard driving cycles (Muneer et al., 2015; Rangaraju et al., 2015; Saxena et al., 2014; Wang et al., 2015; Wu et al., 2015). Mechanical energy consumption models that calculate the energy consumption based on specific driving profiles and internal efficiencies are an alternative to standardized energy consumption values (Yazdanie et al., 2016). Increasingly the Worldwide harmonized Light vehicles Test Procedure (WLTP) is taken as the basis for these models (Bauer et al., 2015; Cox et al., 2018; Garcia et al., 2017).[2] Using numerical simulation models allows the consideration of different scenarios, e.g., developments in component efficiencies or increased auxiliary demand (Bauer et al., 2015; Cox et al., 2018; Li et al., 2016). Only a few studies rely on the third option, long-term real-world energy consumption values (Faria et al., 2013; Muneer et al., 2015; Plötz et al., 2017). Of these, even fewer include other pollutants than CO_2 (Donateo et al., 2014, 2015; Rangaraju et al., 2015) and even less conduct a full LCA (Held et al., 2016; Helmers et al., 2017). The use-case and the field of deployment can have a significant impact on the mobility patterns and therefore the energy required for propulsion and auxiliaries (Schücking et al., 2016). Even though, a detailed analysis of site-specific use-cases based on long-term empirical values is missing from the literature (Egede et al., 2015).

Next to energy consumption, previous studies conclusively demonstrate that the indirect emissions resulting from the used energy carrier have a notable influence on the environmental impact of BEVs. The used energy is the largest source of variability in the prognosis of future LCA development (Cox et al., 2018). Therefore, a well-to-wheel (WTW) scope considering the energy supply chain from extraction, transport, and conversion is indispensable. Previous studies have simulated the influence of different energy markets (Doucette and McCulloch, 2011; Egede et al., 2015; Faria et al., 2013; Woo et al., 2017), average mixes to electricity from a single renewable energy source (RES) (Held et al., 2016; Helmers et al., 2017; Helms et al., 2011), different regional grids (Macpherson et al., 2012), as well as an electricity system with to one without a high storage capacity (Garcia et al., 2017). However, we are not aware of any study that empirically analyses the influence of different energy markets on cross-border transport.

The EoL treatment consisting of recycling, recovery, and disposal makes up only a comparatively minor share of the overall impact but is still subject to considerable uncertainty (Hawkins et al., 2013a, 2013b). The recycling, recovery, and disposal of the glider is similar for the different powertrain technologies. Hence, the research focus of LCA for BEVs lies on the powertrain

[1] Some papers do not extensively assess the environmental impacts but add direct urban air pollutants such as Sulfur dioxide (SO_2), nitrogen oxides (NO_X) and particulate matters (PM) to their analysis (Donateo et al., 2014, 2015; Rangaraju et al., 2015).

[2] The WLTP was introduced to reduce the gap between the values stated by the manufacturer and the real-world consumption values. It is compulsory for all new vehicles in the European Union starting from the 1st of September 2018 (European Commission, 2017).

components and the battery. Analog to the cradle-to-gate processes, the larger the battery, the higher the environmental burden of recycling and disposal. Different publications analyze potential recycling processes for different Lithium-ion (Li-ion) battery technologies (Buchert et al., 2011; Buchert and Sutter, 2015; Cerdas et al., 2018). Based on empirical research projects, some suggest a potentially positive contribution of recycling by closing the loop for rare materials used in battery and powertrain components and hence avoiding primary material production (Buchert et al., 2011; Buchert and Sutter, 2015). However, on energy and material flows which cause high uncertainty in the EoL treatment and its environmental impact, there is only limited first-hand data available (Ellingsen et al., 2017). In particular, there are still significant gaps concerning the commercial recycling processes for BEV batteries.

1.2. Contribution of the study

Overall, previous LCA studies concur in their key findings when comparing the environmental impact of BEVs and ICEVs: Firstly, the introduction of BEVs increases the environmental impact from cradle-to-gate. However, depending on the circumstances of utilization in some impact categories these can be more than compensated. Secondly, in terms of the circumstances of utilization, the following parameters and inventories have the most notable influence on the overall performance: electricity used for charging, vehicle size and topology, lifetime, driving patterns, and battery size (Cox et al., 2018; Egede et al., 2015; Ellingsen et al., 2014).

The strong influence of the utilization on the overall environmental performance of BEVs justifies the need for a use-case specific analysis. Plötz et al. (2017) underline the necessity to consider individual mobility patterns in the environmental assessment of BEVs. (2017)(2017)(2017)(2017)(2017) A few long-distance trips, which require a large battery, often dominate private mobility patterns. Under the premise of full substitution, BEVs are less beneficial in comparison to PHEVs according to the lifetime CO_2 emissions since a notable share of the battery capacity remains unused for most of the time but causes a high environmental impact offset from cradle-to-gate (Plötz et al., 2017). On the other hand, regular mobility patterns on fixed routes allow for a constantly high degree of battery capacity utilization (Schücking et al., 2017). In commercial use-cases, this type of mobility patterns with limited variance is widespread (Ketelaer et al., 2014).

However, most publications that assess the environmental impacts of BEVs have neglected specific use-cases and long-term empirical energy consumption values. They rely on general assumptions concerning lifetime mileage and mixed route profiles (urban, interurban, or motorway) not considering the substitution potential of BEVs in detail. The few papers that use actual data from BEV deployment either lack a full LCA or do not focus on specific use-cases (Donateo et al., 2015, 2014; Helmers et al., 2017; Rangaraju et al., 2015).

This study attempts to fill this gap in the literature by presenting a detailed case-driven LCA for BEVs and ICEVs. It makes the following contributions:

1. Presenting the empirical energy consumption of two BEV types deployed over two years in two cross-border commercial use-cases that allow for a high operating grade.
2. Conducting an LCA and analyzing the effect of the high operating grade, different energy mixes on both sides of the border, and vehicle types on the lifetime environmental impact as well as the respective break-even points according to three impact categories and the primary energy demand as an indicator for the depletion of nonrenewable energetic resources.

The primary goal of the presented analysis is to gain a better understanding of the environmental performance of BEVs in realistic use-cases and to derive key characteristics and boundary conditions required for an environmentally beneficial introduction of BEVs in mobility systems.

The subsequent sections of the paper are structured as follows: Chapter 2 describes the applied methodology, main assumptions, and the case-study parameters. Chapter 3 presents the results of the LCA for the two use-cases. Chapter 4 discusses the results and deduces recommendations for an environmentally beneficial deployment of BEVs. Chapter 5 concludes the paper by summarizing and providing an outlook for future work.

2. Method & data

The environmental analysis of the investigated BEV use-cases is conducted by using the method of Life-Cycle Assessment (LCA). This method follows a standardized framework described by the DIN EN ISO 14040 and 14044 that was last updated in 2006. The LCA is a quantitative method that covers all material and energy flows throughout the process chains of the whole product life-cycle.

The LCA approach consists of four steps: Goal and Scope, Life-Cycle Inventory (LCI), Life-Cycle Impact Assessment (LCIA), and Results and Interpretation. Since the goal of the study is to gain a better understanding of the environmental performance of BEVs in realistic use-cases the LCA input data, and main assumptions are chosen accordingly.

2.1. System boundaries

The system boundaries of this LCA study cover the whole life-cycle of the investigated BEVs including the expenses for the required energy, material, and auxiliaries (Fig. 1). The cradle-to-gate phase includes the complete supply and production chain of all used materials and auxiliaries as well as the corresponding process steps. The analysis considers the powertrain and battery specific materials, components, and assembly processes individually. It does not include the transportation of intermediate products for assembly in the production phase, nor general maintenance measures of vehicles and components. Due to the lack of reliable data on

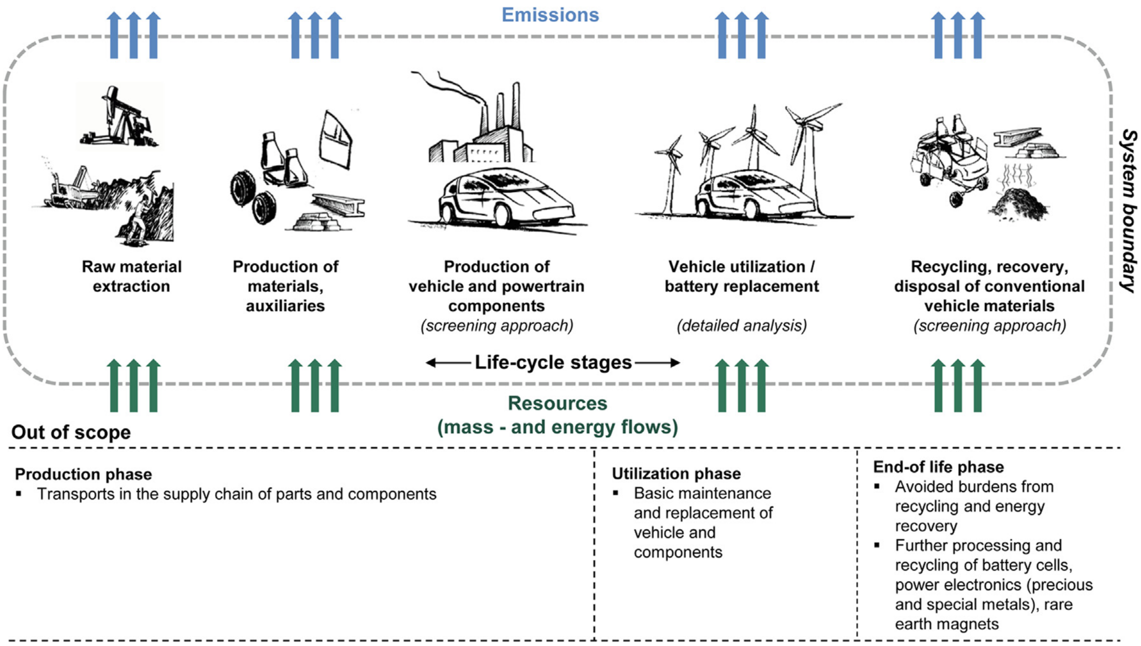

Fig. 1. System boundaries of the presented LCA approach.

the EoL treatment and recycling of Li-ion batteries, this phase is represented by the EoL treatment of conventional industrial materials such as steel and iron, lightweight and non-ferrous metals or plastics. For the modeling of the EoL phase, a cut-off approach is used. Hence, the reduced environmental impact of used secondary materials in vehicle production is accounted for in the production phase. These are mainly the common secondary materials shares represented in the production mixes of the used LCI dataset for steel, copper, and aluminum. The recycling of used precious and rare materials of BEVs at the EoL phase is a crucial aspect for the future security of resources. However, recycling scenarios on the battery cells and rare earth magnets of PMSM motors have not been accounted for in the analysis, mainly due to the lack of primary data on the processing and recovery rates of materials. Therefore, further processing and recycling are not covered in the scope of this analysis.

2.2. Simplified screening approach

Since no car manufacturer was directly involved in this study for exchanging specific inventory data on the vehicle and powertrain components in a consistent level of detail a simplified internal LCA screening model approach for estimating the environmental impacts from production and the EoL of the investigated vehicle types is used (Fig. 2).

The approach is based on a generic model, which was developed by Held (2014). The model allows the calculation of specific vehicle layouts, powertrain concepts, and technologies for the full life-cycle. It consists of generic and parameterized LCA modules, which are hierarchically structured into the main life-cycle phases, functional groups, and powertrain components. The parameterization allows a comprehensive adjustment of the vehicle specifications as well as for single components according to their technical properties (e.g., the cell chemistry, energy density, type, module, and system specifications, performance, and use parameters of the battery system). Also, it can be applied by making more profound adjustments of material mixes, main processing steps, and critical performance data. Hence, this approach is a flexible framework. Depending on the level of detail and quality of available input data the model allows for a detailed specification of process data, material mixes, and technologies, as well as a simplified LCA of vehicles using pre-configured modules. These are adjusted according to the main technical specifications of the vehicle and power train components (for example the total mass of battery system, used battery technology, cell types, chemistry of active materials, energy density and energy capacity of the battery systems).

In this paper, the model is applied in the latter version as a simplified screening approach by estimating the environmental burdens resulting from the production and EoL according to the main technical specifications of the BEV and ICEV models deployed in the use-cases. This approach is selected since the focus of the analysis lies on the influence of utilization and the lack of detailed LCI. Based on the available information, such as components, technologies, and performance data, the generic modules are scaled and adjusted by calculated parameters and scaling factors. Therefore, the results do not represent specific LCIA results of specific BEV or ICEV models but provide a robust estimate of the environmental performance of vehicles with comparable technical specifications and dimensions.

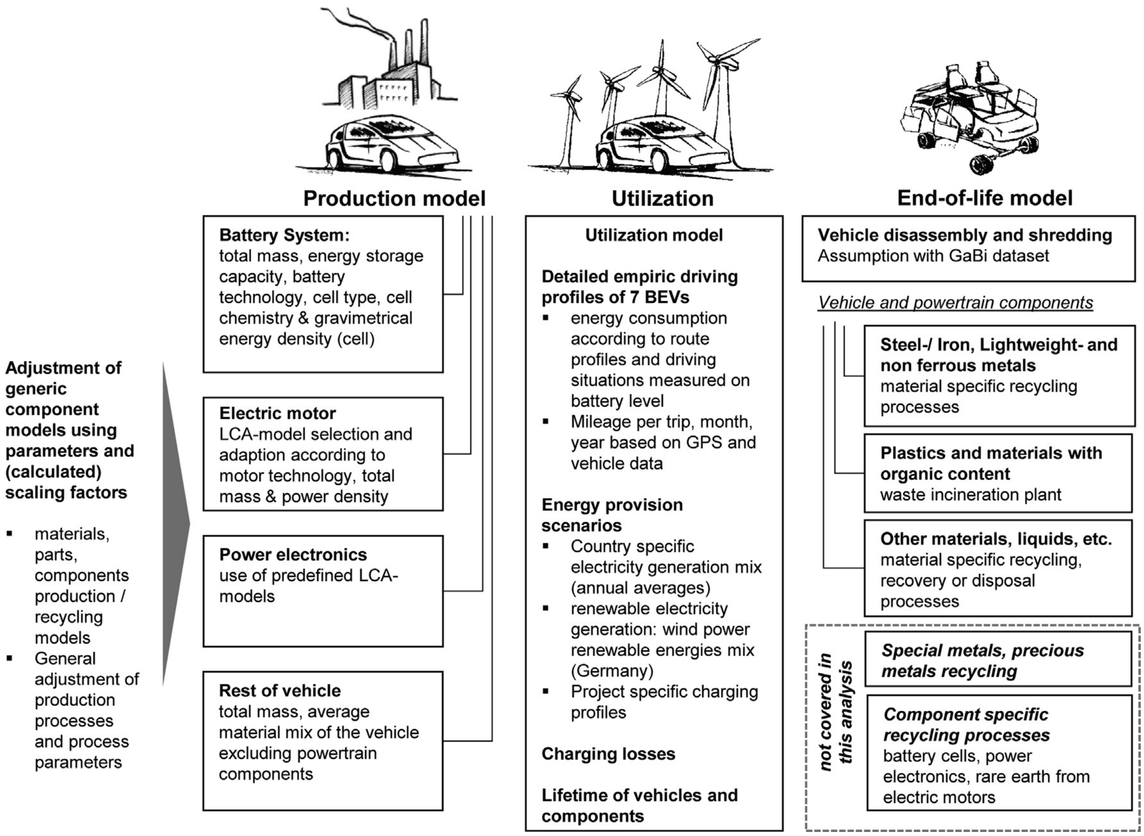

Fig. 2. Simplified screening model for estimating the cradle-to-gate and EoL phase of BEVs by using generic models and parameterization.

2.3. Functional unit

In line with previous research, the environmental profile per kilometer traveled over the full lifetime under the specific conditions of the investigated use-cases is taken as the functional unit to ensure the comparability of the results. Additionally, a comparative break-even analysis relative to the lifetime mileage is provided for the different powertrain technologies. It offers a good indication for the influence of the BEV's operating grade on its overall environmental performance.

2.4. Geographical scope

The vehicle production and EoL processing, the used energy provision, and materials are considered according to the German production and import mixes as represented in the used LCI database (GaBi Databases, SP36, 2018). For the Li-ion battery systems of the BEVs, this study assumes a mix of the specific energy mixes of Japan and Korea (Buchenau, 2018; The Economist, 2017). Since the use-cases of the study represent findings from a cross-border fleet project between France and Germany, the emission intensities of both electricity mixes, as well as a combination of them and other scenarios, are included.

2.5. Impact categories under consideration

The environmental assessment methodology in this study is based on CML2001 (Institute of Environmental Sciences (CML), 2001). The results of the following impact categories are presented in this paper:

- The Global Warming Potential (GWP) is selected as an indicator of the contribution to the greenhouse effect. There is a wide range of emissions that contribute to the GWP such as carbon dioxide (CO_2), methane (CH_4), and fluorine compounds. The reference unit is expressed in kg CO_2-eq.
- The Acidification Potential (AP) is taken as an indicator of damage on organic and inorganic materials due to an increase of acidifying chemicals which lead to an altering of the pH of the receiving medium. Relevant emissions contributing to this category are, amongst others, sulfur oxides (SO_x), nitrogen oxides (NO_x), hydrochloric acid (HCl), and ammonia (NH_3). The reference unit is expressed in kg SO_2-eq.
- The Eutrophication Potential (EP) is included as an indicator for the addition of nutrients that cause excessive biomass growth,

decay in water or soil which lead to oxygen depletion. Relevant emission of this category are compounds of nitrogen or phosphorous. The reference unit is expressed in kg phosphate-eq.

Additionally, the primary energy demand from non-renewable resources (PED) is assessed to represent the use of natural resources within the full life-cycle.

This paper focusses on these impact categories for several reasons: The applied simplified screening approach allows calculating resilient LCIA results for the stable impact categories such as AP, EP, GWP, POCP, and PED. These categories also cover the most relevant emissions of energy conversion processes, raw material extraction, and processing as well as from the use of ICEVs (e.g., exhaust emission profiles) and BEVs (electricity generation). Furthermore, these parameters are the most common and their plausibility can be compared with the published LCIA results from other studies or car manufacturers.

Despite these arguments, the results of the ozone creation potential (POCP, also known as summer smog), are not presented in this paper. The CML2001 method provides a negative characterization factor for nitrogen monoxide (NO). In this, it differs with other impact methods, such as ReCiPe. In the case of the driving emissions of the gasoline and diesel vehicles, this leads to negative POCP resulting from utilization. Although the negative characterization factor of NO can be comprehensively explained, the LCIA results of the POCP might allow misleading conclusions. For this reason, decisions based on these results should be critically questioned and are not further evaluated in this analysis.

Furthermore, the results of other essential impact categories, e.g., toxicity or abiotic resource depletion (ADP), are also excluded from this paper. The first reason is the lower stability of the underlying characterization methods. The second reason is that the simplified screening model is not applicable to generate reliable results in impact categories where a higher precision level of inventory data for specific inventory flows is required, e.g., in case toxicity or ADP. A reliable assessment requires a consistent quality of used inventory data for all vehicle components in terms of foreground and background data covering all used materials and substance contents in the final products as well as the production processes. Since, even little deviances of substances and elementary flows can have a significant influence on the results and can lead to highly biased results, e.g., precious metals use in power electronic components. With the chosen approach for scaling the power train components based on our generic screening model, these impact categories cannot be assessed in acceptable quality.

2.6. Data sources and main assumptions

The LCA conducted in this study uses the empirical input data from two use-cases: The commuting of shift workers in car-pool groups and the business trips of employees between two production sites located in France and Germany. These were selected since they both operated on fixed routes, which facilitate a simple technical substitution of ICEVs by BEVs. The departure predictability distinguishes both use-cases. On the one hand, based on the rolling shift schedule the mobility demand of the commuters was thoroughly predictable. On the other hand, business trips could occur at any time during the day, which sets a higher demand for the required charging power. Due to the different sized user groups, two different vehicle types were deployed. The shift workers in their larger groups had minivans, e-Wolf Delta 2. For the business trips one compact car, Nissan Leaf, was deployed. Also, the lifetime mileages for the two use-cases differ. The commuter vehicles with daily distances of 160 km reached annual mileages of around 36,000 km. The less frequent use of the business trip vehicle led to around half the annual mileage. A more detailed description of the two use-cases and the charging strategies that were implemented to increase the operation grade are presented in Schücking et al. (2017). Table 1 and Table 2 give an overview of the experimental boundary conditions and main assumptions.

Predicting the aging of Li-Ion battery cells is highly complex. In general, cyclical aging and calendar aging depending can be distinguished (Schoch et al., 2018). Detailed overviews of the underlying electrochemical processes, their dependencies on influence factors such as charging power, depth of discharge, temperature, and SOC, as well as different empirical long-term measurements and modeling approaches, can be found in the literature (Barré et al., 2013; Pelletier et al., 2017; Smith et al., 2012; Vetter et al., 2005). During the project, the battery aging indicators, such as capacity and internal resistance, were exemplary measured, but no detailed prediction model was developed. Therefore, this paper takes a practical approach by making the simplifying worst-case assumption, that at the end of the guaranteed battery life at 200,000 km the battery needs to be replaced.

For the two use-cases, the empiric energy consumption data used in this study was recorded during a long-term research project. The sensitivity of the LCA results to the BEV energy consumption made a detailed analysis indispensable. A detailed description of the empirical data, as well as a corresponding theoretical energy consumption model for the two BEV types, can be found in Schücking et al. (2016). Both vehicle types were equipped with data loggers recording the battery, powertrain, and GPS data. For the minivans, the battery and powertrain data were retrieved from the CAN bus system which amongst others provided access to the battery management system (BMS). The recorded battery and powertrain data is used to calculate the tank-to-wheel energy consumption of the deployed BEVs. The energy consumption measured this way includes propulsion, the energy gained through regenerative braking, and the energy consumed by the auxiliaries. The compact car was equipped with a Bluetooth data logger connected to the OBD interface providing full battery and powertrain data to assess the energy consumption and the quality of the online available energy consumption values for the individual trips provided by the manufacturer. Over the analyzed period of 2.5 years, data from over 450,000 km was logged in total.

The emissions resulting from the energy carrier are based on two different databases. The calculation of the ICEV tailpipe emissions is based on the HBEFA v3.2 which provides a comprehensive estimate of exhaust gas emissions, related to the specific drive situations (iNFRAS, 2014). The environmental profiles of the evaluated electricity mixes are based on SP36 (the reference year 2014) (GaBi Databases, SP36, 2018). Table 3 lists the respective values for France, Germany, the 50/50 mix, the renewable energy mix in

Table 1
Empirical boundary conditions and main assumptions for the minivans used for commuting.

	BEV	ICEV, gasoline	ICEV, diesel	Comment
Production phase				
Vehicle mass [kg]	1,700	1,400	1,550	
Battery system: Technology/Storage capacity [kWh]/Total mass [kg]	Li-Ion (NMC/C)/24.2 kWh/250 kg			
Power electronics (inverters, etc.) mass [kg]	35			
Engine performance [kW]	60	81	81	
Engine displacement, combustion engine [l]	–	1.6	1.5	
Utilization				
Vehicle lifetime [a]	12			
Battery life for replacement scenario [change interval after km traveled]	200,000	–	–	
Average trip distance [km/trip]	~73			
Average monthly mileage [km/month]	~3,000			
Assumed total mileage of base scenario [km/lifetime]	400,000			
Average speed [km/h]	57			
Average energy consumption [kWh/100 km]	23.8	–	–	The measured average value in fleet operation
Energy consumption stated by the manufacturer (NEDC) [kWh/100 km]	20.0	–	–	Datasheet manufacturer
Additional energy demand due to charging losses	15%	–	–	Measured in fleet operation
Fuel consumption of ICEV [l/100 km]	–	8.13*	5.5**	*Measured value in the field test **Assumption, 12% higher than NEDC value (based on the measured deviation of gasoline vehicle)
Calculation of tailpipe emission profile based on HBEFA 3.2 (iNFRAS, 2014), EURO 6 standard (vehicles with cylinder capacity from 1,4–2,1 l), calculation of CO_2 and SO_2 (fuel: 10 ppm sulfur content) emissions based on fuel consumption values				
End of Life				
Calculation according to a cut-off approach based on the World Steel Association (2011).				

Table 2
Empirical boundary conditions and the main assumptions for the compact car used for business trips.

	BEV	ICEV, gasoline	ICEV, diesel	Comment
Production phase				
Vehicle mass [kg]	1,550	1,200	1,300	
Battery system: Technology/Storage capacity [kWh]/Total mass [kg]	Li-Ion (NMO-NCA Blend/C)/24 kWh/250 kg			
Power electronics (inverters, etc.) mass [kg]	35			
Engine performance [kW]	80	81	81	
Engine displacement, combustion engine[l]	–	1.0	1.6	
Utilization				
Vehicle lifetime [a]	12			
Battery life for replacement scenario [change interval after km traveled]	200,000	–	–	
Average trip distance [km/trip]	~70			
Average monthly mileage [km/month]	~1,230			
Assumed total mileage of base scenario [km/lifetime]	200,000			
Average speed [km/h]	74			
Average energy consumption [kWh/100 km]	19.0	–	–	The measured average value in fleet operation
Energy consumption stated by the manufacturer (NEDC) [kWh/100 km]	17.3	–	–	Datasheet manufacturer
Additional energy demand due to charging losses	15%	–	–	Measured in fleet operation
Fuel consumption of ICEV [l/100 km]	–	5.5**	4.37**	**Assumption, 12% higher than NEDC value (based on the measured deviation of gasoline vehicle)
Calculation of tailpipe emission profile based on HBEFA 3.2 (iNFRAS, 2014)], EURO 6 standard (vehicles with cylinder capacity < 1,4 l (gasoline); vehicles with cylinder capacity from 1,4–2,1 (diesel)), calculation of CO_2 and SO_2 (fuel: 10 ppm sulfur content) emissions based on fuel consumption values				
End of Life				
Calculation according to cut-off approach according to the World Steel Association (2011).				

Table 3
Environmental profiles of the electricity mixes (per kWh electricity generation).

Impact category	Acidification potential (AP) [kg SO_2-eq./kWh]	Eutrophication potential (EP) [kg PO_4^{3-}-eq./kWh]	Global warming potential (GWP) [kg CO_2-eq./kWh]	Primary energy demand (PED) [MJ/kWh]
Electricity mix France	1.84E−04	2.41E−05	5.57E−02	9.01E+00
Electricity mix Germany	8.99E−04	1.46E−04	5.91E−01	7.63E+00
Electricity mix 50/50	5.41E−04	8.52E−05	3.23E−01	832E+00
Renewable energy mix Germany	9.06E−04	1.83E−04	7.85E−02	5.31E−01
Electricity from wind power	3.76E−05	3.94E−06	1.23E−02	1.59E−01

Germany, and for electricity from wind power.

3. Results

This chapter presents the results in three parts. First, a short assessment of the empiric energy consumption is provided. Second, the results of the LCIA are shown for the three environmental impact categories and PED over the lifetime in total and respective to the functional unit. Third, the break-even points for the GWP and AP depending on the lifetime mileage and the used electricity mix for charging are calculated.

3.1. Energy consumption

The assessment of the energy consumption indicates key influence factors and the uncertainty in the actual energy consumption. A detailed description of the energy model, the empirical data, and the influence factors can be found in Schücking et al. (2016). As can be seen in Table 4 the average specific energy consumption varies between the vehicles deployed. Since the e-Wolf Delta 2 is a minivan vehicle and the Nissan Leaf a compact car, this result is not surprising. The second characteristic is the variance of the specific energy consumption between the commuting routes (CO.1-CO.6). The different profiles can mainly explain the variance. For example, route CO.4 with a large motorway share has the highest average speed of 60 km/h, which leads to the comparably higher energy consumption required to overcome the drag.

The six commuter vehicles with their large number of individual trips allow a more detailed analysis. In total, 5,404 single long trips over 60 km were recorded. The frequency distribution is close to a normal distribution (Fig. 3). The minimum value for the specific energy consumption is 151 Wh/km and the maximum 367 Wh/km. The mean and the median are both 238 Wh/km. Hence, 238 Wh/km is taken as the average input value for the LCI. Additionally, the 5% and the 95%-quantile are added as upper and lower boundaries for the following LCIA (Fig. 4) to illustrate the influence of the specific energy consumption on the different impact categories. For the commuting use-case, 186 Wh/km is the 5% and 287 Wh/km the 95% quantile.

For the business trips, the average value of 183 Wh/km is taken as input with the 140 Wh/km as the 5% and 250 Wh/km as the 95% quantile.

The input values for both vehicle types and use-cases are significantly higher than the NEDC value stated by the manufacturer underlining the importance of a realistic energy consumption assessment.

3.2. Life-cycle impact assessment

The following section presents the LCIA results of the two use-cases. For the investigated impact categories, the relevant parameters and influencing factors are identified and discussed for the individual life-cycle phases and in relation to the full life-cycle. A detailed analysis is set on the utilization phase and its parameters.

3.2.1. LCIA for both use-cases

The results of the BEVs and the gasoline and diesel ICEV alternatives vary significantly between the impact categories depending

Table 4
Overview of route characteristics and specific energy consumption values.

Route		CO.1	CO.2	CO.3	CO.4	CO.5	CO.6	BT.1
Vehicle type		Minivan	Minivan	Minivan	Minivan	Minivan	Minivan	Compact
Distance	[km]	80	76	76	62	75	70	70
Max. elevation difference	[m]	110	112	361	38	158	135	66
Average speed	[km/h]	55	58	56	60	55	58	74
Specific energy consumption(lowest month)	[Wh/km]	235	227	227	230	224	209	152
Specific energy consumption(highest month)	[Wh/km]	258	248	260	271	241	255	214
Specific energy consumption(2-year average)	[Wh/km]	243	236	240	251	230	233	183

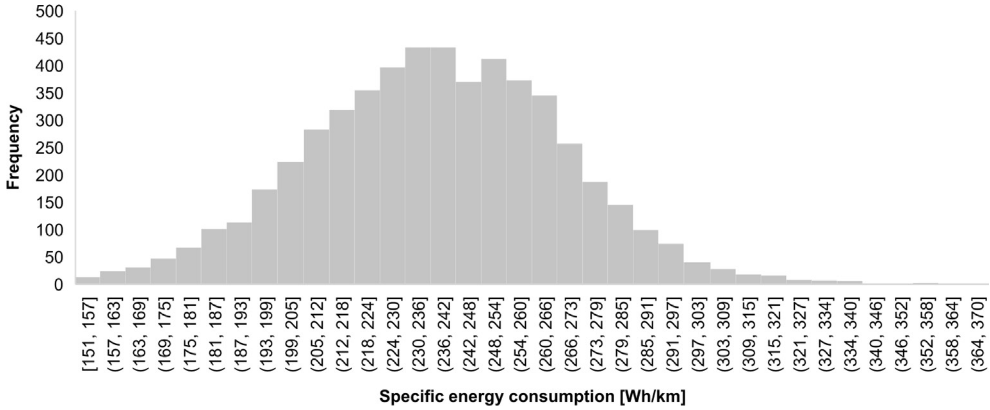

Fig. 3. Frequency distribution of all specific energy consumption values measured for the commuter vehicles.

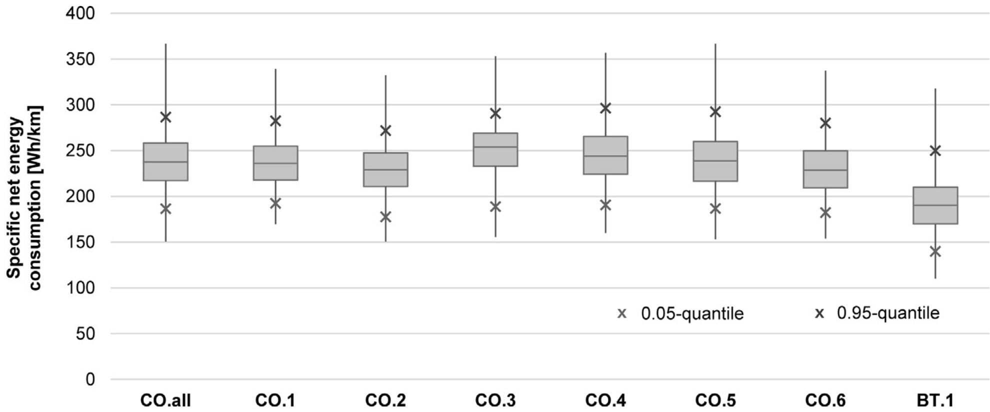

Fig. 4. Specific net energy consumption values minivans and compact car.

on the vehicle segment and the energy used for charging. The impacts of the individual life-cycle phases are separated to allow conclusions about their relevance to the full life-cycle (Figs. 5 and 6). The manufacturing steps of the BEVs are broken down further to assess the effect of the single components. The comparison of the 50/50 cross-border electricity mix, that was charged by the BEVs, and the German energy mix from RESs as an alternative scenario illustrate the influence of the electricity used for charging. Additionally, the lower and upper boundary values show the bandwidths of the utilization phase impacts related to the measured energy consumption of the vehicles. Tables 5 and 6 provide detailed environmental impacts based on the functional unit.

In the cradle-to-gate phase, both BEV types show notably higher impacts of the BEV in comparison to the ICEVs (Figs. 5 and 6). The battery system production as well as the extraction and processing of the required active material for the battery cells, in this case, graphite (anode) and Li-NMC (cathode), cause these higher impacts. These high-tech materials represent a significant share in the material mix of the battery system and have notably higher environmental impacts in the extraction and processing than conventional materials used in the vehicle production, such as iron-steel, non-ferrous and lightweight metals as well as polymers. The impact is most notable on the AP from cradle-to-gate.

Depending on the underlying electricity mix in the BEV utilization phase, a share of the relatively higher GWP from production can be compensated. Again, both car types show similar tendencies. Concerning the GWP the main influence factors are the specific energy consumption, the mileage, the environmental profile of the electricity mix used for charging, and the necessity of a battery system replacement (Table 5). The high mileage of the minivans can lead to significant GWP improvements compared to minivans with combustion engines. In the set boundary conditions, the GWP for the minivans can be reduced by ~20 t CO_2-eq. (diesel vehicle) and ~46 t CO_2-eq. (gasoline vehicle). In the RESs scenario, improvements from ~47 t CO_2-eq. (diesel vehicle) to ~73 t CO_2-eq. (gasoline vehicle) are possible. For the compact car, the lower lifetime mileage, as well as the comparably lower fuel consumption values for the investigated ICEVs, lead to smaller total GWP savings (Fig. 6). The lowest comparable savings under the set circumstances are ~8 t CO_2-eq. compared to a diesel vehicle. Under the RESs scenario the highest comparable benefit of ~23 t CO_2-eq. can be achieved in comparison to a gasoline vehicle. These results underline the high reduction potential of BEV deployment on the lifetime GWP when using electricity from renewable energy sources.

Based on the boundary conditions of the use-cases and selected energy mixes the high AP of the BEV production phase cannot be compensated relative to the ICEVs during the vehicle operation (Figs. 5 and 6). Over the ICEV life-cycle, the contributions to the AP of the gasoline and diesel production are mainly caused by the released SO_2, NO_x and NH_3 emissions during the production process

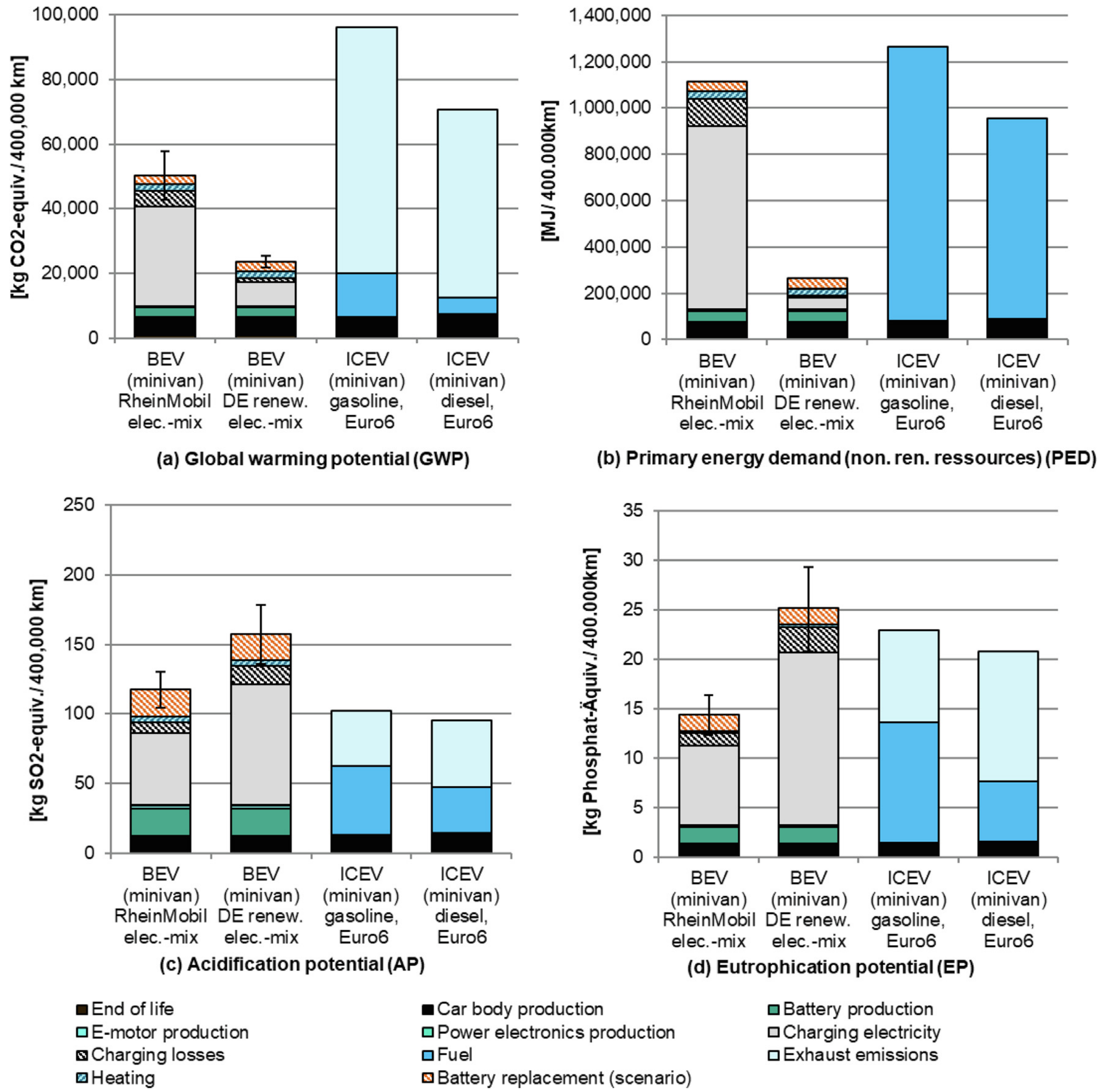

Fig. 5. LCIA results of BEV and ICEV minivan operation in commuter traffic.

chains. For the car operation, main exhaust gas emissions are NH_3, NO and minor contributions of SO_2.

The EP of the utilization phase highly depends on the electricity and fuel mix used. The BEVs charged with the 50/50 electricity mix have the lowest EP impact. It lies below the level of the compared ICEVs. In the RESs scenario, the BEV's EP values are about the same as the ones for the gasoline vehicle (Figs. 5 and 6). The higher EP values are a consequence of the biogas and biomass shares in the German RESs mix and their respective impacts from the cultivation. In the investigated use-cases, the contributions of the fuel production routes and exhaust emissions differ for the diesel and gasoline vehicle. The production route of the gasoline shows a higher contribution than diesel. The high EP of gasoline production results from the biofuel content in the fuel production mix and related nitrogen and nitrate emissions into the water during the cultivation of energy crops. The effects of the cultivation on EP caused by agricultural processes such as fertilizing are significantly higher than those from the production of crude oil-based fuels. Therefore, biofuels in the diesel mix also increase the EP. Furthermore, diesel shows higher impacts based on exhaust emissions, mainly caused by higher NO_x emissions.

Regarding the EoL phase of the vehicles, the calculation of the impacts is done with the cut-off approach. Hence, no credits are given for the recycling of materials or energy recovery from waste incineration. This approach is chosen due to the lack of reliable process data for Li-Ion battery recycling. Under these conditions, notable contributions of the vehicle's EoL phase are mainly in terms of GWP which can be attributed to the electricity required for dismantling, separation, and the vehicle shredder as well as to the emissions that occur during the thermal recycling of combustible materials (e.g., plastics).

In conclusion, due to the high lifetime mileage, in both use-cases, the higher impacts of vehicle production in GWP, EP, and PED

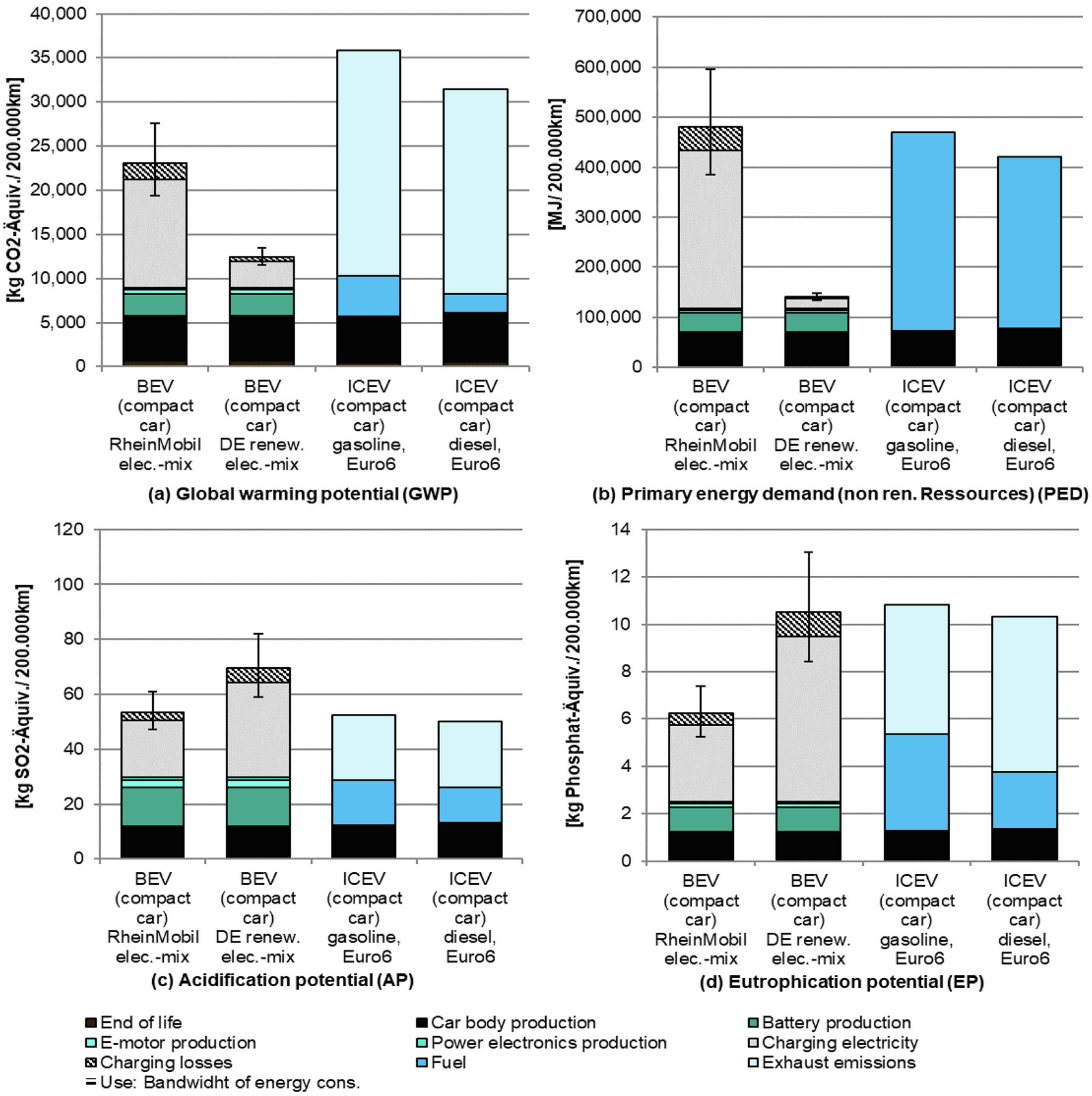

Fig. 6. LCIA results of BEV and ICEV compact car operation for business trips.

can be compensated for by the lower environmental impacts during utilization with the actual benefit depending highly on the electricity mix used of charging. Using electricity from RESs delivers additional benefits for all impact categories besides EP. Concerning the AP, in the investigated use-cases in both electricity mix scenarios, the 50/50 cross-border electricity mix and the German energy mix from RESs, the lifetime environmental impact of the BEV models is always higher than the one of the comparable ICEVs.

3.2.2. The influence of the use-case parameters mileage and electricity mix

In the following, the influences of the use-phase parameters mileage and electricity mix are investigated further to illustrate the required conditions for an environmentally beneficial deployment of BEVs. The GWP and the AP LCA results for the BEVs and ICEVs deployed in both use-cases under additional energy mix scenarios, the German electricity mix and electricity from wind power, are presented depending on the traveled mileage.

These two impact factors vary significantly in their results for the comparable environmental benefit to ICEV. The lines in Figs. 7–10 illustrate the impact during the utilization phase. The grey area represents the total mileage bandwidth for the different commuter routes. The mileage is extrapolated over the assumed lifetime of 12 years based on the monthly mileages recorded during the fleet test. For the two exemplary impact factors, the diagrams determine the mileage-dependent break-even points for the BEVs in comparison to the ICEVs. The initial offset represents the higher environmental impacts of BEV production compared to ICEV. Tables 7 and 8 list the results for all three impact factors and the PED.

Table 5
LCIA results of the investigated vehicles in the minivan commuter use-case.

Impact category Reference unit	Acidification potential (AP) [kg SO2-eq./km]	Eutrophication potential (EP) [kg phosphate-eq./km]	Global Warming Potential (GWP) [kg CO2-eq./km]	Primary energy demand (non-renewable) (PED) [MJPE/km]
Environmental profile of commuting shift workers				
Assumptions: No change of battery during use phase required; total mileage 400,000 km				
5%-quantile energy consumption value (0.186kWh/km)				
Electric minivan, RheinMobil electricity mix	2.13E − 04	2.68E − 05	9.94E − 02	2.18E + 00
Electric minivan, German (DE) renewable energy mix	2.91E − 04	4.78E − 05	4.70E − 02	5.14E − 01
Average energy consumption value (0.238kWh/km)				
Electric minivan, RheinMobil electricity mix	2.46E − 04	3.19E − 05	1.19E − 01	2.68E + 00
Electric minivan, German (DE) renewable energy mix	3.45E − 04	5.88E − 05	5.17E − 02	5.46E − 01
95%-quantile energy consumption value (0.287kWh/km)				
Electric minivan, RheinMobil electricity mix	2.76E − 04	3.67E − 05	1.37E − 01	3.15E + 00
Electric minivan, German (DE) renewable energy mix	3.97E − 04	6.91E − 05	5.61E − 02	5.76E − 01
Minivan, gasoline engine	2.56E − 04	5.73E − 05	2.41E − 01	3.17E + 00
Minivan, diesel engine	2.39E − 04	5.18E − 05	1.77E − 01	2.39E + 00
Environmental profile of commuting shift workers				
Assumptions: One battery change required during use phase; total mileage 400,000 km				
5%-quantile consumption value (0.186kWh/km)				
Electric minivan, RheinMobil electricity mix	2.62E − 04	3.09E − 05	1.07E − 01	2.29E + 00
Electric minivan, German (DE) renewable energy mix	3.40E − 04	5.19E − 05	5.44E − 02	6.26E − 01
Average energy consumption value (0.238kWh/km)				
Electric minivan, RheinMobil electricity mix	2.94E − 04	3.60E − 05	1.26E − 01	2.79E + 00
Electric minivan, RheinMobil electricity mix	3.94E − 04	6.28E − 05	5.90E − 02	6.58E − 01
95%-quantile energy consumption value (0.287kWh/km)				
Electric minivan, RheinMobil electricity mix	3.25E − 04	4.08E − 05	1.44E − 01	3.26E + 00
Electric minivan, German (DE) renewable energy mix	4.45E − 04	7.32E − 05	6.35E − 02	6.88E − 01

Table 6
LCIA results of the investigated compact car in the business trip use-case.

Impact category Reference unit	Acidification potential (AP) [kg SO2-eq./km]	Eutrophication potential (EP) [kg phosphate-eq./km]	Global Warming Potential (GWP) [kg CO2-eq./km]	Primary energy demand (non-renewable) (PED) [MJPE/km]
Environmental profile of business trips				
Assumptions: No change of battery during use phase required; total mileage 200,000 km				
5%-quantile energy consumption (0.14kWh/km)				
Electric compact car, RheinMobil electricity mix	2.36E − 04	2.62E − 05	9.69E − 02	1.92E + 00
Electric compact car, German (DE) renewable energy mix	2.95E − 04	4.20E − 05	5.74E − 02	6.71E − 01
Average energy consumption (0.19kWh/km)				
Electric minivan, RheinMobil electricity mix	2.67E − 04	3.11E − 05	1.15E − 01	2.40E + 00
Electric minivan, German (DE) renewable energy mix	3.47E − 04	5.26E − 05	6.19E − 02	7.01E − 01
95%-quantile energy consumption (0.25kWh/km)				
Electric compact car, RheinMobil electricity mix	3.05E − 04	3.70E − 05	1.38E − 01	2.98E + 00
Electric compact car, German (DE) renewable energy mix	4.10E − 04	6.52E − 05	6.73E − 02	7.38E − 01
Compact car, gasoline engine	2.62E − 04	5.41E − 05	1.79E − 01	2.35E + 00
Compact car, diesel engine	2.51E − 04	5.16E − 05	1.57E − 01	2.11E + 00

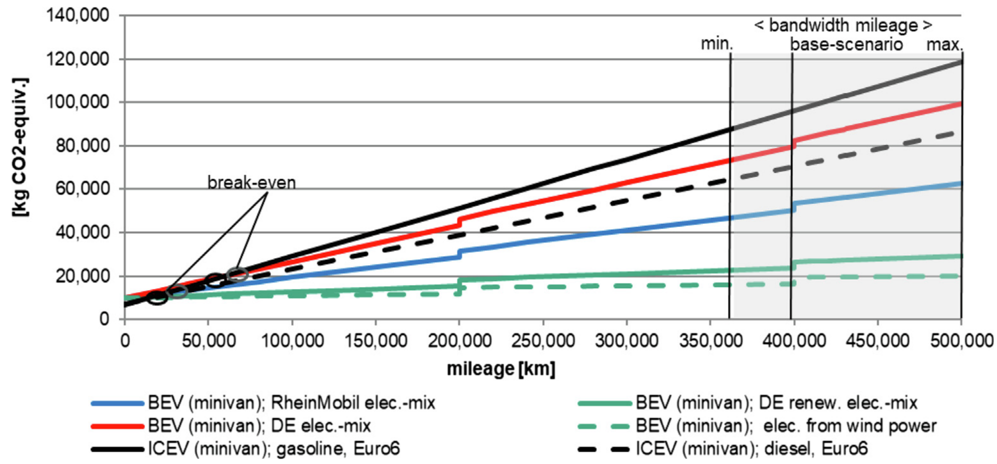

Fig. 7. GWP results of the BEV minivan based on the commuting use-case's boundary conditions.

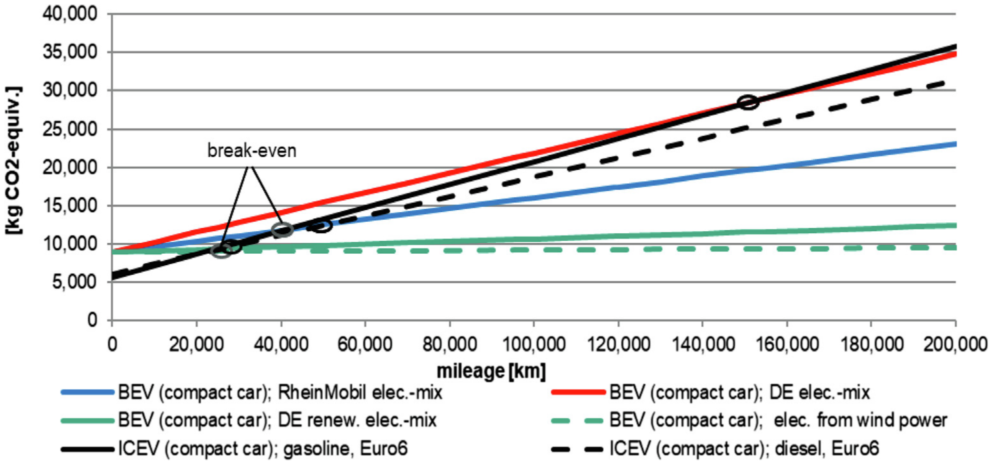

Fig. 8. GWP results of the BEV compact car based on the business trip use-case's boundary conditions.

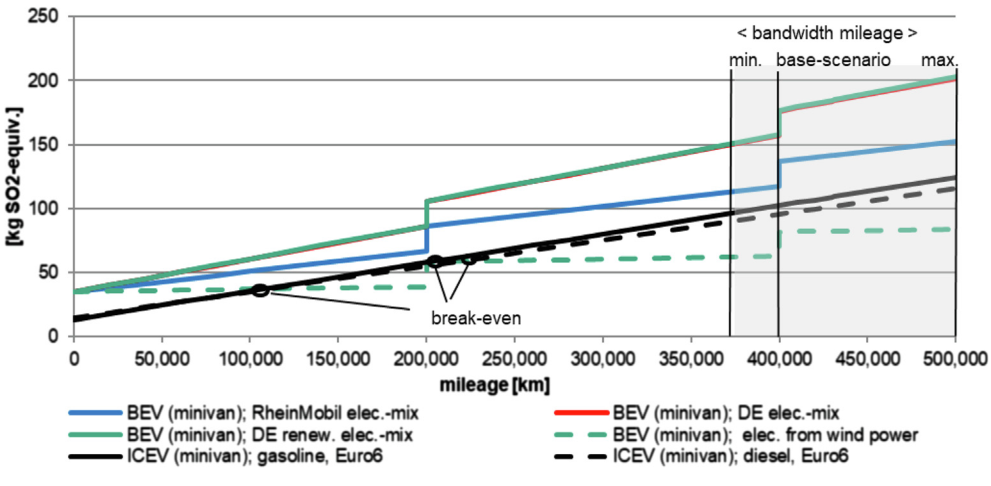

Fig. 9. AP results of the BEV minivan based on the commuting use-case's boundary conditions.

As indicated by the previous results the higher GWP impacts from production can be compensated during the utilization depending on the energy mix. Under the specific boundary conditions and use-cases, the GWP break-even points of the minivans in the commuter traffic use-case vary between 20,000 km (wind power) to 60,000 km (German electricity mix) in comparison to the

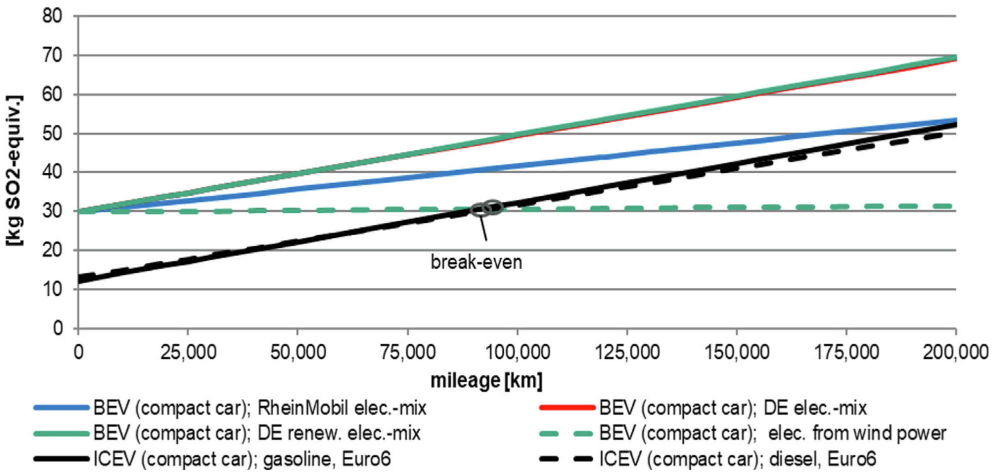

Fig. 10. AP results of the BEV compact car based on the business trip use-case's boundary conditions.

Table 7
Break-even points for the minivans deployed in the commuter use-case for different energy mixes.

	Acidification Potential (AP)	Eutrophication Potential (EP)	Global Warming Potential (GWP)	Primary energy demand (non-renewable) (PED)
Break-even points against gasoline vehicle (rounded to 5,000 km); *[including 1 battery replacement during utilization after 200,000 km]*				
Electricity mix 50/50	340,000 km	60,000 km	30,000 km	80,000 km
	[–]	*[60,000 km]*	*[30,000 km]*	*[80,000 km]*
German (DE) electricity mix	–	135,000 km	60,000 km	60,000 km
	[–]	*[260,000 km]*	*[60,000 km]*	*[60,000 km]*
German (DE) renewable energy mix	–	–	20,000 km	20,000 km
	[–]	[–]	*[20,000 km]*	*[20,000 km]*
Electricity from wind power	110,000 km	35,000 km	20,000 km	20,000 km
	[205,000 km]	*[35,000 km]*	*[20,000 km]*	*[20,000 km]*
Break-even points against diesel vehicle (rounded to 5,000 km); *[including 1 battery replacement during use phase]*				
Electricity mix 50/50	–	70,000 km	40,000 km	–
	[–]	*[70,000 km]*	*[40,000 km]*	*[–]*
German (DE) electricity mix	–	*225,000 km*	–	–
	[–]	*[–]*	*[–]*	*[–]*
German (DE) renewable energy mix	–	–	20,000 km	20,000 km
	[–]	*[–]*	*[20,000 km]*	*[20,000 km]*
Electricity from wind power	110,000 km	35,000 km	20,000 km	20,000 km
	[220,000 km]	*[35,000 km]*	*[20,000 km]*	*[20,000 km]*

Table 8
Break-even points for the compact car deployed in the business trips use-case for different energy mixes.

	Acidification Potential (AP)	Eutrophication Potential (EP)	Global Warming Potential (GWP)	Primary energy demand (non-renewable) (PED)
Break-even against gasoline vehicle (rounded to 5,000 km)				
Electricity mix 50/50	–	45,000 km	40,000 km	–
German (DE) electricity mix	–	80,000 km	150,000 km	140,000 km
German (DE) renewable energy mix	–	160,000 km	25,000 km	25,000 km
Electricity from wind power	90,000 km	30,000 km	25,000 km	25,000 km
Break-even against diesel vehicle (rounded to 5,000 km)				
Electricity mix 50/50	–	45,000 km	50,000 km	–
German (DE) electricity mix	–	90,000 km	–	–
German (DE) renewable energy mix	–	–	30,000 km	30,000 km
Electricity from wind power	95,000 km	25,000 km	25,000 km	25,000 km

gasoline ICEV (Table 7) and between 20,000 km (wind power) to no break-even (German electricity mix) in comparison to the diesel vehicle. The assumed battery replacement after 200,000 km causes the additional vertical increase. For the compact car used for business trips, the earliest break-even to comparable diesel or gasoline vehicles lies at 30,000 km (wind power). The influence of the German electricity mix is even stronger than in the case of the vans. The break-even point is at 150.000 km for the gasoline vehicle, and again no break-even is reached compared to the diesel vehicle. These results can be explained by the high GWP of the German electricity mix compared to the other investigated electricity mixes. Also, the compact ICEV deployed had shown low fuel consumption values leading to a gradient that is almost identical to the one of the BEV charged with the Germany electricity mix (Fig. 8).

As shown in Section 3.2.1 in the case of the AP the impact of the BEV production phase is notably higher than for comparable ICEV. The extended analysis shows that break-even for both vehicle types can only be reached under particular conditions (Figs. 9 and 10). For both use-cases and vehicle types, a break-even can only be reached over the lifetime (including a battery system change) if electricity from wind power is used exclusively (Tables 7 and 8). Even under these favorable conditions, the break-evens lie between 90,000 and 110,000 km, and the potential environmental benefits remain small. The potential battery replacement during utilization leads to another significant AP increase pushing the break-even points even further (Fig. 9).

4. Discussion

The results of this study demonstrate that a case-specific LCA can deliver valuable insights for the environmentally beneficial introduction and operation of BEVs. It provides examples of how the comparably higher environmental impact from BEV production can be compensated during utilization. Especially in countries with a low carbon electricity mix, the substitution of ICEVs with BEVs can lead to notable GWP benefits. For the AP and the EP, a break-even can only be reached under specific favorable conditions. The micro perspective approach of this study does not allow predicting the effects of a more widespread introduction BEVs. However, it enables the deduction of general conditions for an environmentally beneficial deployment of BEVs in comparison to ICEVs.

The comparison of the empirical charging data of the BEVs in France and Germany emphasizes the influence of different energy markets. However, not only the region but also the season or time of day can influence environmental performance during utilization. Especially in electricity markets with a high share of RESs, the emission intensity can vary significantly over time (Donateo et al., 2015; Jochem et al., 2015; Rangaraju et al., 2015; Robinson et al., 2013). These fluctuations offer the chance to reduce the environmental impact by postponing the charging processes into periods with lower emission intensity (Jochem et al., 2015; Rangaraju et al., 2015). This deliberate load shifting provides an additional argument for a detailed utilization assessment. However, when shifting the load, it is essential to base the decision on the emission intensity and not just overall demand (Helms et al., 2011). These renewable energies must be provided from additional installed power plants, to avoid a simple shift of burden in the electricity grid mix.

For the local impact factors such as AP and EP, another potential benefit arises from the introduction of BEV. The emissions during utilization shift from the exhaust of the vehicles to power plants that are usually outside of cities (Helmers and Weiss, 2017). Furthermore, the aggregate emission from fewer point sources allows concentrated control and reduction measures such as the installation of SCR (Hawkins et al., 2013a; Ke et al., 2017).

Even though the use-cases demonstrate the positive effect of a high lifetime mileage as an external parameter that can increase the comparable environmental benefits of BEVs it has received little attention in the literature so far. Some studies point out the sensitivities and individual variability of the emissions and LCA results to changes in the battery lifetime and lifetime mileage (Bickert et al., 2015; Cox et al., 2018; Egede et al., 2015). The specific mileage-dependent break-even points for different electricity mixes and ICEV fuel types identified in this study emphasize the importance of a high battery lifetime and lifetime mileage for an overall environmentally beneficial introduction and operation of BEVs.

All three life-cycle phases show high potential for technological progress in reducing the environmental impact of BEVs. The realization of this potential is expected to decrease the environmental impacts of BEVs much faster than the ones from ICEV (Cox et al., 2018; Helmers and Weiss, 2017). The progress can lower the break-even points by decreasing the offset from cradle-to-gate and EoL as well as by reducing the gradient of the BEV impact line.

The results from the presented use-cases allow the deduction of three characteristics for the identification of mobility applications in which the replacement of ICEVs with BEVs can potentially be environmentally beneficial: Firstly, regular and predictable mobility patterns allow potential tailoring of the battery to avoid an additional offset from production. Secondly, a high operating grade and therefore high mileage allows benefitting from the lower impacts during utilization. Thirdly, energy from additional installed RESs, ideally wind power, should be available to avoid a shift of burdens.

The concept of tailoring the battery capacity to the utilization requirements and compensating the initial offset with a high operating grade also fits the criteria for commercial deployment of BEVs. The lower operational cost can compensate for the higher initial investment in comparison to ICEVs. Utilizing this cost-saving potential requires a high annual mileage (Gnann et al., 2015; Schücking et al., 2017). Therefore, economic and environmental benefits align since achieving a high operating grade becomes a core aim of BEV deployment. The same alignment can also be observed for a potential battery replacement. From an economic as well as an environmental point of view a subsequent high mileage after the replacement is required to make it beneficial.

At the current state of technology and market stage, commercial mobility applications are more likely to meet the identified characteristics than private mobility demand. Techno- and socio-economic research has identified several characteristics that make commercial transport applications more advantageous for an early BEV adoption than private mobility demand (Barfod et al., 2016; Gnann et al., 2015; Ketelaer et al., 2014; Plötz et al., 2014; Robinson et al., 2013). Some of them are directly related to the identified characteristics for an environmentally beneficial deployment. The mobility patterns are usually more regular and therefore enable an easier substitution assessment and better utilization of the required battery capacity. In mixed fleets trips over the maximum BEV range can be substituted by an ICEV. Commercial vehicles have higher annual mileages than private ones enabling the commercial and environmental break-even. Moreover, commercial vehicles have a much faster turnover rate than private vehicles making it a promising introductory market with 65% of total first-time registrations in Germany (KBA, 2017a). Of the 34.022 registered BEVs in Germany in 2016, over 85% were registered commercially (KBA, 2017b). In 2020 for 3–5% of all newly registered commercial vehicles BEVs can be operated more economically than ICEVs (Plötz et al., 2014). Specific mobility applications identified by bottom-up analyzes that promise early widespread introduction of BEV are social, security, delivery, and postal services (Hacker et al., 2015; Ketelaer et al., 2014; Wagner et al., 2011).

5. Conclusion

The study at hand compares the environmental impacts of BEVs and ICEVs based on an LCA with emphasis on the utilization phase. The observed energy consumption values from two commercial use-cases that are characterized by a high operating grade and regular mobility patterns are used as a core part of the LCI. The environmental impact is assessed based on a simplified screening model, and comparable break-even points are calculated for the three impact categories GWP, AP, EP as well as PED which are all highly sensitive to the conditions of the utilization phase.

The results demonstrate the importance of a case-specific analysis and confirm that the substitution of ICEVs through BEVs in commercial applications can lead to environmental benefits, e.g., for the GWP, EP, and PED. For the AP, improvements in comparison to ICEVs can only be achieved under specific favorable conditions. BEVs show higher environmental impacts in the production phase than ICEVs which is mainly due to the battery materials and production. Currently, these higher impacts can only be compensated by a lower impact per driven mile during utilization. Therefore, a battery capacity tailored to the mobility demand to avoid unnecessary offset from production, the environmental profile of the used electricity mix for charging, as well as the capacity utilization of vehicles, is of vital importance for an environmentally beneficial deployment of BEVs. Operating BEVs under these conditions can also lead to an economically competitive BEV deployment.

Due to several limitations, generalizing the results and conclusions into a broader context must be done cautiously. The cross-border commuting and business trips, as well as the deployed BEV technologies, represent a unique combination. For future research, various use-case profiles could be compared to allow for broader conclusions. Furthermore, over time the variety of vehicle models grows continuously, the battery materials, production processes and durability changes, the energy efficiency of the powertrains increases, and more detailed information about the recycling phase becomes available. Therefore, future research should expand the models by including the newest technical developments and empirical data, to ensure that the introduction of BEVs into the transport sector leads to long-term environmental benefits. Since the recommendations for an environmentally and economically beneficial deployment are similar in several regards future research could develop a joint optimization model for the design of the vehicle and charging infrastructure.

Acknowledgments

The authors thank the German Federal Ministry of Transport and Digital Infrastructure for supporting the research by funding the RheinMobil project [ref. no: 16SBW007A] as part of the Federal Government's Schaufenster initiative. They also thank their industrial and research partners of the RheinMobil project consortium, who contributed support, time, and funding to make the project possible.

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Part C - Appendix

Contents

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C 1. Data

In this section, the additional data, which was used in the research papers of Part B is presented in detail. The data sources are distinguished into three categories: data recorded from the BEVs, mobility data from other sources, and weather data. For the different data, the source, approach, and frequency of recording, as well as the logged parameters are described. Additional information concerning the measurement precision and errors, as well as data preparations, can be found in the stated references.

C 1.1 Data electric vehicles

For the detailed techno-economic analysis and optimization detailed empirical input data from BEVs in operation was required. Notably, the calibration and validation of the technical models of energy consumption and vehicle charging required empirical data. Additionally, the mobility data of applications with a high degree of utilization was needed to assess the economic potential. Hence, detailed technical and movement data of two BEV types the e-Wolf Delta 2 and the Nissan Leaf, deployed in the RheinMobil research project was recorded. Moreover, the charging curves of other BEV types were logged to compare them and to put the theoretical model on a more resilient basis.

C 1.1.1 Data e-Wolf Delta 2 (EVO)

The vehicle and movement data of the e-Wolf Delta 2 and Delta 2 (EVO) vehicles was recorded in two different ways: directly from the onboard data logger and indirectly via the motion and GPS sensors of a smartphone. The long-term data originates from the onboard data logger with a maximum logging frequency of 0.05 Hz. To assess the accuracy and to scrutinize the effect on the models a smartphone was installed in each vehicle logging the movement data with a frequency of 10 Hz for one week (Stella et al., 2015). This valuation was especially crucial since the recorded vehicle and movement data was the core input for assessing the empirical energy consumption, calibrating the theoretical energy consumption model, and charging curves, as well as measuring the range of efficiency on the dynamometer. The data recorded from the e-Wolf Delta 2 (EVO) vehicles is directly used in the following research papers:

- Schücking et al. (2016)
- Schücking et al. (2017)
- Ensslen et al. (2017)
- Held & Schücking (2019)

In the following, the logging devices, as well as the recorded data, will be explained in more detail.

C 1.1.1.1 Data e-Wolf Delta 2 & Delta 2 (EVO) recorded with an onboard data logger

The vehicle and GPS data of the EV models e-Wolf Delta 2 and Delta 2 EVO was recorded with the onboard data logger VikMote VX20 STD+ Remote Telemetry and Control Unit connected to the CAN-bus of the vehicle. Technical details of the device can be found in the datasheet (Østergaard, 2011). Within the RheinMobil project, each of the six vehicles was deployed for 36 months. During that time the recorded data was sent in fixed intervals via UMTS to an online server. Due to technical difficulties with the BEVs that occurred during the time of deployment the data sets for the vehicles differ in their extent. The data logging frequency changed between the first and the EVO generation. The amount of data collected for each vehicle and the logging frequencies in the different driving states can be found in Table C10. Table C and Table C provide an overview of the logged vehicle and GPS parameters.

Table C10: Overview data logged from the e-Wolf Delta 2 vehicles during the RheinMobil Project

Vehicle	Duration of data recording	Number of data points	Logged distance [km]	Logging frequency while driving [s]	Logging frequency while charging [s]	Logging frequency while plugged in [s]
e-Wolf Delta 2_1	36 Months	390,729	87,452	20	300	-
e-Wolf Delta 2_2	36 Months	277,686	68,638	20	300	-
e-Wolf Delta 2_3	36 Months	352,005	76,947	20	300	-
e-Wolf Delta 2_1_E	36 Months	799,968	65,781	60	60	60
e-Wolf Delta 2_2_E	36 Months	1,219,173	93,983	60	60	60
e-Wolf Delta 2_3_E	36 Months	1,358,466	99,852	60	60	60

Table C2: Overview of the different vehicle parameters recorded with the VikMote VX20 STD+

No.	Category	Parameter	Format	Unit
1		Date & time	YYYY/MM/DD hh:mm:ss	
2	Low voltage system data	KL30	##.###	[V]
3		KL15	##.###	[V]
4	High voltage system data	Battery voltage	###.#	[V]
5		Mean cell voltage	#.###	[V]
6		Battery current	##.##	[A]
7		Cell temperature	##.#	[°C]
8		State of Charge (SOC)	###.#	
9	Distance data	Remaining range	###.#	[km]
10		Speed (odometer)	##	[km/h]
11		Drive mode	NEUTRAL/DRIVE, ECO	
12		Total distance	#,###	[km]

Table C3: Overview of the different GPS parameters recorded with the VikMote VX20 STD+

No.	Parameter	Format	Unit
1	Date & time	YYYY/MM/DD hh:mm:ss	
2	Start	YYYY/MM/DD hh:mm:ss	
3	Stop	YYYY/MM/DD hh:mm:ss	
4	Latitude	##° ##‘ ##.###“	
5	Longitude	##° ##‘ ##.###“	
6	Course	North, NorthWest, West, SouthWest, South, SouthEast, East, NorthEast	
7	Speed (GPS)	##.##	[km/h]
8	Total distance (GPS)	####.##	[km]
9	Satellite	# / #	[km]

C 1.1.1.2 Data e-Wolf Delta 2 & Delta 2 (EVO) recorded with a smartphone

In addition to the onboard data logger, an iPhone 3 smartphone was installed to record the vehicles' movement data. The vehicle movement data was recorded based on the input of the smartphone’s motion and GPS sensors with a specifically developed application by the Fraunhofer Project Group New Drive Systems (NAS). The application allowed a significantly higher logging frequency in comparison to the onboard data logger. The data was logged with 10 Hz. For one week, ten trips were recorded as basis to validate the quality of the lower resolution onboard data logger. The period of the recording was kept to a week since it required additional cooperation of the commuters to start and stop the recording. Table C provides an overview of the logged vehicle motion and GPS parameters.

Table C4: Overview of the different GPS and motion parameters recorded with the smartphone app

No.	Parameter	Format	Unit
1	Date	DD.MM.YYYY	
2	Time	hh:mm:ss:sss	
3	Latitude	###,###	
4	Longitude	###,###	
5	Altitude	###	[m]
6	Speed	##.##	[m/s]
7	Acceleration x-axis	#.###	[g]
8	Acceleration x-axis	#.###	[g]
9	Acceleration x-axis	#.###	[g]

C 1.1.2 Data Nissan Leaf

The vehicle and movement data of the Nissan Leaf was recorded in two different ways: indirectly from the online tool provided by the manufacturer and directly via a smartphone connected to the onboard diagnostics (OBD) system. The online tool provided by the manufacturer only provided data in an aggregated form, which proved insufficient for the detailed techno-economic analysis. Therefore, by connecting a diagnostic socket to the OBD interface and using the smartphone app Leaf Spy Pro much more detailed data could be recorded. Accessing this data was crucial since the recorded vehicle and movement data was the core input for assessing the empirical energy consumption, as well as calibrating the theoretical energy consumption model and charging curves. Analog to the e-Wolf data, the data recorded from the Nissan Leaf is directly used in the following research papers:

- Schücking et al. (2016)
- Schücking et al. (2017)
- Ensslen et al. (2017)
- Held & Schücking (2019)

In the following, the logging devices, as well as the recorded data, will be explained in more detail.

C 1.1.2.1 Data Nissan Leaf online tool

The vehicle data of the Nissan Leaf vehicle deployed in the RheinMobil Project was only made available in aggregated form on the online platform NISSAN CARWINGS. On this platform the current SOC, the remaining range, and charging status of the vehicle was visible. Also, past data concerning individual trips, energy consumption, distance, and saved CO_2 emissions was presented. Details of the parameters available for past trips can be found in Table C. The logging frequency of the data is unknown. Overall 50,397 km were recorded on 851 individual trips.

Table C5: Overview of the different vehicle parameters presented on the online platform

No.	Category	Parameter	Format	Unit
1		Date	MMM/DD	
2		Number of trips per day	##	
3	Energy consumption	Net consumption	##.##	[kWh]
4		Gross consumption	##.##	[kWh]
5		Recuperated energy	##.##	[kWh]
6		Specific net energy consumption	###.##	[kWh/100 km]
7		Covered distance	##.##	[km]
8		Reduction of CO_2 emissions	##	[kg]

C 1.1.2.2 Data Nissan Leaf recorded via the onboard diagnostics (OBD) system

Since the online platform did neither provide the required transparency nor level of detail an additional data logging system was installed on-board of the vehicle for three months as well as for two weeks in a Nissan eNV200. An onboard diagnostics (OBD)-2 scanner was connected to the diagnostic socket, which send the data via Bluetooth transmission to a smartphone. The Leaf Spy Pro application was installed on the Android operating system of the smartphone to interpret and store the received data. The data was retrieved from the smartphone via USB. The amount of data collected for each vehicle and the logging frequencies be found in Table C. Table C provides an overview of the logged vehicle and GPS parameters.

Table C6: Overview data logged from the Nissan Leaf vehicle via the OBD-2 scanner

Vehicle	Duration of data recording	Number of data points	Logged distance [km]	Logging frequency while driving [s]	Logging frequency while charging [s]
Nissan Leaf	3 Months	37,800	858	3	3
Nissan eNV200	2 Weeks	15,120	130	3	3

Table C7: Overview of the different vehicle and GPS parameters recorded via the OBD-2 scanner

No.	Parameter	Format	Unit	Description
1	Date	DD.MM.YYYY		Date of the recording
2	Time	Hh:mm:ss		Time of the recording
3	Latitude	##:##.#####		GPS latitude
4	Longitude	##:##.#####		GPS longitude
5	Elevation	###	[m]	GPS elevation
6	Speed	###	[km/h]	Current speed of the vehicle
7	Gids	###		
8	SOC	###,###		Battery state of charge
9	AHr	###,###		Battery state of health
10	Pack Volts	###.##	[V]	Battery voltage
11	Pack Amps	##.#	[A]	Battery current
12	Max CP mV	#,###	[mV]	Maximum cell voltage
13	Min CP mV	#,###	[mV]	Minimum cell voltage
14	Avg CP mV	#,###	[mV]	Average cell voltage
15	CP mV Diff	##	[mV]	Difference of cell voltages

16	Judgment Value	#	0 = ok, 1 = problem	State of the battery
17	Pack T1 F (1 to 4)	##.#	[°F]	Temperature for all 4 battery packs
18	Pack T1 C (1 to 4)	##.#	[°C]	Temperature for all 4 battery packs
19	CP1 (1 to 96)	#,###	[mV]	Cell voltage for all 96 cells
20	12v Bat Amps	#.##	[A]	Current in the low volt circuit
21	VIN			Vehicle identity number
22	Hx	###.##		
23	12v Bat Volts	##	[V]	Voltage of the 12 V battery
24	Odo(km)	##,###	[km]	Odometer
25	QC	###		Number of fast charging events
26	L1/L2	###		Number of conventional charging events
27	TP (FL, FR, RL, RR)	#.#	[bar]	Tire pressure for all four tires FL, FR, RL, RR
28	Ambient	#	[°C]	Ambient temperature
29	SOC	###	[%]	State of Health
30	RegenWh	##	[Wh]	Recuperated energy
31	BLevel			Battery level before warning of low SOC
32	epoch time	#,###,###,###	[s]	Time passed since the first trip
33	Motor Pwr(100w)	###	[100 w]	Power electric motor
34	Aux Pwr(100w)	##	[100 w]	Power auxiliaries
35	A/C Pwr(250w)	##	[250 w]	Power A/C
36	A/C Comp(0.1MPa)	#	[0.1MPa]	Air pressure A/C
37	Est Pwr A/C(50w)	##	[50 w]	Estimated power of A/C
38	Est Pwr Htr(250w)	##	[250 w]	Estimated power charging
39	Plug State	#	0 = no 1 = plugged-in	State of the charging plug
40	Charge mode	#	0 = no 2 = conventional 3 = fast charge	Charging mode
41	OBC	##,###	[W]	Charging power

C 1.1.3 Charging curves recorded with an energy cost measurement device

The energy cost measurement device VOLTCRAFT ENERGY-LOGGER 4000 was used to record the Mode 1 and Mode 2 charging curves of different EV. It was put between the standard power outlet and the charging cable. Overall the charging curves of eight different EV types were recorded. With a frequency of one measurement point per minute, the data recorded is listed in .

Table C8: Overview of the different charging parameters recorded with the energy cost measurement device

No.	Parameter	Format	Unit
1	DateTime	DD.MM.YYYY hh:mm	
2	Voltage	###,#	[V]
3	Current	##,###	[A]
4	Power Factor	#.##	
5	Actual Consumption	#,###.##	[W]
6	Apparent Consumption	#,###.##	[W]

The data was used in the following research papers:

- Schücking et al. (2017)
- Schücking & Jochem (2019)
- Ensslen et al. (2017)

C 1.2 Mobility data

Extensive mobility data of vehicles deployed in specific commercial use-cases was required in addition to the movement data recorded directly from the deployed BEVs. Therefore, the data from the regional eco mobility 2030 (REM2030) project was taken (REM2030 Daten v2015, Fraunhofer-Institut für System- und Innovationsforschung ISI, Karlsruhe). It consists of 91,422 single trips from 630 commercial ICEVs that were deployed by various companies from different economic segments over an average period of three weeks. For each trip the time of departure, arrival, the distance traveled, and the distance to the company are recorded. Also, metadata concerning the vehicles and companies is available. A detailed overview can be found in the REM2030 codebook (REM2030, 2015). The data of the vehicles can be found Table C. Table C provides an overview of the time and GPS parameters recorded for individual vehicles. The data was used in the following research paper:

- Schücking & Jochem (2019)

Table C9: Overview of the REM2030 vehicle data parameters

No.	Variable	Format	Description
1	ID	YYMMKKKKKK	A unique primary key consisting of the year (YY), month (MM) and the last 6 digits of the data logger ID (KKKKKKK)
2	Vehicle_size	Small, Midsize, Large, Transporter	Size class of the vehicle
3	Economic_sector	Classification according to SOURCE DeStatis 2008	Business sector of the company
4	NACE_section	Classification according to SOURCE DeStatis 2008	
5	Economic_segment	Classification according to SOURCE DeStatis 2008	Business segment of the company
6	NACE_division	Classification according to SOURCE DeStatis 2008	
7	Company_description		Free text according to the company
8	City_size	< 20,000, 20,000 to 100,000, > 100,000	Population
9	Company_size	< 10, 10 to 50, 51 to 250, 251 to 1,000, 1,001 to 5,000 > 5,000	Number of employees
10	Comment		Free optional comments
11	Vehicle_utilization	Fleet vehicle, Company car	Utilization of the vehicle
12	Number_of_users	One user, More than one user	Number of users
13	Parking_spot	Fixed spot on the company premises, changing spots on	Parking situation of the vehicle

		the company premises, no parking spot on the company premises	
14	Federal_state	Two-digit according to ISO 3166-2:DE	Federal state in Germany
15	Company_ID	#	Ongoing and unique for each company

Table C10: Overview of the REM2030 trip data parameters

No.	Parameter	Format	Description
1	ID	YYMMKKKKKK	A unique primary key consisting of the year (YY), month (MM) and the last 6 digits of the data logger ID (KKKKKKK)
2	DepYear	####	Departure time (year)
3	DepMonth	##	Departure time (month)
4	DepDay	##	Departure time (day)
5	DepHour	##	Departure time (hour)
6	DepMinute	##	Departure time (minute)
7	ArrYear	####	Arrival time (year)
8	ArrMonth	##	Arrival time (month)
9	ArrDay	##	Arrival time (day)
10	ArrHour	##	Arrival time (hour)
11	ArrMinute	##	Arrival time (minute)
12	Distance	##,##	Distance traveled [km]
13	Distance_to_company	###,##	Distance to the company [km]

C 1.3 Weather data

Including detailed weather data in the techno-economic assessment and optimization of BEVs is important for two reasons: the influence of the auxiliaries, especially cooling and heating of the passenger cabin, on the specific energy consumption of the BEV and the influence on the battery temperature. However, the restricting effects of low or high battery temperatures on the usability of the BEV are neglected in the research presented in this book. The focus lies on the effect of the auxiliaries. Two different approaches were taken to get outside temperature data. Firstly, temperature loggers were installed in the deployed e-Wolf Delta 2 (EVO) vehicles and the Nissan Leaf to record temperature data directly at the BEV. Secondly, long-term empirical data was downloaded from Germany's National Meteorological Service (DWD) which is a public institution with partial legal capacity under the Federal Ministry of Transport and Digital Infrastructure. The data was used in the following research paper:

- Schücking et al. (2016)
- Schücking et al. (2017)
- Schücking & Jochem (2019)

In the following, the logging devices, as well as the recorded data, will be explained in more detail.

C 1.3.1 Outside temperature recorded at the vehicles

The surrounding temperature data of the deployed EV was recorded with the Tempod MP-1 data logger. Technical details can be found in the datasheet (TempSen, 2018). Within the RheinMobil project, one logger was installed into each of the seven vehicles. During the 36 months of deployment, the data was saved on the logger and monthly retracted. The amount of data collected for each vehicle and the logging frequencies can be found in Table C. Table C provides an overview of the logged parameters.

Table C11: Overview outside temperature data logged from the vehicles during the RheinMobil Project

Vehicle	Duration of data recording	Number of data points	Logging frequency [s]
e-Wolf Delta 2_1	36 Months	105,216	20
e-Wolf Delta 2_2	36 Months	105,216	20
e-Wolf Delta 2_3	36 Months	105,216	20
e-Wolf Delta 2_1_E	36 Months	105,216	60
e-Wolf Delta 2_2_E	36 Months	105,216	60
e-Wolf Delta 2_3_E	36 Months	105,216	60

Table C12: Overview of parameters recorded via the Tempod MP-1 datalogger

No.	Parameter	Format	Description
1	Date and time	DD.MM.YYYY hh:mm:ss	Date and timestamp of the measurement
2	Outside temperature	##.#	Outside temperature [°C/°F]

C 1.3.2 Deutscher Wetterdienst (DWD)

The publicly available database from the DWD was used to include long-term empirical data of the outside temperature. The database offers data from numerous weather stations in Germany with an hourly, daily, monthly, annual or multi-annual resolution. Recently, even 1-minute precipitation measurements and 10-minute measurements of temperature, precipitation, wind, and sunshine are made available. All data is provided on an openly accessible server (ftp://ftp-cdc.dwd.de/../). In this book, hourly temperature values were used. More details can be found in the data set description (DWD Climate Data Center (CDC), 2018). Table C1311 provides an overview of the available parameters.

Table C1311: Overview of parameters provided by the DWD Climate Data Center (CDC)

No.	Parameter	Format	Description
1	Station ID	####	Individual ID of the station
2	Measurement time	DD.MM.YYYY hh:mm:ss	Date and timestamp of the measurement
3	Data quality	#	Quality level - coding see datasheet
4	Air temperature (2 m)	##.#	Measured at 2 m above ground [°C]
5	Relative humidity (2 m)	##	Measured at 2 m above ground [%]

C 2. Source Code

In the following the source code of the stochastic program, the scientific modeling of the electric vehicles, the training, and scoring of the HMM, as well as the calculation of the scenario reduction is presented. The code was applied to calculate the Results of the Paper Schücking & Jochem (2019). The code was programmed in SPYDER.

C 2.1 Sample average approximation optimization program

In the following, the modulation of the optimization program as well as the electric vehicles are presented. The author added the comments to the source code.

C 2.1.1 Optimization program

The optimization program used the Gurobi Python interface as well as the standard libraries: matplotlib, csv, openpyxl, pandas, numpy and math.

```
#Created on Tue Aug 22 15:54:48 2017

#@author: maximilian schuecking

#Optimization for one EV with SAA
#Variable temperature and mobility scenarios
#Optimization period: 1 week
```

```
#Investment period: 3 years

#step 0: Importing packages

import gurobipy as gp
import EV as ev
import matplotlib.pylab as plt
import csv
from openpyxl import load_workbook
import pandas as pd
import numpy as np
import math as math

#step 1: data import

#step 1.1: data time index
#Setting the period in number of days (365 is basic setting)
period_d = 7
period_a = period_d / 365
period_inv = 3
period_min = period_d * 24 * 60

#Setting the time resolution [min]
time_res = 1

#Index t
T = int(period_min / time_res)

#step 1.2: data EVSE
#Number of EVSE alternatives
EVSE_a = 4

#EVSE data maximum power, reduction point, charging mode, investment, installation cost
EVSE_data = {}
EVSE_data.update({("EVSE_1","max_power") : 2200})
EVSE_data.update({("EVSE_1","red_pnt") : 1000})
EVSE_data.update({("EVSE_1","ch_mode") : 2})
EVSE_data.update({("EVSE_1","ch_inv") : 0})
EVSE_data.update({("EVSE_1","ch_inst") : 0})

EVSE_data.update({("EVSE_2","max_power") : 3700})
EVSE_data.update({("EVSE_2","red_pnt") : 1000})
EVSE_data.update({("EVSE_2","ch_mode") : 3})
EVSE_data.update({("EVSE_2","ch_inv") : 600})
EVSE_data.update({("EVSE_2","ch_inst") : 100})

EVSE_data.update({("EVSE_3","max_power") : 11000})
EVSE_data.update({("EVSE_3","red_pnt") : 3500})
EVSE_data.update({("EVSE_3","ch_mode") : 3})
EVSE_data.update({("EVSE_3","ch_inv") : 1200})
EVSE_data.update({("EVSE_3","ch_inst") : 200})

EVSE_data.update({("EVSE_4","max_power") : 22000})
EVSE_data.update({("EVSE_4","red_pnt") : 7000})
EVSE_data.update({("EVSE_4","ch_mode") : 3})
EVSE_data.update({("EVSE_4","ch_inv") : 1800})
EVSE_data.update({("EVSE_4","ch_inst") : 300})

#amortization period EVSE
EVSE_T = 8

#EVSE maintenance cost factor [%/a]
EVSE_mnt_fac = 0.1

step 1.3: data EV
#Charging efficiency grid to battery
ch_eff = 0.85
```

```
#discharging efficiency battery to grid
dch_eff = 0.85

#Faktor of net battery capacity used
bat_gn_factor = 0.87

#Battery warranty in years
bat_war_time = 8

#Battery warranty max. distance
bat_war_dist = 160000

#Battery warranty capacity
bat_war_cap = 0.7

#EV price (compact class net without battery)
EV_price = 20000

#parameters residual value
EV_RV_alpha = 0.97948
EV_RV_beta_1 = -0.01437
EV_RV_beta_2 = -0.000117
EV_RV_beta_3 = 0.91569

#battery price on modul level in 2017 [€/kWh]
bat_pr_17 = 210

#battery price on modul level in 2020 [€/kWh]
bat_pr_20 = 185

#battey second life value factor
bat_sl_f = 0.5

#battery refurbishment cost 50 €/kWh
bat_ref_c = 50

#cost of EV maintenance [€/km]
EV_mnt = 0.024

#insurance cost EV [€/a]
EV_insur = 450

#tax EV [€/a]
EV_tax = 0

#interest rate for investment model
interest_rate = 1.0502

#step 1.4: electricity data
#importing external data for electricity prices
wb = load_workbook(…)
ws = wb.active
energy_df = pd.DataFrame(ws.values)
energy_data = energy_df.values.tolist()
energy_pr_buy = []
for i in range(len(energy_data)):
    energy_pr_buy.extend(energy_data[i])
#from €/kWh to €/Wh
for i in range(len(energy_pr_buy)):
    energy_pr_buy[i] /= 1000

#importing external data for selling electricity
wb = load_workbook(…)
ws = wb.active
energy_df = pd.DataFrame(ws.values)
energy_data = energy_df.values.tolist()
```

```
energy_pr_sell = []
for i in range(len(energy_data)):
    energy_pr_sell.extend(energy_data[i])
#from €/kWh to €/Wh
for i in range(len(energy_pr_buy)):
    energy_pr_sell[i] /= 1000

#gas price set at net 1.2 €/l
gas_pr_buy = [1.2 for t in range(T)]

#step 1.5: data outside temperature
#Number of temperature scenarios
T_S = 10

#importing external data for annual hourly temperature profile
wb = load_workbook(…)
ws = wb.active
temp_df = pd.DataFrame(ws.values)
temp_data = temp_df.values.tolist()

temp_scen_prob = []

for ts in range(T_S):
    temp_scen_prob.append(temp_data[ts][0])
    x = temp_data[ts][0]
    temp_data[ts].remove(x)

#step 1.6: data mobility demand
#number of scenarios
M_S = 15
#import the relevant scenarios and their probabilities
wb = load_workbook(…)
ws = wb.active
mob_scen_df = pd.DataFrame(ws.values)
mob_scen_data = mob_scen_df.values.tolist()

mob_scen_list = []
mob_scen_prob = []

for ms in range(M_S):
    mob_scen_list.append(mob_scen_data[ms][0])
    x = mob_scen_data[ms][0]
    mob_scen_data[ms].remove(x)
    mob_scen_prob.append(mob_scen_data[ms][0])

mob_drv = [ms for ms in range(M_S)]
mob_crg = [ms for ms in range(M_S)]
mob_spd = [ms for ms in range(M_S)]

#importing external data for each scenario
for ms in range(M_S):

    wb = load_workbook(…)
    ws = wb.active
    mob_df = pd.DataFrame(ws.values)
    mob_data = mob_df.values.tolist()

    #changing form from long to integer
    for i in range(len(mob_df.index)):
        mob_data[i] = [int(x) for x in mob_data[i]]

    mob_drv[ms] = []
    mob_crg[ms] = []
    mob_spd[ms] = []

    #rows 0,3,… are the driving state
    for i in range (0, period_d * 3, 3):
```

```
        mob_drv[ms].extend(mob_data[i])
    #rows 1,4,... are the charging state
    for i in range (1, period_d * 3, 3):
        mob_crg[ms].extend(mob_data[i])
    #rows 2,5,... are the average speed
    for i in range (2, period_d * 3, 3):
        mob_spd[ms].extend(mob_data[i])
```

step 1.7: data collection

```
res_crg_power = []
res_crg_mode = []
res_opt_val = []
res_bat_cap_g = []
res_bat_cap_n_start = []
res_bat_cap_n_end = []
res_drv_time_avg = []
res_stp_time_avg = []
res_crg_time_avg = []
res_crg_energy_avg = []
res_dcrg_energy_avg = []
res_drv_dist_avg = []
res_period_d = []
res_period_inv = []
```

step 2: model

step 2.1: defining model

```
#for each charging alternative there must be a separate run to keep the LP
for c in range(0, EVSE_a):

    #creating an empty model
    m = gp.Model("one_EV_MobS_" + str(M_S) + "_TempS_" + str(T_S))

    #step 2.2: variables
    #charging power in each period for each scenario
    crg_power = {}
    for ms in range (M_S):
        for ts in range (T_S):
            for t in range (T):
                crg_power.update({(ms, ts, t): m.addVar(lb=0, vtype=gp.GRB.CONTINUOUS,
                            name="crg_power" + str(ms) + str(ts) + str(t))})

    #discharging power in each period for each scenario
    dcrg_power = {}
    for ms in range (M_S):
        for ts in range (T_S):
            for t in range (T):
                dcrg_power.update({(ms, ts, t): m.addVar(ub=0, vtype=gp.GRB.CONTINUOUS,
                            name="dcrg_power" + str(ms) + str(ts) + str(t))})

    #state of charge measured in Wh for each period in each scenraio
    EV_SOC = {}
    for ms in range (M_S):
        for ts in range (T_S):
            for t in range(T):
                EV_SOC.update({(ms, ts, t): m.addVar(lb=0, vtype=gp.GRB.CONTINUOUS,
                            name="EV_SOC" + str(ms) + str(ts) + str(t))})

    #gross battery capacity measured in kWh of the initial investment
    #integer variable
    bat_cap_g = m.addVar(lb=0, vtype=gp.GRB.INTEGER, name="bat_cap_g")

    #net battery capacity measured in kWh
    bat_cap_n_start = m.addVar(lb=0, vtype=gp.GRB.CONTINUOUS, name="bat_cap_n_start")

    #net battery capacity measured in kWh
    bat_cap_n_end = m.addVar(lb=0, vtype=gp.GRB.CONTINUOUS, name="bat_cap_n_end")
```

step 2.3: updating model
m.update()

step 2.4: target function
#minimization of the TCO (investment and operation cost)

```
#EV investment without battery in €
TF_EV_inv = m.addVar()
TF_EV_inv = EV_price

#investment in battery in €
TF_bat_inv = m.addVar()
TF_bat_inv = bat_cap_g * bat_pr_17

#residual value of EV in € after 3 years of use
#depends on the use/mobility scenario only the temperature scenario is here not necessary
    TF_EV_RV = m.addVar()
TF_EV_RV = sum((((np.exp(EV_RV_alpha) * np.exp(12 * EV_RV_beta_1 * period_inv) *
np.exp(EV_RV_beta_2 * (sum((time_res / 60) * mob_spd[ms][t] for t in range(T)) / (period_a)) / 12) *
math.pow(EV_price, EV_RV_beta_3)) / math.pow(interest_rate, period_inv))) * mob_scen_prob[ms] for ms in range(M_S))


#residual value of battery in € after 3 years of use
#depends only on the time not the use/mobility scenario in this case
TF_bat_RV = m.addVar()
TF_bat_RV = ((((((bat_sl_f - bat_war_cap) / (1 - bat_war_cap))+ (((1 - bat_sl_f) / (1 - bat_war_cap)) *
                (1- (period_inv * 0.3 / bat_war_time))))
* bat_pr_20) - bat_ref_c) * bat_cap_g)/ math.pow(interest_rate, period_inv)

 #Investment in EVSE and additional costs for installation in €
TF_EVSE_inv = m.addVar()
TF_EVSE_inv = EVSE_data["EVSE_" + str(c+1),"ch_inv"] + EVSE_data["EVSE_" + str(c+1),"ch_inst"]

#residual value charging infrastructure in € after 3 years of use
TF_EVSE_RV = m.addVar()
TF_EVSE_RV = EVSE_data["EVSE_" + str(c+1),"ch_inv"] * ( 1 - (period_inv / EVSE_T)) / math.pow(interest_rate, period_inv)

#charging cost of EV in € depending on the (use) mobility scenario
#minute index transformed to hourly energy prices
TF_EV_crg_cost = m.addVar()
for ts in range(T_S):
    for ms in range(M_S):
        TF_EV_crg_cost += mob_scen_prob[ms] * temp_scen_prob[ts] * (sum(crg_power[(ms, ts, t)] *
                                energy_pr_buy[int(math.floor(t/60))] * time_res / 60 for t in range(T)) * (period_inv / period_a))

#discharging cost of EV in € depending on the (use) mobility scenario
#minute index transformed to hourly energy prices
TF_EV_dcrg_cost = m.addVar()
for ts in range(T_S):
    for ms in range(M_S):
        TF_EV_dcrg_cost += mob_scen_prob[ms] * temp_scen_prob[ts] * (sum(dcrg_power[(ms, ts, t)] *
                                energy_pr_sell[int(math.floor(t/60))] * dch_eff *
                                time_res / 60 for t in range(T)) * (period_inv / period_a))

#additional fixed costs: insurance and tax in €
#discounted over time, paid at the start of the year
TF_EV_fix_cost = m.addVar()
for t in range(period_inv):
    TF_EV_fix_cost += (EV_insur + EV_tax) / math.pow(interest_rate, t)

#maintenance cost of EV in € depending on the (use) mobility scenario
TF_EV_mnt_cost = m.addVar()
for ms in range(M_S):
    TF_EV_mnt_cost += mob_scen_prob[ms] * (sum(EV_mnt * mob_spd[ms][t] *
                            time_res / 60 for t in range(T)) * (period_inv / period_a))

#maintenance cost of EVSE in € set at 10% of the investment cost
```

```
#discounted over time, paid at the end of the year
TV_EVSE_mnt_cost = m.addVar()
for t in range(period_inv):
    TF_EV_fix_cost += (EVSE_data["EVSE_" + str(c+1),"ch_inv"] * EVSE_mnt_fac) / math.pow(interest_rate, t + 1)

#final target function
TF_all = (TF_EV_inv + TF_bat_inv - TF_EV_RV - TF_bat_RV + TF_EVSE_inv - TF_EVSE_RV +
          TF_EV_crg_cost + TF_EV_dcrg_cost + TF_EV_fix_cost + TF_EV_mnt_cost + TV_EVSE_mnt_cost)

#minimizing the TCO
m.setObjective(TF_all, gp.GRB.MINIMIZE)
```

#step 2.5: constraints

```
#EV can only charge on company ground
for ts in range(T_S):
    for ms in range(M_S):
        for t in range(T):
            m.addConstr(crg_power[(ms, ts, t)] * (mob_drv[ms][t] + 1 - mob_crg[ms][t]) == 0)

#EV can only discharge when they are on company ground
for ts in range(T_S):
    for ms in range(M_S):
        for t in range(T):
            m.addConstr(dcrg_power[(ms, ts, t)] * (mob_drv[ms][t] + 1 - mob_crg[ms][t]) == 0)

#max. charging power depending on EVSE alternative
for ts in range(T_S):
    for ms in range(M_S):
        for t in range(T):
            m.addConstr(crg_power[(ms, ts, t)] <= EVSE_data["EVSE_" + str(c+1),"max_power"])

#max. charging power reduction on EVSE alternative
for ts in range(T_S):
    for ms in range(M_S):
        for t in range(T):
            m.addConstr(crg_power[(ms, ts, t)] <= EV_SOC[(ms, ts, t)] * ((-EVSE_data["EVSE_" + str(c+1),"max_power"]) /
                                                  EVSE_data["EVSE_" + str(c+1),"red_pnt"]) +
                                                 (bat_cap_n_end * 1000 * EVSE_data["EVSE_" + str(c+1),"max_power"]  /
                                                 EVSE_data["EVSE_" + str(c+1),"red_pnt"]))

#max. discharging power including the discharging efficiency
for ts in range(T_S):
    for ms in range(M_S):
        for t in range(T):
            m.addConstr((dcrg_power[(ms, ts, t)] / dch_eff) >= -EVSE_data["EVSE_" + str(c+1),"max_power"])

#SOC transition function
for ts in range(T_S):
    for ms in range(M_S):
        for t in range(T-1):
            m.addConstr(EV_SOC[(ms, ts, t+1)] == EV_SOC[(ms, ts, t)] + (((crg_power[(ms, ts, t)] * ch_eff) + dcrg_power[(ms, ts,
           t)]) * time_res / 60) - (mob_spd[ms][t] * ev.energy_consumpt(mob_spd[ms][t], temp_data[ts][int(math.floor(t/60))],
           bat_cap_g) * time_res / 60))

# SOH limiting the SOC
for ts in range(T_S):
    for ms in range(M_S):
        for t in range(T):
            m.addConstr(EV_SOC[(ms, ts, t)] <= bat_cap_n_end * 1000)

#no additional gains through discharging from the first to the last period
for ts in range(T_S):
    for ms in range(M_S):
        m.addConstr(EV_SOC[(ms, ts, 0)] == EV_SOC[(ms, ts, T-1)])

# aging of the battery, linear reduction up to 30% in 8 years of battery guarantee
m.addConstr(bat_cap_n_end == bat_cap_n_start * (1- (period_inv * 0.3 / bat_war_time)))
```

```
#relation gross to net battery capacity
m.addConstr(bat_cap_g * bat_gn_factor == bat_cap_n_start)

#step 2.6: solving model
m.optimize()

#step 3: output of results
#writing the individual results of the scenarios
for ts in range(T_S):
  for ms in range(M_S):
      #naming file, e.g. "results_S1-2_3700"
      csv_file =  open(…)

      #general information about the scenario
      writer_csv.writerow(("opt. period [days]", "avg. temperature [°C]", "avg. energy price buy [€/wh]",
                  "avg. energy price sell [€/wh]", "energy charged [Wh]", "energy discharged [Wh]",
                  "avg. SOC [Wh]", "avg. SOH [Wh]", "driving time [h]",
                  "stopping time [h]", "charging time [h]", "distance travelled [km]"))

      writer_csv.writerow((str(period_d), str(sum(temp_data[ts][int(math.floor(t/60))] for t in range(T)) / T),
                  str(sum(energy_pr_buy[int(math.floor(t/60))] for t in range(T)) / T),
                  str(sum(energy_pr_sell[int(math.floor(t/60))] for t in range(T)) / T),
                  str(sum(time_res * crg_power[(ms, ts, t)].x / 60 for t in range(T))),
                  str(sum(time_res * dcrg_power[(ms, ts, t)].x / 60 for t in range(T))),
                  str(sum(EV_SOC[(ms, ts, t)].x for t in range(T)) / T),
                  str(sum(time_res * mob_drv[ms][t] for t in range(T))),
                  str(sum(time_res * (1 - mob_crg[ms][t]) * (1 - mob_drv[ms][t]) for t in range(T))),
                  str(sum(time_res * mob_crg[ms][t] for t in range(T))),
                  str((sum(time_res * mob_spd[ms][t] / 60 for t in range(T))))
                  ))

      writer_csv.writerow(("time [min]", "temperature [°C]", "energy price buy [€/wh]",
                  "energy price sell [€/wh]", "charging power [W]",
                  "discharging power [W]", "SOC [Wh]", "SOH [Wh]",
                  "driving state", "stopping state", "charging state", "avg. speed [km/h]"))
      for t in range(T):
        writer_csv.writerow((str(t+1), str(temp_data[ts][int(math.floor(t/60))]), str(energy_pr_buy[int(math.floor(t/60))]),
                  str(energy_pr_sell[int(math.floor(t/60))]),str(crg_power[(ms, ts, t)].x),
                  str(dcrg_power[(ms, ts, t)].x), str(EV_SOC[(ms, ts, t)].x),
                  str(mob_drv[ms][t]), str((1 - mob_crg[ms][t]) * (1 - mob_drv[ms][t])),
                  str(mob_crg[ms][t]), str(mob_spd[ms][t])
                  ))

      csv_file.close()

#writing the overall results for all EVSE alternatives
res_crg_power.append(EVSE_data["EVSE_" + str(c+1),"max_power"])
res_crg_mode.append(EVSE_data["EVSE_" + str(c+1),"ch_mode"])
res_opt_val.append(m.objVal)
res_bat_cap_g.append(bat_cap_g.x)
res_bat_cap_n_start.append(bat_cap_n_start.x)
res_bat_cap_n_end.append(bat_cap_n_end.x)
res_drv_time_avg.append(sum(sum(time_res * mob_drv[ms][t] for t in range(T)) *
                mob_scen_prob[ms] for ms in range(M_S)) / 60 )
res_stp_time_avg.append(sum(sum(time_res * (1 - mob_crg[ms][t]) * (1 - mob_drv[ms][t]) for t in range(T)) *
                mob_scen_prob[ms] for ms in range(M_S)) / 60)
res_crg_time_avg.append(sum(sum(time_res * mob_crg[ms][t] for t in range(T)) *
                mob_scen_prob[ms] for ms in range(M_S)) / 60)
res_crg_energy_avg.append(sum(sum(sum(time_res * crg_power[(ms, ts, t)].x / 60 for t in range(T)) *
                mob_scen_prob[ms] for ms in range(M_S)) * temp_scen_prob[ts] for ts in range(T_S)))
res_dcrg_energy_avg.append(sum(sum(sum(time_res * dcrg_power[(ms, ts, t)].x / 60 for t in range(T)) *
                mob_scen_prob[ms] for ms in range(M_S)) * temp_scen_prob[ts] for ts in range(T_S)))
res_drv_dist_avg.append(sum(sum(time_res * mob_spd[ms][t] / 60 for t in range(T)) * mob_scen_prob[ms] for ms in
range(M_S)))
res_period_d.append(period_d)
res_period_inv.append(period_inv)
```

```
#writing the overall results of the optimization
csv_file =  open("results_MS" + str(M_S) + "_TS" + str(T_S) + ".csv", "wt")
writer_csv = csv.writer(csv_file)
writer_csv.writerow(("charging power [W]", "charging mode", "opt. value [€]", "gross capacity [kWh]",
                     "net capacity [kWh]", "end SOH [Wh]", "driving time avg. [h]",
                     "stopping time avg. [h]", "charging time avg. [h]","energy charged avg. [Wh]",
                     "energy discharged avg. [Wh]", "distance travelled avg. [km]",
                     "optimization period [days]", "investment period [years]"))

for c in range(EVSE_a):
    writer_csv.writerow((str(res_crg_power[c]), str(res_crg_mode[c]), str(res_opt_val[c]),
                         str(res_bat_cap_g[c]),str(res_bat_cap_n_start[c]),str(res_bat_cap_n_end[c]),
                         str(res_drv_time_avg[c]), str(res_stp_time_avg[c]),
                         str(res_crg_time_avg[c]), str(res_crg_energy_avg[c]), str(res_dcrg_energy_avg[c]),
                         str(res_drv_dist_avg[c]), str(res_period_d[c]), str(res_period_inv[c])
                         ))

csv_file.close()
```

C 2.1.2 EV module

```
#Created on Wed May 10 09:37:20 2017

#@author: maximilian schuecking

#electric vehicle charging curves
#electric vehicle energy consumption
```

1. EV charging curves

```
def charging_curve(Charge_mode, max_power_EVSE, Charge_eff, SOC, SOH):

    max_charge_power = 0.0

    #charging mode 2, max. charging power 2,000 W
    if Charge_mode == 2.0:
        #constant part of the charging curve until 1,000 Wh remaining capacity
        if (SOC <= SOH - 1000.0):
            max_charge_power = 2200.0
        #second part of the charging curve, constant linear reduction
        else:
            max_charge_power = (-2200.0 / 1000.0 * SOC) + (2200.0 + ((SOH - 1000.0) * 2200.0 / 1000.0))

    #charging mode 3, max. charging power 3,700 W, 11,000 W & 22,000 W
    if Charge_mode == 3:
        #charging curve 3,700 W
        if max_power_EVSE == 3700.0:
            #constant part of the charging curve until 1,000 Wh remaining capacity
            if (SOC <= SOH - 1000.0):
                max_charge_power = 3700.0
            #second part of the charging curve, constant linear reduction
            else:
                max_charge_power = (-3700.0 / 1000.0 * SOC) + (3700.0 + ((SOH - 1000.0) * 3700.0 / 1000.0))
        #charging curve 11,000 W
        if max_power_EVSE == 11000.0:
            #constant part of the charging curve until 3,500 Wh remaining capacity
            if (SOC <= SOH - 3500.0):
                max_charge_power = ((11.0/185.0 * SOC + (9900.0 - (SOH - 3500.0) * 11.0/185.0))) * (1.0 / Charge_eff)
            #second part of the charging curve, constant linear reduction
            else:
                max_charge_power = (((-9900.0 / 3500.0) * SOC) + (9900.0 + ((SOH - 3500.0) * (9900.0 / 3500.0)))) * (1.0 /
                Charge_eff)
        #charging curve 22,000 W
        if max_power_EVSE == 22000.0:
            #constant part of the charging curve until 7,000 Wh remaining capacity
```

```
        if (SOC <= SOH - 7000.0):
            max_charge_power = ((11/75) * SOC + (19800.0 - (SOH - 7000.0) * 11.0/75.0)) * (1.0 / Charge_eff)
        #second part of the charging curve, constant linear reduction
        else:
            max_charge_power = (((-19800.0 / 7000.0) * SOC) + (19800.0 + ((SOH - 7000.0) * (19800.0 / 7000.0)))) * (1.0 /
            Charge_eff)

    #charging mode 3, max. charging power 20,000 W 50,000 W
    if Charge_mode == 4:
        #charging curve 20,000 W
        if max_power_EVSE == 20000.0:
            #constant part of the charging curve until 9,000 Wh remaining capacity
            if (SOC <= SOH - 9000.0):
                max_charge_power = (0.14 * SOC + (18500.0 - (SOH - 9000.0) * 0.14)) * (1.0 / Charge_eff)
            #second part of the charging curve, constant linear reduction
            else:
                max_charge_power = (((-18500.0 / 9000.0) * SOC) + (18500.0 + ((SOH - 9000.0) * (18500.0 / 9000.0)))) * (1.0 /
                Charge_eff)
        #charging curve 50,000 W
        if max_power_EVSE == 50000.0:
            #constant part of the charging curve until 12,000 Wh remaining capacity
            if (SOC <= SOH - 12000.0):
                max_charge_power = (0.4 * SOC + (47300.0 - (SOH - 12000.0) * 0.4)) * (1.0 / Charge_eff)
            #second part of the charging curve, constant linear reduction
            else:
                max_charge_power = (((-47300.0 / 12000.0) * SOC) + (47300.0 + ((SOH - 12000.0) * (47300.0 / 12000.0)))) * (1.0 /
                Charge_eff)

    return max_charge_power
```

2. EV energy consumption

```
#specific energy consumption based on average speed, outside temperature, and battery weight

def energy_consumpt(avg_speed ,amb_temp, batt_kap):

    #energy for propelling EV forward linear approximated
    prop_el_energy_consumpt = 0
    if avg_speed == 0.0:
        prop_el_energy_consumpt = 0
    if (avg_speed > 0.0 and avg_speed < 18.5):
        prop_el_energy_consumpt = 0 * avg_speed + 115.45
    if (avg_speed >= 18.5 and avg_speed < 63):
        prop_el_energy_consumpt = 0.5693 * avg_speed + 104.92
    if (avg_speed >= 63):
        prop_el_energy_consumpt = 1.863 * avg_speed + 23.43

    #additional consumption through battery weight
    batt_weight_energy_consumpt = batt_kap * 0.2524

    #energy consumed by the auxiliaries
    #factor determines multiples of 500 W for the auxiliaries' demand
    aux_el_energy_consumpt = 0
    if (amb_temp <= 0.0):
        factor = 4
    if (amb_temp > 0.0 and amb_temp <= 10.0):
        factor = 3
    if (amb_temp > 10.0 and amb_temp <= 15.0):
        factor = 2
    if (amb_temp > 15.0 and amb_temp <= 25.0):
        factor = 1
    if (amb_temp > 25.0 and amb_temp <= 30.0):
        factor = 2
    if (amb_temp > 30.0):
        factor = 3

    #calculating energy consumption based on the factor, linear approximated
    if (avg_speed > 0.0 and avg_speed < 5.0):
```

```
    aux_el_energy_consumpt = (-40 * factor) * avg_speed + (300 * factor)
  if (avg_speed >= 5.0 and avg_speed < 10.0):
    aux_el_energy_consumpt = (-10 * factor) * avg_speed + (150 * factor)
  if (avg_speed >= 10.0 and avg_speed < 20.0):
    aux_el_energy_consumpt = (-2.5 * factor) * avg_speed + (75 * factor)
  if (avg_speed >= 20.0 and avg_speed < 40.0):
    aux_el_energy_consumpt = (-0.625 * factor) * avg_speed + (37.5 * factor)
  if (avg_speed >= 40.0):
    aux_el_energy_consumpt = (-5/48 * factor) * avg_speed + (50/3 * factor)

  return (prop_el_energy_consumpt + batt_weight_energy_consumpt + aux_el_energy_consumpt)
```

C 2.2 Training and scoring HMM

The training and scoring of the HMM used the hmmlearn library as well as the standard libraries: openpyxl, pandas, and numpy.

```
#Created on Wed Apr 5 09:37:20 2017

#@author: maximilian schuecking

#multinomial hidden markov model
#Evaluation AIC, BIC, 4-fold cross-validation
#5 em-EM Baum-Welch (10 times, 10 different random initial parameters, 50 iterations, 200 iterations for the version with highest ML)


#step 0: Importing packages
from __future__ import division
import numpy as np
from hmmlearn import hmm
from openpyxl import load_workbook
import pandas as pd

#step 1: setting parameters
#number of hidden states
NoHdStat = 5
#number of parameters
NoParams = 40
#number of observations
NoObs = 27642
#number of total runs
NoExtRun = 10
#number of different initial distributions
NoIntRun = 10
#number of iterations in the first step
NoIt1stStep = 50
#number of iterations in the second step
NoIt2ndStep = 200
#number of validation sets
NoCrossVal = 4

start_pro_matrix_f = {}
trans_pro_matrix_f = {}
em_pro_matrix_f = {}
likeli_matrix_f = {}

#step 2: training the model
for c in range(NoExtRun):

  #allgemeine Initialisierung des HMM, entsprechend dann für alle erweitern
  states = ["Z1", "Z2", "Z3", "Z4", "Z5"]

  n_states = len(states)
  observations = ["stopp", "fahren", "halten"]
  n_observations = len(observations)
```

```
start_pro = np.array([])
trans_pro = np.array([ [], [], [], [], [] ])
em_pro = np.array([ [], [], [], [], [] ])
start_pro_matrix = {}
trans_pro_matrix = {}
em_pro_matrix = {}
likeli_matrix = {}

#start of full run
for a in range(NoIntRun):

    model = hmm.MultinomialHMM(n_components=n_states, n_iter=NoIt1stStep, params="te", init_params="te")

    model.startprob_=start_pro
    model.transmat_=trans_pro
    model.emissionprob_=em_pro

    #importing tour profiles
    name_train = 'Tourprofile_120501.xlsx'
    wb = load_workbook(name_train)
    ws =wb.active
    df_train = pd.DataFrame(ws.values)
    df_train.fillna(-1, inplace=True)
    data_train = df_train.values.tolist()
    for i in range(len(df_train.index)):
        data_train[i] = [x for x in data_train[i] if x != -1.0]

    for i in range(len(df_train.index)):
        data_train[i] = [int(x) for x in data_train[i]]

    #training the model
    model.fit(data_train)

    #saving the data of the first step runs
    start_pro_matrix[a+1] = model.startprob_
    trans_pro_matrix[a+1] = model.transmat_
    em_pro_matrix[a+1] = model.emissionprob_


    #calculating the ML of the individual runs
    likeli = 0.0
    for i in range(len(df_train.index)):
        likeli += model.score(data_train[i])

    #saving the data
    likeli_matrix[a+1] = likeli

#identifying the best first step run
MaxLikelIns = -1e6
MaxVarIns = 0
for b in range(NoIntRun):
    if likeli_matrix[b+1] > MaxLikelIns:
        MaxLikelIns = likeli_matrix[b+1]
        MaxVarIns = b+1

#Parameters of highest scoring run are now starting parameters
model_f = hmm.MultinomialHMM(n_components=n_states, n_iter=NoIt2ndStep, params="te", init_params="")

model_f.startprob_= start_pro_matrix[MaxVarIns]
model_f.transmat_= trans_pro_matrix[MaxVarIns]
model_f.emissionprob_= em_pro_matrix[MaxVarIns]

#training the model
model_f.fit(data_train)

#calculating the ML of the total run
likeli_f = 0.0
```

```
    for i in range(len(df_train.index)):
        likeli_f += model_f.score(data_train[i])

    #saving the data of the total runs
    start_pro_matrix_f[c+1] = model_f.startprob_
    trans_pro_matrix_f[c+1] = model_f.transmat_
    em_pro_matrix_f[c+1] = model_f.emissionprob_
    likeli_matrix_f[c+1] = likeli_f

#identifying the best total run
MaxLikelIns_f = -1e6
MaxVarIns_f = 0
for d in range(NoExtRun):
    if likeli_matrix_f[d+1] > MaxLikelIns_f:
        MaxLikelIns_f = likeli_matrix_f[d+1]
        MaxVarIns_f = d+1

#step 3: scoring the model

#AIC, BIC
AIC_2 = (-2*likeli_matrix_f[MaxVarIns_f]) + 2*NoParams
BIC_2 = (-2*likeli_matrix_f[MaxVarIns_f]) + NoParams*np.log(NoObs)

#4-fold cross-validation
cross_likeli = {}
for e in range(NoCrossVal):

    #run the model for one of the 4 cross-validation sets
    #identical to the model training above for the total sets
    start_pro_matrix_f = {}
    trans_pro_matrix_f = {}
    em_pro_matrix_f = {}
    likeli_matrix_f = {}

    for c in range(NoExtRun):
        states = ["Z1", "Z2", "Z3", "Z4", "Z5"]
        n_states = len(states)
        observations = ["stopp", "fahren", "halten"]
        n_observations = len(observations)

        start_pro = np.array([])
        trans_pro = np.array([ [], [], [], [], [] ])
        em_pro = np.array([ [], [], [], [], []
        start_pro_matrix = {}
        trans_pro_matrix = {}
        em_pro_matrix = {}
        likeli_matrix = {}

        for a in range(NoIntRun):

            model = hmm.MultinomialHMM(n_components=n_states, n_iter=NoIt1stStep, params="te", init_params="te")

            model.startprob_=start_pro
            model.transmat_=trans_pro
            model.emissionprob_=em_pro

            name_train = 'Tourprofile_120501_'
            name_train += str(e+1)
            name_train += '_Train.xlsx'
            wb = load_workbook(name_train)
            ws =wb.active
            df_train = pd.DataFrame(ws.values)
            df_train.fillna(-1, inplace=True)
            data_train = df_train.values.tolist()
            for i in range(len(df_train.index)):
                data_train[i] = [x for x in data_train[i] if x != -1.0]
            for i in range(len(df_train.index)):
```

```
            data_train[i] = [int(x) for x in data_train[i]]

        model.fit(data_train)

        start_pro_matrix[a+1] = model.startprob_
        trans_pro_matrix[a+1] = model.transmat_
        em_pro_matrix[a+1] = model.emissionprob_

        likeli = 0.0

        for i in range(len(df_train.index)):
            likeli += model.score(data_train[i])

        #hinzufügen zur Likelihood
        likeli_matrix[a+1] = likeli

    MaxLikelIns = -1e6
    MaxVarIns = 0

    for b in range(NoIntRun):
        if likeli_matrix[b+1] > MaxLikelIns:
            MaxLikelIns = likeli_matrix[b+1]
            MaxVarIns = b+1

    model_f = hmm.MultinomialHMM(n_components=n_states, n_iter=NoIt2ndStep, params="te", init_params="")

    model_f.startprob_= start_pro_matrix[MaxVarIns]
    model_f.transmat_= trans_pro_matrix[MaxVarIns]
    model_f.emissionprob_= em_pro_matrix[MaxVarIns]

    model_f.fit(data_train)

    likeli_f = 0.0

    for i in range(len(df_train.index)):
        likeli_f += model_f.score(data_train[i])

    start_pro_matrix_f[c+1] = model_f.startprob_
    trans_pro_matrix_f[c+1] = model_f.transmat_
    em_pro_matrix_f[c+1] = model_f.emissionprob_
    likeli_matrix_f[c+1] = likeli_f

MaxLikelIns_f = -1e6
MaxVarIns_f = 0

for d in range(NoExtRun):
    if likeli_matrix_f[d+1] > MaxLikelIns_f:
        MaxLikelIns_f = likeli_matrix_f[d+1]
        MaxVarIns_f = d+1

#calculation of the cross-validation values

name_test = 'Tourprofile_120501_'
name_test += str(e+1)
name_test += '_Test.xlsx'
wb = load_workbook(name_test)
ws =wb.active
df_test = pd.DataFrame(ws.values)
df_test.fillna(-1, inplace=True)
data_test = df_test.values.tolist()
for i in range(len(df_test.index)):
    data_test[i] = [x for x in data_test[i] if x != -1.0]
for i in range(len(df_test.index)):
    data_test[i] = [int(x) for x in data_test[i]]

#calculating the log-likelihood
likeli_test = 0.0
```

```
    for i in range(len(df_test.index)):
        likeli_test += model.score(data_test[i])

    cross_likeli[e+1] = likeli_test

cross_likeli_avg = 0
for f in range(NoCrossVal):
    cross_likeli_avg += cross_likeli[f+1]
cross_likeli_avg = cross_likeli_avg / NoCrossVal
```

C 2.3 Scenario reduction

The algorithms for the scenario reduction is separated into the calculation of the Kantorovich distance between the individual scenarios and the reduction algorithms. Here only the source code for the Fast Forward Selection (FFS) algorithm is presented, since it was the only one applied in the paper.

C 2.3.1 Calculation Kantorovich distance

```
#Created on Sep 19 17:20:49 2017

#@author: maximilian schuecking

#calculating the Kantorovich distance at the example of the mobility scenarios

#step 0: Importing packages
from openpyxl import load_workbook
import pandas as pd
import csv
import math

step 1: data import & variables
#number of scenarios
no_scen = 500

mob_drv = [ms for ms in range(no_scen)]
mob_crg = [ms for ms in range(no_scen)]
mob_spd = [ms for ms in range(no_scen)]

#importing data
wb = load_workbook(…)
ws = wb.active
raw_data_df = pd.DataFrame(ws.values)
raw_data = raw_data_df.values.tolist()
for i in range(len(raw_data_df.index)):
    raw_data[i] = [int(x) for x in raw_data[i]]

for ms in range (no_scen):
    mob_drv[ms] = []
    mob_crg[ms] = []
    mob_spd[ms] = []

    #21 because the scenarios are one week (7x3)
    #rows 0,3,... are the driving state
    for i in range ((ms * 21) + 0, (ms * 21) + 21, 3):
        mob_drv[ms].extend(raw_data[i])
    #rows 1,4,... are the charging state
    for i in range ((ms * 21) + 1, (ms * 21) + 21, 3):
        mob_crg[ms].extend(raw_data[i])
    #rows 2,5,... are the average speed
    for i in range ((ms * 21) + 2, (ms * 21) + 21, 3):
        mob_spd[ms].extend(raw_data[i])
```

T = len(mob_drv[0])

step 2: calculating the Kantorovich distance

```
kant_dist = [[0 for i in range(no_scen)] for i in range(no_scen)]

#Euclidian norm
for i in range(no_scen):
    print (i+1)
    for j in range(no_scen):
        kant_dist[i][j] = sum(math.sqrt(math.pow(mob_drv[i][k] - mob_drv[j][k], 2) +
                math.pow(mob_crg[i][k] - mob_crg[j][k], 2) +
                math.pow(mob_spd[i][k] - mob_spd[j][k], 2)) for k in range(T))
```

step 3: output of results

```
csv_file =  open(…)
writer_csv = csv.writer(csv_file)

for i in range(no_scen):
    writer_csv.writerow((str(kant_dist[i][j]) for j in range(no_scen)))

csv_file.close()
```

C 2.3.2 Scenario reduction (an example of fast-forward reduction algorithm)

#Created on Tue Sep 19 11:43:19 2017

#@author: maximilian schuecking

#step 0: Importing packages

```
from openpyxl import load_workbook
import pandas as pd
```

#step 1: data import & variables

```
#number of selected scenarios
target_scen = 5

#importing the Kantorovich distances
wb = load_workbook(…)
ws = wb.active
c_a_val_df = pd.DataFrame(ws.values)
c_a_val = c_a_val_df.values.tolist()
no_scen = len(c_a_val)

#list for remaining scenarios
rem_scen = [i+1 for i in range(no_scen)]

#list for deleted scenarios
sel_scen = []

#list for scenario probabilities
scen_prob = [1/no_scen for i in range(no_scen)]

scen_prob_p = [1/no_scen for i in range(no_scen)]

#list for c_u_k values that are updated in each reduction step
c_b_val = [[[0 for i in range(no_scen)] for i in range(no_scen)] for j in range (no_scen - target_scen)]
```

#step 2: scenario reduction
#step 2.1: initial reduction step

```
#adding the current values to the list
for k in range(no_scen):
    for u in range(no_scen):
```

```
        c_b_val[0][u][k] = c_a_val[u][k]

#z_value vector for identifying the next deleted scenario
#default values are 0, so deleted scenarios cannot be deleted againg
z_val = [0 for i in range(no_scen)]

#calculating the z_values
for l in rem_scen:
    z_val[l-1] = sum(scen_prob[k] * c_b_val[0][l-1][k] for k in range(no_scen))

#identifying scenario
z_min =  min(i for i in z_val if i > 0)

#identifying scenario index
index_sel = z_val.index(z_min) + 1

#adding deleted scenario index to the list
sel_scen.append(index_sel)

#deleting from available scenarios
rem_scen.remove(index_sel)

#step 2.2: iterative scenario redcution

for scen in range (1, target_scen):

    for k in rem_scen:
        for u in rem_scen:

            c_b_val[scen][u-1][k-1] = min(c_b_val[scen - 1][u-1][k-1],c_b_val[scen - 1][index_sel-1][k-1])

    #setting all values back to 0
    z_val = [0 for i in range(no_scen)]

    #calculating the z_values
    for l in rem_scen:
        z_val[l-1] = sum(scen_prob[k-1] * c_b_val[scen][l-1][k-1] for k in rem_scen)

    #identifying scenario
    z_min =  min(i for i in z_val if i > 0)

    #identifying scenario index
    index_sel = z_val.index(z_min) + 1

    #adding deleted scenario index to the list
    sel_scen.append(index_sel)

    #deleting from available scenarios
    rem_scen.remove(index_sel)


    #step 3: allocating the probabilities of the deleted scenarios
    #list for reduced scenario probabilities
    scen_prob_red = scen_prob

    #for all deleted scenarios
    for l in rem_scen:
        #values for all unselected scenarios are set to 0, so they are excluded
        for k in rem_scen:
            c_a_val[l-1][k-1] = 0

        #index of the remaining scenario with the smallest distance
        j = c_a_val [l-1].index(min(i for i in c_a_val[l-1] if i > 0))

        #adding the probability of the deleted scenario l to the identified scenario j
        #setting the probability of the deleted scneario to 0
        scen_prob_red[j] += scen_prob[l-1]
```

```
    scen_prob[l-1] = 0

  #resetting the values
  scen_prob = [1/no_scen for i in range(no_scen)]
  c_a_val_df = pd.DataFrame(ws.values)
  c_a_val = c_a_val_df.values.tolist()
```

C 3. References

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