THESIS FOR THE DEGREE OF DOCTOR OF PHILOSOPHY

Electrification of Private Mobility

Driving Patterns, Multi-Car Households and Infrastructure

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Göteborg, Sweden 2019

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ISBN: 978-91-7905-215-7

Doktorsavhandlingar vid Chalmers tekniska högskola

Ny serie nr 4682
ISSN 0346-718X

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Printed by Reproservice
Göteborg, Sweden 2019

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Abstract

Electrification of personal vehicles has the potential to significantly reduce carbon emissions. However, a large-scale transition to electric vehicles may be difficult as there are many individuals who collectively need to transition to this technology. Thus, it is important to understand car users' needs, and to what extent a fully battery electric vehicle (BEV) fulfill these needs. In particular, batteries have been expensive and charging infrastructure scarce, thus creating a trade-off between the price of the car, and its driving range.

We use several GPS-measured driving data sets, interview data, and charging infrastructure data to analyse potential BEV adoption in multi-car households. Furthermore, we develop methods with regards to driving data modelling and analysis. We also estimate the size of a future charging infrastructure network.

We find that for short-range BEVs (120 km), a noteworthy adaptation is required for most users. However, within multi-car households, approximately 50% of the second cars need to adapt less than one day per month. We also assess how users in two-car households adapt to a BEV replacing one of their ordinary cars. We find large heterogeneity in how users adapt, where some increase the use of the BEV compared to the replaced car, and some decrease it. From interview data we find that most households have experienced no actual problems with the range limitation, but most would prefer a range of 200 km.

As a methodological contribution, we analyze the effect of modelling driving data with three probability distributions. Contrary to earlier literature we find that the Weibull and Log-Normal distributions overall fit driving data better than the Gamma distribution. But when estimating the frequency of long-distance driving we find that Weibull and Gamma perform better than Log-Normal. Finally, we have extended the traditional driving data analysis beyond distance analysis to destination analysis. One of the results is that BEVs drive a significantly larger share of their driving to their most common destinations compared to a conventional car.

Keywords: Battery electric vehicles, GPS-measured driving data, two-car households, user-centered analysis, destination-based analysis

List of publications

I. Niklas Jakobsson, Till Gnann, Patrick Plötz, Frances Sprei and Sten Karlsson, “Are multi-car households better suited for battery electric vehicles? - Driving patterns and economics in Sweden and Germany”, *Transportation Research Part C: Emerging Technologies*, **65:1-15**, (2016).
PP and FS conceived the research idea. NJ and TG developed the method and did the analysis with contributions from PP, FS and SK. NJ worked on the Swedish data, and TG on the German data. NJ, TG, PP and FS contributed to writing the paper, with NJ as lead author. SK planned and initiated the original Swedish data collection.

II. Patrick Plötz, Niklas Jakobsson and Frances Sprei, “On the distribution of individual daily driving distances”, *Transportation Research Part B: Methodological*, **101:213-227**, (2017).
PP conceived the research idea. PP developed the method with contributions from NJ and FS. PP analyzed the German data, and NJ the Swedish data, PP, NJ and FS wrote the paper with PP as lead author.

III. Till Gnann, Simon Funke, Niklas Jakobsson, Patrick Plötz, Frances Sprei, and Anders Bennehag, “Fast charging infrastructure for electric vehicles: Today’s situation and future needs”, *Transportation Research Part D: Transport and Environment* **62:314-329**, (2018).
TG, NJ, PP and FS conceived the research idea. TG, SF and PP developed the queuing model with contributions from NJ and FS, NJ developed the methods for data analysis with contributions from TG, SF, PP, FS and AB. NJ performed the data analysis with contributions from AB. All authors developed the connection between between the data and the queuing model. AB and NJ gathered the original data.

IV. Niklas Jakobsson, Sten Karlsson, and Frances Sprei, “How do users adapt to a battery electric vehicle in a two-car household?”, *Working paper* (2018).
SK, FS and NJ conceived the research idea. NJ and FS designed the interview method and performed the interviews. NJ designed the data analysis methods for both data sets and their mixed methods aspects. NJ did the analysis. NJ wrote the paper with comments from FS and SK. SK organized the GPS data collection, and NJ cleaned the GPS data.

V. Niklas Jakobsson, Frances Sprei, and Sten Karlsson, “A destination-based analysis of electric, and conventional, cars in two-car households”, *Working paper* (2019).
NJ conceived the research idea. NJ designed the method and did the data analysis. NJ wrote the paper with comments from FS and SK.

Relevant publications not included in this thesis

Scott Hardman, Alan Jenn, Gil Tal, Jonn Axsen, George Beard, Nicolo Daina, Erik Figenbaum, Niklas Jakobsson, Patrick Jochem, Neale Kinnear, Patrick Plötz, José Pontes, Nazir Refa, Frances Sprei, Tom Turrentine, Bert Witkamp, "A review of consumer preferences of and interactions with electric vehicle charging infrastructure", *Transportation Research Part D: Transport and Environment* **62:508-523**, (2018).

Tom Turrentine, Scott Hardman, Ken Kurani, Jeff Allen, George Beard, Erik Figenbaum, Niklas Jakobsson, Alan Jenn, Sten Karlsson, José Pontes, Nazir Refa, Frances Sprei, Bert Witkamp, "Driving the market for plug-in vehicles: increasing consumer awareness and knowledge", *International EV Policy Council Policy Brief*, March 2018, available at: https://phev.ucdavis.edu/international-ev-policy-council-policy-briefs/.

Scott Hardman, Gil Tal, Tom Turrentine, Jonn Axsen, George Beard, Nicolo Daina, Erik Figenbaum, Niklas Jakobsson, Alan Jenn, Patrick Jochem, Neale Kinnear, Patrick Plötz, José Pontes, Nazir Refa, Frances Sprei, Bert Witkamp, "Driving the market for plug-in vehicles: developing charging infrastructure for consumers", *International EV Policy Council Policy Brief*, March 2018, available at: https://phev.ucdavis.edu/international-ev-policy-council-policy-briefs/.

Sten Karlsson, Niklas Jakobsson, Frances Sprei, "The variation of BEV energy use and range with climate and driving behaviour in real driving in Sweden", *Proceedings of EEVC, European Electric Vehicle Congress*, March 14-16, 2017 9-11, 2017, Geneva, Switzerland.

Sten Karlsson, Niklas Jakobsson, Frances Sprei, "Indicating and managing BEV range issues in two-car households", *Proceedings of EVS30, Electric Vehicle Symposium and Exhibition*, Oct 9-11, 2017, Stuttgart, Germany.

Till Gnann, Daniel Goldbach, Niklas Jakobsson, Patrick Plötz, Anders Bennehag, Frances Sprei, "A Model for Public Fast Charging Infrastructure Needs", *Proceedings of EVS29, Electric Vehicle Symposium*, Jun 20, 2016, Montreal, Canada .

Niklas Jakobsson, Sten Karlsson, Frances Sprei, "How are driving patterns adjusted to the use of a battery electric vehicle in two-car households?", *Proceedings of EVS29, Electric Vehicle Symposium*, Vol. 2, p. 1021-1030, Jun 20, 2016, Montreal, Canada.

Patrick Plötz, Niklas Jakobsson, Frances Sprei, Sten Karlsson, "On the distribution of individual daily vehicle driving distances", *European Electric Vehicle Congress*, Belgium, 3rd - 5th December 2014.

Niklas Jakobsson, Patrick Plötz, Till Gnann, Frances Sprei, Sten Karlsson, "Are electric vehicles better suited for multi-car households?", *European Electric Vehicle Congress*, Belgium, 3rd - 5th December 2014.

Acknowledgements

Thank you Frances for guidance and support during these years. Thank you Sten for sharing your wisdom as well, and for teaching me to look for the delta.

I also want to thank my co-authors Patrick, Till and Simon for a great collaboration. I am also grateful for friends and colleagues at Physical Resource Theory.

Finally, I thank my family for the support that have made this work possible. And especially, Mariliis, for love and patience.

This research has been funded by the Area of Advance Transport and the Swedish Energy Agency.

Göteborg, November 2019
Niklas Jakobsson

Contents

Chapter 1

Introduction

1.1 Background

Climate change is a major challenge facing humanity. The Intergovernmental Panel on Climate Change Assessment Report 5 states that the increase in global mean temperature is likely to exceed 2 degrees Celsius by the year 2100 compared to the pre-industrial level due to anthropogenic greenhouse gas emissions (GHG) (IPCC (2014)). A significant reduction of greenhouse gas emissions (GHG) will involve all sectors of society.

The transport sector accounts for a quarter of all GHG emissions in Europe (Hill et al. (2012)), in Sweden it is 30% (SOU (2013)) of which roughly 63% come from cars and 93% from all road transport (SCB (2019)). Also, besides GHG, conventional cars emit local pollutants from fuel combustion, wearing of brake linings, wearing of tires, and re-suspended road dust, that all contribute to urban pollution. In 2012, urban pollution, from all sources, caused 3.7 million premature deaths according to the OECD and World Health Organisation (OECD (2014)). In Europe WHO estimated "tens of thousands of deaths" due to road transport pollution in 2005 (Krzyżanowski et al. (2005)).

One way to reduce the impact of these two problems is electrification of cars. The fully electric vehicle, or battery electric vehicle (BEV) has no tail-pipe emissions and may have lower well-to-wheel GHG emissions depending on the electricity system within which it operates. Electric vehicles have also been identified as an important technology to reach the climate targets (Williams et al. (2012), McCollum et al. (2014)).

But the transportation sector can be difficult to change (McCollum et al.

(2014)). This is partly due to decentralized decision-making in the sense that many individuals need to collectively switch to a more sustainable solution since the lions share of transport emissions come from road transport, and cars. A large-scale transition from internal combustion engine vehicles (ICEV) to BEVs will require that many vehicle users find the BEV desirable enough to choose it in lieu of an ICEV. Thus, it is important to understand the needs and requirements of the users.

From a user's perspective, currently, the two main drawbacks of the BEV are that it has a limited electric driving range, based on the size of the battery, and that the battery is expensive, creating a trade-off between the price of the car, and the range need of the user. A possible third drawback is that there has been limited charging infrastructure available for fast re-charging of the battery, and that high-power re-chargers are expensive to build and may need to be subsidised (Hardman et al. (2018)). The limited charging infrastructure man thus impede the possibility to drive far on a single day with a BEV. These drawbacks have resulted in efforts from the research community to find user groups which can use a BEV under these circumstances (see Section 1.3), while also motivating governments to support the introduction of BEVs with different types of subsidies. A technological suggestion from car companies has been the development of plug-in hybrid electric vehicles (PHEVs) that combine an electric engine with a conventional engine. This type of vehicle may use the electric engine for shorter trips and be re-charged at night, while still being usable for long-distance driving using its conventional engine.

In order to determine a good battery size for a BEV, and how well existing BEVs fulfil user needs, it becomes important to know how cars actually are used, and especially the driving over a longer period with a combination of shorter and longer trips. This has prompted the collection of GPS-measured driving data sets of different user groups to complement traditional mobility surveys.

1.2 Aim of this thesis

This thesis mainly contains work on GPS-measured driving data sets. The work is two-fold in that one part concerns users of BEVs and their needs in relation to their vehicles, with a special focus on multi-car households (mainly Papers 1, 4, and 5), and the other concern development of methods for driving data analysis (mainly Papers 2 and 5). In addition, a possible mitigation of driving range limitations is an extensive fast charging infrastructure network, and the size of such a network has been analysed in Paper 3.

The overall aims of this thesis have thus been to explore the following two questions:

- How can driving data contribute to the understanding of a broad BEV adoption in society?
- Do short-range BEVs fulfil the needs in multi-car households?

This research is data-driven. This means that we use empirical data-sets in all the papers, but employ different methods to analyse these data sets. The specific methods are presented under their respective categories in 2.2. Throughout the thesis and papers, I take a user's perspective in the sense that I analyse the driving needs and economics of the individual user of a BEV, rather than optimizing average battery sizes for the whole car fleet.

It is appropriate to already here include a general reflection on this thesis. It is devoted to analyses of a field exposed to rapid technological development and then a few years can be a long time. Since the start of this thesis work in 2013 and the first data collection in 2010, BEV development has been fast. The early cars, with the exception of the longer-range and more expensive Tesla cars, typically had a battery size of around 24 kWh, such as the Nissan Leaf (model years 2010-2014), the early Renault Zoe and Volkswagen e-Golf. These short-range BEVs would yield real-world driving distances of about 120 km, dependent on weather, temperature and driving speed. At the time of this writing (Fall 2019), many cars are available with real-world driving distances of 250 km and above, such as the 40 kWh Nissan Leaf (model year 2018), and bigger batteries are coming, for example the recently announced Volkswagen ID3 with up to 82 kWh. This development have been driven by rapidly falling prices on batteries (Nykvist and Nilsson (2015)). Thus, in the earlier papers included in this thesis we are often comparing driving distances with what on today's car market would be considered really short-range BEVs of 120 km of range.

1.3 Related work

Early suggestions for potential first user groups to adopt BEVs were that they are likely to be used in large cities due to their limited range and small size (Biere et al. (2009)). Also, an early stated-preference-study in the US found that likely early adopters of BEVs are young or middle-aged, well-educated (BA or higher degree) and had made life-style changes to help the environment. The same study found no evidence that household income would affect BEV adoption

(Hidrue et al. (2011)), nor that being a multi-car household impacted the likelihood to adopt an EV. However, other studies have found that costs and range are the most important considerations for BEV adoption, such as Egbue and Long (2012). This is also in line with general knowledge that cost is one of the determining factors for vehicle choice (Bolduc et al. (2008), Horne et al. (2005), Sprei et al. (2013)). A study from Germany that used empirical data on actual early adopters, in combination with survey respondents who expressed a strong desire to purchase a BEV, found that these were middle-aged men with technical professions living in rural or suburban multi-person households (Plötz et al. (2014)). In contrast to Hidrue et al. (2011), some other studies found that multi-car households are more likely to adopt BEVs. Anable et al. (2011) focused on demographic and attitudinal variables in the adoption likelihood of BEVs and found that these cars are considered as possible second household cars. Kurani et al. (1996) also found that being a multi-car household increases the probability for adoption.

Up until 2016, the usage of GPS-based data to inform electric vehicle studies was rare. An early study was Pearre et al. (2011) who use measured data on 484 ICEVs in Atlanta USA greater metropolitan area for a period up to a year and assume that the drivers, if using a BEV, would charge once a day, and have unchanged driving patterns. In these circumstances, the authors find that 9% of the vehicles in their sample could fulfil all their driving with a BEV that had a 160 km range. Another conclusion from the paper was that the variance in daily driving distances are important for identifying suitable users of BEVs. This motivates further GPS-based driving data analysis.

Two other early studies that use multi-day GPS-based data were Khan and Kockelman (2012) as well as Tamor and Milačić (2015) who both use a GPS measured driving data set for the Seattle region in the US to investigate how BEVs can be adopted in multi-car households. Khan and Kockelman (2012) investigate the effect of replacing the car that drives the least in the household with a BEV of 160 km (100 miles) range and find that 80% of multi-car households would need to adapt their driving less than four days per year, compared to 50% for single-car households. Tamor and Milačić (2015) differ from Khan and Kockelman (2012) in assuming that the BEV will drive the longer daily trip of the two vehicles in a household, as long as this distance is below the vehicle's range. This leads to a higher electric travel distance, as well as lower travel cost for the household. Based on this assumption, they find a BEV with 100 km of range (60 miles) to obtain the same number of days per year requiring adaptation as a BEV with range 190 km (120 miles) when using direct replacement over the whole car fleet. Tamor and Milačić (2015) also compare the incremental cost of a battery with higher range to the fuel cost savings of electrifying more travel. They find that the optimal range of a BEV adopted in a two-car household is 110 km (70 miles) at a battery costs of 350 $/kWh when assuming an acceptance of three days per year of unfulfilled driving. This would then lead to BEV adoption in about 30% of two-car households.

After 2016, more studies have been published using GPS-collected driving data to analyse BEV adoption or related questions. An Italian data set consisting of 900-1000 ICE cars have been used by the collaborating authors Sodenkamp et al. (2019) and Wenig et al. (2019). Sodenkamp et al. (2019) differ from other studies in that they use k-means clustering to create segments of drivers that are similar to each other with respect to 9 different indicators in the GPS data (such as round-trip distance, speed, median parking duration, etc.). They name the identified segments as: frequent local driver, short and long distance commuter, short and long distance delivery vehicles, service provider vehicle, and company representative vehicle. The naming of the categories are based on conjecture for what types of users that would have the specific driving patterns in each group. The conclusion is that these different segments of drivers have different needs with regards to battery sizes and charging power. In Wenig et al. (2019) the authors analyse the trade-off between larger battery sizes and an extended charging infrastructure for PHEVs. Included in the trade-off analysis are several indicators such as electric drive fraction, electric reachability of destinations, grid impact and peak energy demand. They generally find that for realistic battery sizes, PHEVs do not need an extensive charging infrastructure. However, a major conclusion is also that when segmenting the users along the segments from Sodenkamp et al. (2019), the different segments can have very different outcomes on the indicators included in the trade-off between battery size and charging infrastructure.

Karlsson (2017) use the SMCD2 data (see Section 2.1) to analyse the potential to optimize the use of a BEV in two-car households. Using measurements from both cars driving in 64 two-car households he develops several strategies that could be used by the households to select either a BEV or an ICEV for intended trips in order to effectively use the BEV for the longer of these trips, without using up all the energy in the battery. When allowing for a large degree of flexibility in car choice he finds that the households can cover 75-80% of their driven distance using a BEV with medium-sized batteries (120-180 km).

GPS-measured driving data of BEVs in multi-car households has also been employed in other studies. Jensen and Mabit (2017) compare the usage of BEVs and ICEVs in 100 households in Denmark, where each household owned at least one ICEV to participate in the study. The BEV, that could be one of three different models, but all with less than 90 km driving range in practice according to the study, replaced one ICEV during the trial period, and data was gathered on the BEV for 3 months. Data was also gathered for the ICEV that it replaced one month prior to the study, and one month after the study. The researchers claim they encouraged the households to use the BEV as the primary car. The researchers conclude that the BEV is used differently compared to the CV. They find that it is used less on weekends compared to the ICEV, the BEV is also used less when there is lower temperatures and higher wind speeds, it is mostly used for shorter trips during morning peaks on weekdays.

Chapter 2

Methods and Data

2.1 A data-driven approach

This research is based on real-world data sets. Throughout the papers, we use eight data sets, of which I am the main analyst of five. Five of the eight data sets consist of GPS measured driving data, one of surveyed driving data, one of BEV user interviews, and one of charging infrastructure data. Table 2.1 contains an overview of the driving data sets used, and Table 2.2 gives an overview of the charging data used. In relation to SCMD3, interview data was gathered for 25 households both before and after the measurement period as well.

	Location	Method	Sample size	Avg. observation period
SCMD1	Sweden	GPS	429	58 days
SCMD2	Sweden	GPS	130	74 days
SCMD3	Sweden	GPS	40	103 days
MoP	Germany	Survey	6399	7 days
PSRC	USA	GPS	420	260 days
Winnipeg	Canada	GPS	72	216 days

Table 2.1: *Description of driving data sets*

Two data sets should be especially highlighted. The Swedish Car Movement Data (SCMD1) set consists of cars which were randomly sampled from the national vehicle registry and then had its drivers enquired for participation in the measurement project. Up until recently, large data sets with representative driving has not been widely available to researchers. Prior to 2014 discourse con-

Location	Number of 50 kW chargers	Avg. number of sessions / charger
Sweden	32	573
Norway	192	2011

Table 2.2: *Description of the charging data sets. The displayed data is collected from November 2015 to November 2016. Data is licensed under CC 3.0, attributed to Nobil, Enova, Norway.*

cerning BEVs in electromobility conferences and workshops tended to focus on trip distances rather than daily distances and were occasionally based on survey data that systematically under-count total driving distance (Stopher et al. (2007)). Furthermore, if one, for simplicity, consider average driving distance, either for individual drivers, or for the whole fleet, these averages tend to be below the range limitation of BEVs. However, they do not catch how often the range limitation is actually breached given current movement patterns. That we use real-world GPS measurements over several months, instead of national or fleet averages of trip or daily driving, enables us to make statements about how often individual drivers will be limited by the range of a BEV. In the context of driving data, this is a part of what we mean by maintaining a user's perspective.

The second important data set is SCMD3. This data set consists of households that are a subset of those in SCMD2 where we first measured the driving of 65 two-car households in Western Sweden. The 65 households were randomly selected from the vehicle registry for enquiry of participation with some selection criteria: the households should have a minimum of two actively used driving licences; have (exactly) two cars, of which at least one used for commuting at least 10 km one way; and the cars were restricted in terms of engine power, size and age. In SCMD3 a subset of 25 of the original 65 households were measured again, but with one car of their choice replaced by a Volkswagen e-Golf with a 24 kWh battery. This data set is, to our knowledge, unique in that we have access to the driving patterns of both cars in two-car households *before* and *during* a BEV trial. Another key feature of SCMD3 is that the data come from households who did not themselves take the initiative to obtain an electric car. Instead a selection of the original 65 households was presented with the option of doing so, to which the vast majority answered positively, and thus, cannot necessarily be considered early adopters, but instead might represent an early majority, using the terminology of Rogers (2003). In this sense, our study differs from most other travel measurements of electric vehicle users. Note however, that since the sample size in SCMD3 is quite small, the results should be considered as illustrative of possible behaviours rather than representative of car users in general.

Besides the GPS measurements in the SCMD3 data collection, we performed interviews with the household members. One interview just before the trial period started, and one when it ended. Both interview sessions were semi-structured and contained mainly open-ended questions, however they had different focus. The first session was intended to gather information on the users' expectations of BEVs in general and the trial period in particular, it also gathered information on car purchase history, regular and irregular trips that the household may do, as well as various needs that a car may fulfil for them (e.g., towing, goods or tool transport etc.). The second session focused on the experiences from the trial period, initially letting the participants guide the discussions to whichever topic had made an impression (charging, range limits, size etc.), and later on being more guided to cover relevant topics. The first interview session averaged 37 min of length, and the second session averaged 43 min of length. All but three interviews were carried out by two researchers and all but one were at the participating households' home (this interview was carried out at a restaurant). The interviews were recorded and later transcribed. Notes were also taken separately by both researchers.

These data sets have different strengths and weaknesses with respect to each other, the employed methods and the research questions put forward. The SCMD1 data set used in Paper 1 is a medium-sized data set that is intended to be representative for Swedish drivers. Therefore, we can make statements about differences between car categories such as first and second cars. However, these statements should not be considered final. One reason is simply that the average measurement period is only about two months. This means that we do not capture possible seasonal individual variation in driving that may impact, for instance, how often users drive above the range limitation[1]. Another reason is the assumptions we make in the same paper, one being that cars actually can be classified into two different car categories called 'first cars' and 'second cars'. The validity of this mental model can be discussed, and is further discussed in Paper 1. But against the backdrop of this thesis, and its overarching question "Do short-range BEVs fulfil the needs in multi-car households?" we can combine the general conclusion of Paper 1, with that of the closely connected Paper 4. Since Paper 4 also studies multi-car households, but does so without a first/second-car distinction, and also by using different data sets and methods, we strengthen the overall conclusion

[1]As measurements for different users are spread over the year, it would be possible to compare e.g. the median summer driver with the median spring driver but then we make an implicit assumption that these can be compared, and we no longer employ a strict user-perspective.

that short-range BEVs can be adopted in multi-car households.

Concerning the connection between Paper 1 and Paper 4, their different data sets and methods bestow them with different strengths and weaknesses, but they complement each other. A notable property of the method and data in Paper 1 is that aspects besides driving distances are unaccounted for, this is as it should, as the research focus in this paper is the driving range of BEVs and how well they fit in multi-car households from this perspective. However, if considering a background question, such as the one phrased in this thesis: "Do short-range BEVs fulfil the needs in multi-car households?", then this question entails other aspects than driving. Such aspects can be: possibility of home-charging, need for towing, or other unknown aspects. This can instead be studied in a BEV trial where interview data is gathered, such as the one in Paper 4. This is thus a strength of Paper 4 compared to Paper 1. Also, a main purpose of Paper 4 is to compare the actual usage of BEVs and adaptation to BEVs with our results from Paper 1. A clear downside of SCMD3 is the small sample size, and this is due to the high-cost of data gathering in this case. Due to the small sample, we can only make statements on possible adaptations in multi-car households, and not generalizations.

From a practical perspective, GPS measurements often contain broken data for a variety of reasons. A GPS may take time to find its location after the car is started and occasionally they may lose satellite reception, resulting in longer trips being cut up in sequences of small trips. The lost distance driven in the data can often be recreated due to knowledge of geographical position at start of different trips (see Björnsson and Karlsson (2015), and Jakobsson et al. (2018) for details of data cleaning in SCMD1 and SCMD3 respectively). However, this leads to a lower accuracy when it comes to single trip analysis and location analysis. Therefore, in most of the results presented we have aggregated trips to daily distances, this more often leads to accurate distance measurements on individual days since the driven distance is either not lost, or can be recreated when it has been lost. This also effectively means that we assume charging once a day in most cases (overnight charging) when we analyse the data in SCMD1 and MoP.

2.2 Research themes

2.2.1 Days Requiring Adaptation

When fully replacing an ICEV and its driving with a BEV, how easy it is to use the BEV depends on how often, and when, one would need to recharge it. In areas without public charging infrastructure, it may only be possible to recharge the BEV overnight. Therefore, it is desirable for a user that the range of the car is sufficient to last throughout the full day. From Norwegian user surveys, it was found that the possibility to charge at home at night, and not having to go to a gas station during the day, is seen as a benefit of the BEV compared to an ICEV (Figenbaum and Kolbenstvedt (2016)). Therefore, the main indicator we use to analyse if a BEVs range would be sufficient for a user is how many days they would drive above the range limitation as measured on their regular ICEVs. This quantity is denoted ‘days requiring adaptation’ (DRA), as it refer to days in which the user of the BEV would need to adapt their driving in some way (Pearre et al. (2011)). Possible adaptations could be, for instance, to recharge during the day, to move planned trips in time or between cars, to rent another car, or to use other modes of transport. The DRA measure has also been used by several other studies (see Section 1.3).

The DRA measure can be directly obtained from the daily driving distances for each car. For comparison, the DRA for a vehicle is then scaled to annual basis for all individuals in those data sets that have a long enough measurement period to perform a direct extrapolation (e.g. SCMD1, PSRC, SCMD3).

In the MoP data used in Paper 1, which has a short measurement period of seven days we have assumed that daily driving distances follow a Log-Normal distribution:

$$f(r) = \frac{\exp\left(\frac{-(\ln r - \mu)^2}{2\sigma^2}\right)}{r\sqrt{2\pi}\sigma} \tag{2.1}$$

From this, the probability for a DRA can be calculated as the integral summed from the range limitation to infinity: $\int_L^\infty f(r)dr = 1 - F(L)$. The annual number of DRA can then be scaled up as $D(L) = 365(\frac{n}{N}(1 - F(L))$ where $\frac{n}{N}$ is the share of driving days in the measurement period. Note that the assumption of a Log-Normal distribution is further discussed in Section 3.2 below.

2.2.2 BEVs in multi-car households

When BEVs are adopted in multi-car households, there are possibilities to alleviate or circumvent the range limitation. The line of argumentation builds on two assumptions. The first assumption is that these households have cars for different purposes; where one car is used for towing, longer trips, and when transporting more people, while another car is used for shorter everyday trips. The second car usage scenario could then be satisfied by a short-range BEV more easily. The second assumption is that households may be able to shift trips between the cars to circumvent the range limitations of the BEV.

Investigation of these two assumptions requires different types of analysis. The first assumption that BEVs may be more easily adopted as a second car in two-car households without any adaptation requires driving pattern analysis of ICEVs in such two-car, or multi-car, households. This is the topic of Paper 1, which analyses the SCMD1 and MoP data from this perspective. Note though, that it is reasonable to assume that some adaptation may be easily done by the households (such as charging at work, shifting some trips between cars, etc.). An analysis akin to Paper 1 is thus a conservative estimate for how well BEVs may be adopted in multi-car households. An alternative approach is to focus on the second assumption, that households can shift trips in-between the cars in the household. An analysis which optimizes such shifting could reveal a high possibility for short-range BEV adoption in two-car households. Such analysis has been done on the SCMD2 data in Karlsson (2017). However, it is unlikely that a household will do such an optimization based on the distances and point of times for the driving only, as various needs from cars, such as trunk size, towing, sense of personal ownership of the car etc. may play a role in car choice for different trips. Thus, an optimization of trip shifting may correspond to an optimistic, or upper-bound, assessment of how well short-range BEVs can be adopted in two-car households.

To get a sense of where the middle-ground of these approaches may lie, a more user-centered approach, where we observe the actual use of a BEV in two-car households, is required. This is one of the topics of Paper 4, which utilize the SCMD3 data in combination with the SCMD2 data to investigate how two-car households adapt to the use of a short-range BEV. Besides GPS data analysis, in Paper 4 we also utilize the pre- and post-trial interviews that were done in connection with the SCMD3 data gathering. We are thus able to compare the experienced driving need fulfillment with the expected driving need fulfillment from analysis of SCMD2.

In Paper 5 we extend the traditional GPS-based analysis that focuses on driven distances to also include a focus on reached destinations. The motivation for this is that we know that a number of factors beyond trip distance impact which car a user selects for a specific trip. This was also evident in the interview material presented in Paper 4, where a few possible motivations were: a sense of personal ownership over a specific car, a need for towing, and large trunk size. Which motivation that determined the choice of car for a specific trip cannot be consistently revealed by GPS data, neither with distance analysis nor with destination analysis. But extending the analysis beyond distance may provide additional information on how cars are used. Also, with our case study of comparing the usage of BEVs with ICEVs in two-car household, we may reveal if there are additional systematic differences in the usage of these two car types.

Part of the study in Paper 5 is exploratory, with the intent to investigate how a destination-based analysis can be used to complement distance analysis when exploring BEV adoption in two-car households. We thus have a research question consisting of two parts: "What destination-based measures can be used to analyse the usage of BEVs and ICEVs in two-car households?", and, "Do destination-based analysis contribute added understanding to how BEVs are used in two-car households compared to the traditional distance-based analysis?"

2.2.3 Probability distributions for daily driving distances

As described in Section 2.2.1, we use a Log-Normal distribution to model the daily driving distances for the MoP data in Paper 1 (see Table 2.1). As briefly outlined in this paper, this choice is not obvious, and there are several distributions that could be considered for modelling daily driving data. With access to data sets with longer measurement period and a decent sample size, such as SCMD1, PSRC and the Winnipeg data, we can test whether this probability distribution is a good choice, which is the topic of Paper 2.

The choice of distribution may be crucial when applied to electric vehicles. Specific interests may here be in either days requiring adaptation for BEVs, or electric drive fraction for PHEVs. These measures are mainly influenced by particularly long, and short, driving, respectively. The choice of distribution would mainly affect predictions of long distance (the tail of the distribution) and short distance driving.

Earlier literature has argued that driving distance data follow peaked and right-skewed distributions, such as the Weibull, Log-Normal and Gamma distributions. Specifically, Greene (1985) and Lin et al. (2012) analyse two data sets and argue that the Gamma distribution is the most suitable for driving data. However, there have also been other findings. Blum (2014) and Plötz et al. (2012) argue that the Log-Normal distribution provides the best fit for most drivers. Thus, research is required to judge not only the overall best distribution for driving data, but also to investigate the effects of choosing one distribution over another for common measures relating to electric vehicles. These two questions are treated in Paper 2 where the Log-Normal, Weibull and Gamma distributions are compared to each other and to empirical data with respect to the DRA and EDF measures.

2.2.4 Usage of charging infrastructure

An alternative to focus on multi-car households to deal with the range limitation, as explored in Papers 1 and 4, is to extend the range by usage of public charging infrastructure. Public charging can either be slow (below 50 kW) or fast (50 kW or higher). The slow and fast chargers serve different purposes in that the slow ones are more usable when a car stands idle for several hours at a specific location, such as work, therefore this type of charger is sometimes referred to as a 'destination charger'. The fast chargers instead best serve their purpose in situations where a user would not want to stay more than approximately half an hour, such as for a meal or at a viewpoint along a highway, thus functioning to extend the range of a BEV. In Paper 3 which analyses fast charging, my co-authors developed a queuing model for estimating the needed number of fast chargers in Sweden and Germany. Such a model is valuable because it can give an estimate of number of chargers, rather than the position of chargers which most earlier work have focused on (Chen et al. (2013), Ge et al. (2011), Lam et al. (2013)). However, a model needs input data and to be verified to be reliable. My contribution to the paper has been to analyse charging data from fast chargers in Sweden and Norway to function both as input to the model, and as verification of the model output. In the paper I also present some general statistics of charging infrastructure usage in Sweden and Norway as of 2016. The data is made available under a CC3.0 license by Nobil, Enova, Norway (Nobil (2015)). I have also contributed pre-processing and aggregation of the SCMD1 data that is used together with the MoP data to determine the re-charging need of the vehicles in the model.

A full description of the queuing model is available in Paper 3. Two aspects of the charging data is used as input: first, the identified distribution form for length of charging times, and second, the distribution of charging over the times of the day. One aspect is used to verify the model output, this is the distribution of inter-arrival times at charging stations. Additionally, the variation in empirical charging distribution over the year is used to inform the discussion of the model results. Note that the charging data cannot provide us with inter-arrival times, it can only yield inter-plugin times. However, the fraction of new connections that happen closely in time (< 5 min) after a prior plug-out is very small; it is 1.2% in the Swedish data, and 2.5% in the Norwegian data. Therefore, inter-arrival times can be reasonably approximated by inter-plugin times.

In Section 3.3 I present an overview of the more important results from the charging infrastructure data used in the paper.

Chapter 3

Research Summary

3.1 Battery Electric Vehicles in Multi-Car Households

This section contains results from Papers 1, 4 and 5, each dealt with in a separate sub-section.

3.1.1 Paper 1 - Are multi-car households better suited for battery electric vehicles?

While using a short-range BEV, and given no adaptation compared to conventional car usage, a large fraction of users will have problems fulfilling their driving needs. Figure 3.1 uses the SCMD1 data and shows the share of users with a certain number of days requiring adaptation (DRA), that is, days where they would drive over the range limit, w.r.t. range. For a common range of 120 km a majority of users would need to adapt at least once a month, with more than 20% adapting more than once a week. The group with no DRA increases approximately linearly with range, adding another two percentage units per extra 10 km of range. Specifically, a BEV with 230 km of range would be needed for half of the users to fulfil all their driving, and 400 km would be needed for 79% of the users to fulfil all their driving. This raises the need to identify specific user groups where driving need could be more easily fulfilled.

In Paper 1 we address the following two questions: 1) Are the second cars in a multi-car household better suited as BEVs from a driving pattern point of view? 2) Taking into consideration total cost of ownership, are these BEVs economical compared to conventional vehicles? Here we define first car as the car in a house-

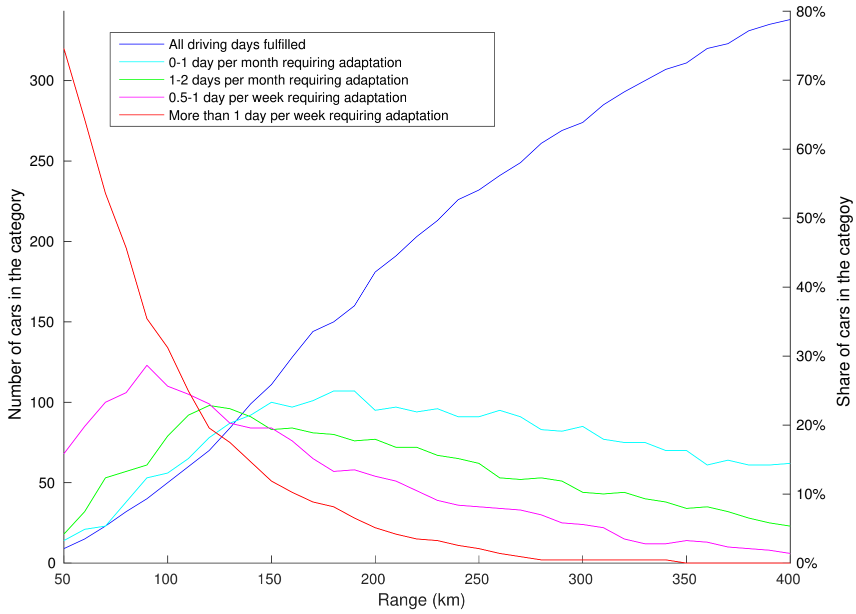

Figure 3.1: *Share of cars with different number of DRA as a function of range in the SCMD1 data. The categories are: cars that fulfil all driving (blue), cars with 0-1 DRA per month (cyan), cars with 1-2 DRAs per month (green), cars with 0.5-1 DRA per week (magenta), and cars with more than 1 DRA per week (red).*

hold that has the highest annual VKT, while second car is the car with a lower annual VKT.

Figure 3.2 shows the share of users with no DRA, and with up to 12 DRA per year separated on first car, second car, and all cars[1] in the SCMD1 data. The group with 12 DRA per year thus represents a group that has to accept some adaptation of their driving. Here it is clear that second cars are better suited to be replaced by BEVs compared to first cars, for a range of 120 km, around 30% of second cars fulfil all their driving compared to first cars, where only 5% fulfil all their driving. It is also noteworthy that a focus on second cars only, would yield as high user shares that fulfil all their driving as a focus on all cars accepting adaptation for 12 days per year.

However, second cars are by definition those cars that have a lower annual VKT. There is thus a possibility that a focus on cars with low annual VKT would

[1] All cars include all cars in multi-car households as well as cars in one-car households

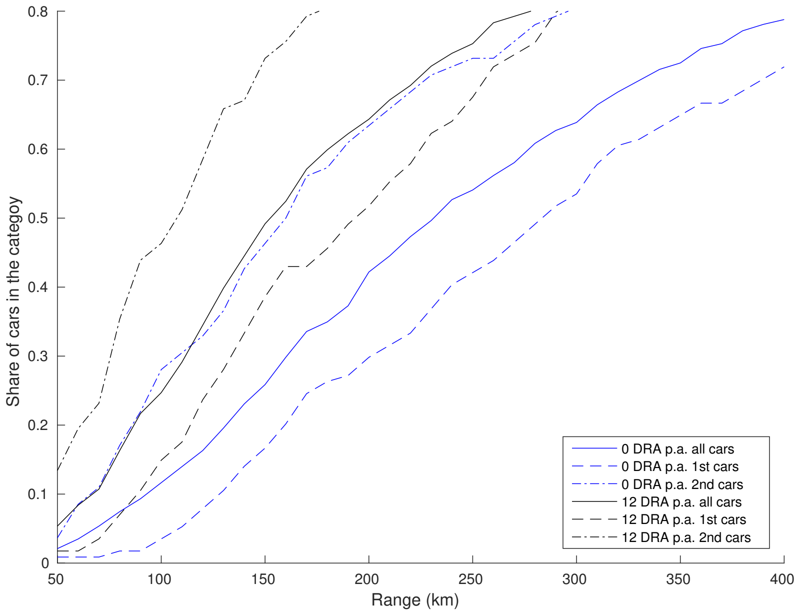

Figure 3.2: *Share of vehicles w.r.t. range for an adaptation acceptance level of zero days, as well as maximally 12 days per annum (blue lines, black lines, respectively) for first cars, second cars and all cars (dashed line, dashed-dotted line, and full line, respectively), SCMD1 data.*

be an as good, or better, group for adopting BEVs. This is undesirable since a BEV has a high investment cost and a low operational cost. It would be better if cars with a high annual VKT should be replaced by BEVs, as these could more easily economize compared to conventional cars. To investigate this, we calculate the total cost of ownership (TCO) for using a BEV, a gasoline car, and a diesel car, for users that have driving patterns according to SCMD1. Important aspects of this calculation are that we impose a cost for DRAs reflecting the cost of a rental car, a cost per kWh for the battery, and that we use economic parameters for 2020, as they were projected by a national investigation into clean transport in Sweden (SOU (2013)) in 2013. The inclusion of a cost for DRA means that cars not only need a high annual VKT, but also a low number of DRAs to economize as BEVs. It is also notable, that the economic conditions in Sweden are significantly more favourable to BEVs than in Germany. This is due to an included direct subsidy in Sweden, as well as cheaper electricity and more expensive gasoline and diesel compared to Germany. In Figure 3.3 is shown the cumulative share of first cars, second cars, and cars in one-car households (single cars), that have a lower TCO when using a BEV compared to the cheapest alternative of a gasoline and diesel car w.r.t. accepted number of DRAs for a range of 120 km. The SCMD1 data is displayed in the left sub-panel and the MoP data in the right sub-panel. In both cases the second car performs better than the first car, though in the MoP case both categories have very low number of economical cars due to the cheaper fuel, more expensive electricity, and lack of direct subsidy in Germany compared to Sweden. For a harsh requirement of no adaptation, almost 14% of Swedish second cars are economical as BEVs.

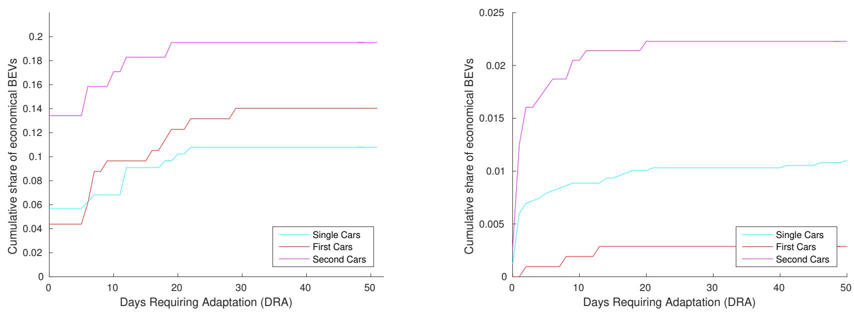

Figure 3.3: *Share of economical BEVs w.r.t car category and less than specified number of DRA. The shares are calculated as quotients of all cars in a specific car category using a range of 120 km. SCMD1 results to the left, MoP results to the right.*

The result from Paper 1 shows that in the general car fleet, a low percentage of cars would fulfil their driving needs. However, for second cars in multi-car households, a more substantial share (30%) of cars fulfil all their driving. When imposing a high cost for DRAs, i.e., equal to the cost for renting a car for these days, for almost 14% of second cars a BEV would have a lower TCO than a conventional car. This means that given range limitations of around 120 km, a focus on multi-car households is warranted.

A reasonable criticism against Paper 1 is that 120 km is a quite low range to assume for BEVs in 2020. However, this range category will remain relevant in the future as well. Even though cost for batteries may decrease over time, they will remain a large part of the full car cost. Large batteries that can run a car for 300 km or more may not be relevant in all usage scenarios. In those cases it may be desirable to keep the car investment cost low. Our results will thus remain relevant to highlight that different battery ranges will have market potential in the future. Furthermore, there may be usage scenarios, such as driving in a cold climate, where specific battery technologies could be desirable. For instance, Ni-MH batteries are about twice as heavy per kWh compared to Li-Ion, but perform better in cold climate. The knowledge that low range is sufficient in some cases can facilitate the use of these alternative battery technologies.

3.1.2 Paper 4 - How do users adapt to a battery electric vehicle in a two-car household?

In Paper 4 we utilize the GPS-measured SCMD2 and SCMD3 data together with the semi-structured open-ended interviews performed before and after the BEV trial in SCMD3. Specifically we have one general research question, followed by four sub-questions:

How do two-car households adapt to a battery electric vehicle?

- RQ1. How well do a BEV fulfil the driving *needs* of the households?
- RQ2. What are the *experiences* of everyday BEV usage?
- RQ3. How do households *adapt* their driving patterns to a BEV?
- RQ4. How can the quantitative adaptation be *explained* using the qualitative data?

We answer the questions through a mixed-method approach using the quantitative and qualitative data. Firstly, we combine results from simultaneous GPS measurement of both cars' driving in two-car households using a BEV in combination with a conventional car with in-depth open-ended interviews on the experiences of the car users in these households (SCMD3 and interviews). Secondly, we combine this SCMD3 GPS data with similar earlier GPS measurements in the same households while they still were using two conventional cars (SCMD2). Thus, we can identify how the users' driving patterns changed when they used a BEV in combination with one of their conventional cars. This adaptation in driving is then also compared to the users' experienced changes based on the interview data. Here I will focus on results related to RQ3 and some results related to RQ4, as these aspects are unique for our research. Answers to all the questions, and a more exhaustive answer to RQ4 is available in Paper 4.

In order to judge how much, and in what way the households change their driving behaviour (i.e. RQ3 above) we have analysed the distribution of daily driving distances. As in Paper 1, we aggregate driving distances to daily basis and compare the driving distances between the household car types. Figure 3.4

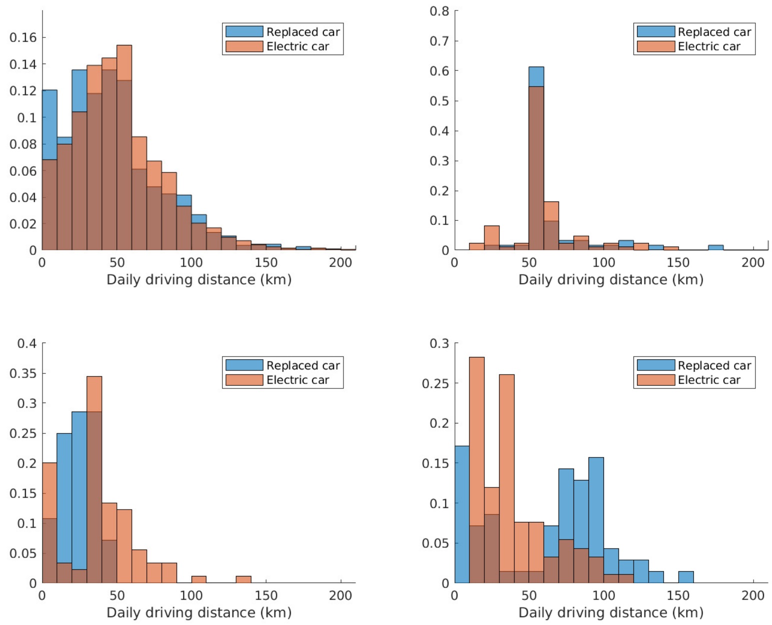

Figure 3.4: *Distribution of daily driving distances for the BEV and the replaced car. The top left figure displays the average of all ten households, the other three figures display some typical results. Blue colour marks the replaced car, light brown marks the electric car, and dark brown shows overlap between the two car types.*

shows these distributions of daily driving distances as normalized histograms for the electric car and the conventional car it has replaced, respectively. The top left sub-panel shows the average distribution over all the households, while the other sub-panels contain three interesting individual results. In the top left sub-panel we can see that there is a tendency for the BEV to take driving tasks within a fairly narrow range of around 40 km to 90 km, while the replaced car increases its driving in the other ranges. Thus the electric car, when compared to the replaced car, both reduces the amount of long distance trips (90-140 km) and increases the number of short distance trips (0-40 km). This might represent both an effect of range anxiety and a wish to utilize the BEV more. The top right figure shows an example of a household that to a large extent keeps the same driving distances for the BEV as for the replaced car; this is also a case of a typical commuting car. The bottom left and bottom right contain households where the electric car to a large extent has increased and decreased driving compared to the replaced cars, respectively. Most households have behaviours in-between these three examples, however the three examples show the heterogeneity of behaviour.

By extrapolating the driven distances in the two measurement periods to annual driving distances we can obtain the fraction of total household distance driven by the BEV in the SCMD3 data, and the corresponding fraction for the replaced car in the SCMD2 data. This, as well as the ratio between them, are shown in Table 3.1. In just over half the cases, the fractional change in driving due to the adoption of a BEV is small, with seven households having a change below 5%, and an additional five between 5-10% change. In these two groups there are also three households that lowered the share of driving of the electric car compared to the replaced one. Of the remaining households, two have a substantial decrease in driving on the electric car compared to the replaced car, with 22% and 44% reduction respectively, while five have a substantial increase of 12% to 42%. Finally, there is a substantial outlier with an increase of 159%.

When interpreting the results relating to RQ3 from Paper 4, we see that the degree of adaptation differs between households. This has implications for how to interpret the results of Paper 1, where the results from Paper 4 suggest that different vehicles in Paper 1 would differ in how many DRA that they can accept. Similarly, the results from Paper 4 suggest that the vehicles in the economic analysis in Paper 1 would have different costs for DRA. However, to understand how many vehicles that would accept a certain number of DRA, a study similar to Paper 4 would need to be redone with a larger sample size.

When combining results from the driving data with the interview data (i.e. RQ4), we find two important results. Some households state that they prefer to use the BEV over the ICEV, but such a preference may not be visible in the driving data for these households. Thus, interviews are unreliable predictors of how households actually are driving. Secondly, according to interviews, no households had experienced that the range limitation forced them to abstain from trips they otherwise would have done. Only one household had abstained from a trip partially due to the range limitation, but that they had other reasons for not performing the trip as well. However, driving data analysis found that only 40% of the analysed households had no DRA during the SCMD2 measurement period (assumed BEV range of 130 km). Thus, ICEV driving data analysis of how well a BEV would fulfil a household's driving needs may suggest that it is harder for the household to adopt a BEV compared to what the household's experiences would suggest. Or, interpreted differently, analysis of driving data may assume that households can accept a higher number of DRA than previously thought.

Household	Electric car	Replaced car	Fractional Increase
1	34%	33%	3%
2	40%	30%	33%
3	67%	50%	34%
4	45%	57%	-22%
5	41%	73%	-44%
6	65%	63%	2%
7	44%	42%	6%
8	35%	34%	4%
9	31%	29%	9%
10	43%	47%	-7%
11	59%	52%	12%
12	58%	63%	-8%
13	58%	59%	-2%
14	52%	20%	159%
15	49%	48%	2%
16	59%	54%	9%
17	46%	40%	17%
18	56%	40%	42%
19	32%	32%	0%
20	35%	35%	0%

Table 3.1: *Share of total household driving distance taken up by the EV in the evaluation period, the replaced car in the comparison period, and the fractional increase of driving for the EV compared to the replaced car.*

3.1.3 Paper 5 - A destination-based analysis of electric, and conventional, cars in two-car households

In this paper we find, in addition to the results from Paper 4, that there is heterogeneity in how cars are used in the households. In Figure 3.5 the number of trips to each of the ten most common destinations are displayed for both cars for four example households. The households are chosen to display different observable behaviors among all 20 households. For all households, both cars have the same most common destination (which is the home in all cases), while the patterns vary for the remainder of the destinations. In the top-left panel we see an example of a highly regular choice of car for each destination, where destination 2 and 3 are visited close to exclusively by one of the cars. In this case, destination 2 and 3 may be the household's two work locations. The top-right panel shows a similar pattern, but with another destination besides the home that is the second most, and equally, common for both cars; perhaps an additional stop each day that is inter-changed by the drivers, such as picking up a child from day-care. The bottom-left panel is an example of a household that prefers to use the electric car for all destinations, and thus probably exhibits a large amount of car shifting between the two adult members of the household. The bottom-right panel is an example of a household where all destinations are visited more equally by both cars. Thus, we observe heterogeneity in how households utilize their cars for their most common destinations, with some appearing to prefer the BEV for all destinations, while others show a strong preference for one of the cars for specific destinations.

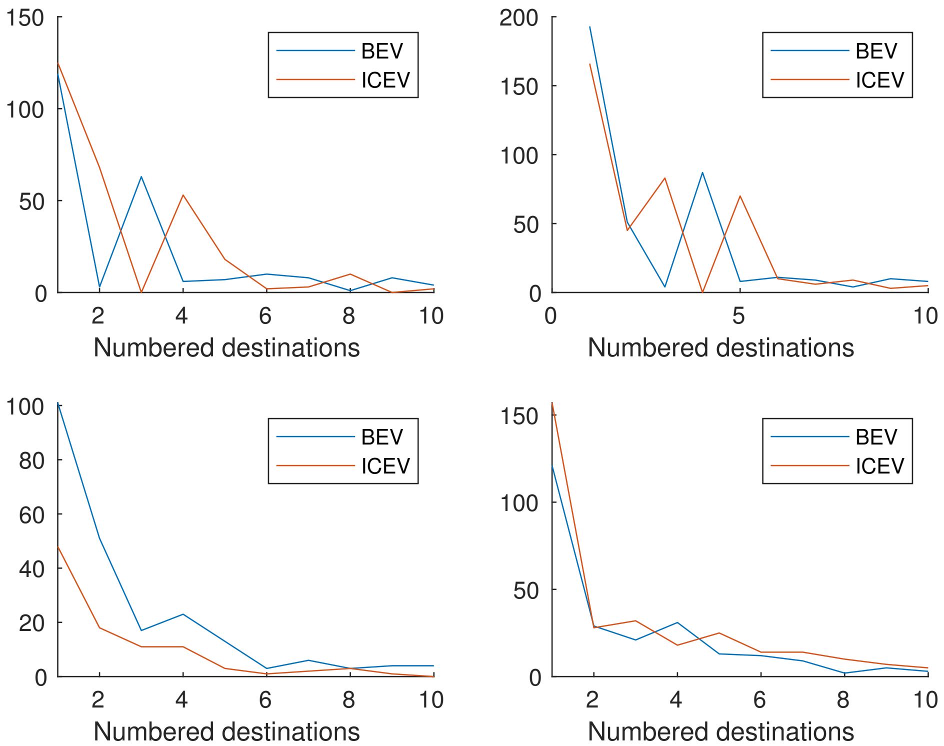

Figure 3.5: *For four households, number of visits by each car type to the household's ten most common destinations, ordered according to number of total visits. The top-left panel is household 12, top-right is household 5, bottom-left is household 11 and the bottom-right is household 8.*

In Figure 3.5 we also see that it is common for the users to drive a large part of all their trips to a few very common destinations, with the remainder of the destinations having few visits. This raises a question of how much of each household's driven distance is made up of the most common destinations. It may be that a user visit several destinations in a sequence before returning home. To investigate this we need to calculate how far they drive on sequences consisting of the most common destinations, instead of just the one-way distance to the most common destinations. We denote such a sequence of trips a trip "chain".

The answer is displayed in Figure 3.6 where the cumulative share of driven distance for all chains that consist of *only* the x most common destinations where x is increased along the x-axis is shown. Again we observe a large heterogeneity, where 4 BEVs and 1 ICEV drive more than 50% of their total distance on chains consisting only of their 5 most common destinations (4 most common destinations plus the home). While at the same time 4 ICEVs drive less than 10% of their total distance on chains including only the 5 most common destinations, with an additional ICEV and a BEV driving marginally more than 10% of their total distance on the 5 most common destinations.

We can also observe an overall tendency that BEVs drive a larger share of their total distance to fewer destinations compared to the ICEVs. This is supported by a two-sided Wilcoxons signed-rank test with the null hypothesis that the distribution of the share distance driven on all chains consisting only of the x (same as in Figure 3.6) most common destinations for the 20 BEVs, subtracted by the same for the 20 ICEVs, have median zero. This null hypothesis is rejected at the 5% significance level for each individual $3 \leq x \leq 10$, while it is not rejected at the 5% significance level for $x \leq 2$. This implies that there is a difference of how large share of their total driving that BEVs and ICEVs do on chains including only their most common destinations. Note that these results should be interpreted cautiously, as the sampling period over the year for each individual household may be important, i.e. if vacation trips are included or not.

Thus we can obtain additional insights in our case study of BEV adoption in two-car households using destination analysis as a complement to distance analysis. Such as recognizing the heterogeneity in household behavior from this perspective, and that BEVs drive a larger fraction of their total distance to destinations closer to home.

3.2 On the distribution of daily driving distances

The reasons that probability distributions have been used to model driving data is that time-series for driving have historically been short, negating the possibility to

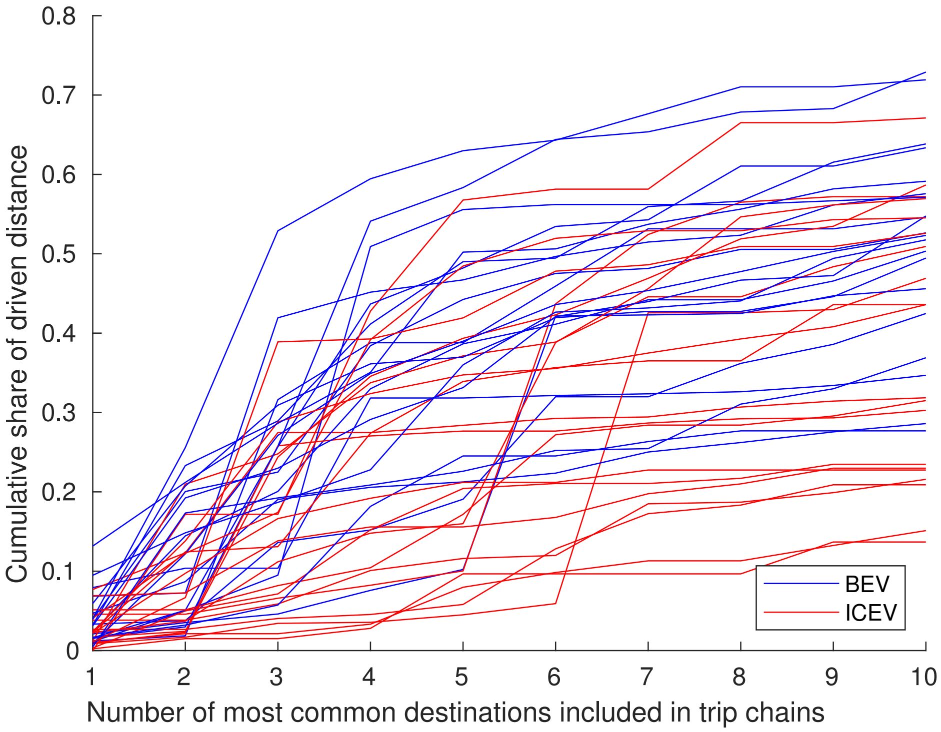

Figure 3.6: *Cumulative share of distance driven on all trip chains consisting only of the most common destinations, where the x-axis is the number of destinations that is considered most common.*

do direct empirical extrapolations. With our access to driving data gathered with longer measurement periods, we can now check how well different probability distributions actually model driving data. We do this with respect to the important measures DRA and electric drive fraction for BEVs and PHEVs respectively.

In this study, we use four data sets to analyse three probability distributions with respect to daily driving data. The distributions analysed are Log-Normal, Weibull and Gamma:

$$Log-Normal: f(r) = \frac{\exp\left(\frac{-(\ln r-\mu)^2}{2\sigma^2}\right)}{r\sqrt{2\pi}\sigma} \tag{3.1}$$

$$Weibull: f(r) = \frac{k}{\lambda}\left(\frac{r}{\lambda}\right)^{k-1}\exp\left(-\left(\frac{r}{\lambda}\right)^k\right) \tag{3.2}$$

$$Gamma: f(r) = r^{k-1} \frac{\exp(-\frac{r}{\theta})}{\Gamma(k)\theta^k} \tag{3.3}$$

The data sets used for analysis is SCMD1, PSRC, the Winnipeg data, and the MoP data. The data sets have complementary properties in that The MoP data set has a large number of users and short measurement period, the Winnipeg data have few users, but a long measurement period, and the SCMD1 and PSRC data fall in-between these. That the data sets are from different countries with different geographical settings make our results more robust. As outlined above, we focus on the following two questions:

- Which is the best overall distribution for daily driving data?
- What consequence does the choice of one distribution have on the results obtained when calculating electric drive fraction for PHEVs, and days requiring adaptation for BEVs?

We estimate the parameters for the probability distributions by maximum likelihood estimates. In order to judge the best overall distribution, we employ four Goodness of Fit (GOF) measures. These are the:

- Akaike information criterion: $AIC = -2LL + 2(p+1)$, p is the number of model parameters and LL the log-likelihood.
- Root mean squared error: $RMSE = \sum_i \sqrt{\frac{(y_i - f_i)^2}{n}}$.
- Mean absolute percentage error: $MAPE = \sum_i |\frac{y_i - f_i}{f_i}|/n$.
- χ^2 statistic: $\chi^2 = \sum_i \frac{(y_i - f_i)^2}{f_i}$.

Where n is the number of driving days, y_i the observed and f_i the expected value at r_i. We calculate the GOF for each driver in each data set separately.

Table 3.2 shows the share of users for which a given distribution performs best according to each of the four GOF measures for the four data sets. Contrary to earlier research, we find a low performance for the Gamma distribution, and a high performance for either the Log-Normal distribution or the Weibull distribution depending on the data set used.

To analyse the second question above we calculate the number of DRA for each distribution. Confidence intervals (95%) are generally calculated as Clopper-Pearson intervals, the exception is mean and median calculations for the DRA and

EDF estimates where they are calculated by BCa bootstrap. Electric drive fraction is calculated by simulating 50 000 driving days for each user and distribution. The resulting individual EDFs are then used to form mean and median EDFs, as well as shares of users with more than 50% and 80% electric drive fractions.

The full results tables can be observed in Tables 5-8 in Paper 2. Though there are various differences among the distributions, the most notable is that in prediction of share DRA Log-Normal differs more from Weibull and Gamma, than Weibull and Gamma do from each other. What should be especially noted, is that Log-Normal estimates a higher fraction of DRAs than Weibull and Gamma. As an example, consider the share of users with DRA<1 for a range of 150 km in the SCMD1 data. Log-Normal predicts 7.9% of these users to have so few DRA, while Weibull and Gamma predict 21.2% and 17.5% respectively. Thus the choice of distribution has a large impact on results when considering DRA. If one wishes to have a conservative estimate of the number of users who would be able to fulfil their driving with a BEV, one might choose to model driving data with the Log-Normal distribution. It should also be noted that the Weibull and Gamma distribution to a larger extent agrees with the empirically measured data.

Similarly, for the EDF of A PHEV the Log-Normal differs more from the other distributions, compared to how much Weibull, Gamma and the empirical calculations differ from each other. Log-Normal consistently estimateS lower EDF than the other distributions and the empirical calculation. This means that a researcher interested in a conservative estimate of the EDF might wish to choose the Log-Normal distribution over the others. However, that the other distributions and the empirical calculation gives similar results hints at that they may give a more accurate prediction of what the electric driving share would be for these users, if they were provided with a PHEV.

With these insights from Paper 2, the results in Paper 1 on the MoP data should be considered as conservative estimates for how many users short-range BEVs would be suitable.

3.3 Fast charging infrastructure for BEVs

In this study we estimate the size of a future charging infrastructure network in Sweden and Germany using a queuing model. Here I will present my contributions to this work, which is to analyse existing charging infrastructure data to provide input to the model, and verify the output of the model.

We use charging data from Sweden and Norway separately, and limit the data to that which was measured from November 2015 to November 2016 to get exactly one full year, while also limiting the effect of increasing usage of the network that otherwise may distort the results.

In the queuing model we assume normally distributed charging times. This can be compared with the empirical charging times from the data. These are available in Figure 3.7, where kernel density estimates (KDEs) of the empirical data are plotted together with a fitted normal distribution with a cutoff at 35 min, which is the time it would take to reach a full charge on short-range BEVs. As is seen in the figure, a normal distribution is not a perfect match to the empirical data. However, the peak of the distribution (the mean), and the spread of the distribution (the variance) are positioned somewhat similarly to the KDEs. These are the two parameters that are relevant for our model, thus the normal distribution predicts these parameters well. In comparison, other distributions, which better account for tail probabilities (such as Weibull and Log-Normal) do not center the peak of the distribution well. Further, it is more important to have a good fit for the mean and the variance, rather than distribution tails, since long charging times reflect users that let their vehicle remain connected to the charging point well after they have been recharged (given current battery sizes).

The queuing model also assumes exponentially distributed inter-arrival times. Figure 3.8 shows empirical inter-plug-in times. As is clear from the figure, there is an important day-night influence on arrivals with fewer arrivals to charge at night and more arrivals at daytime. Norway, which has denser arrivals compared to Sweden, also has more exponentially distributed inter-arrival times, in line with the model assumptions. We interpret this as suggesting that the exponential distribution can be a good choice in a more mature electric vehicle market, especially when focusing on the rush hour demand, but it may be less good in less mature markets.

3.4 Synthesis of research results

In this section I will consolidate common topics among the papers. Paper 1 has often formed the basis for ideas that are explored in the later Papers. This is especially true for Paper 2 and Paper 4, and to some extent Paper 5. Therefore, I will highlight some of the connections between these papers below.

In Paper 2 the consequence of choosing a Log-Normal distribution to model the MoP data, similarly to what was done in Paper 1, is tested and we find that Log-Normal may predict too many DRA compared to what a larger empirical data set would give. Thus, potentially altering some of the results in the paper. If the over-estimation of DRA is even among first cars, second cars, and cars in one-

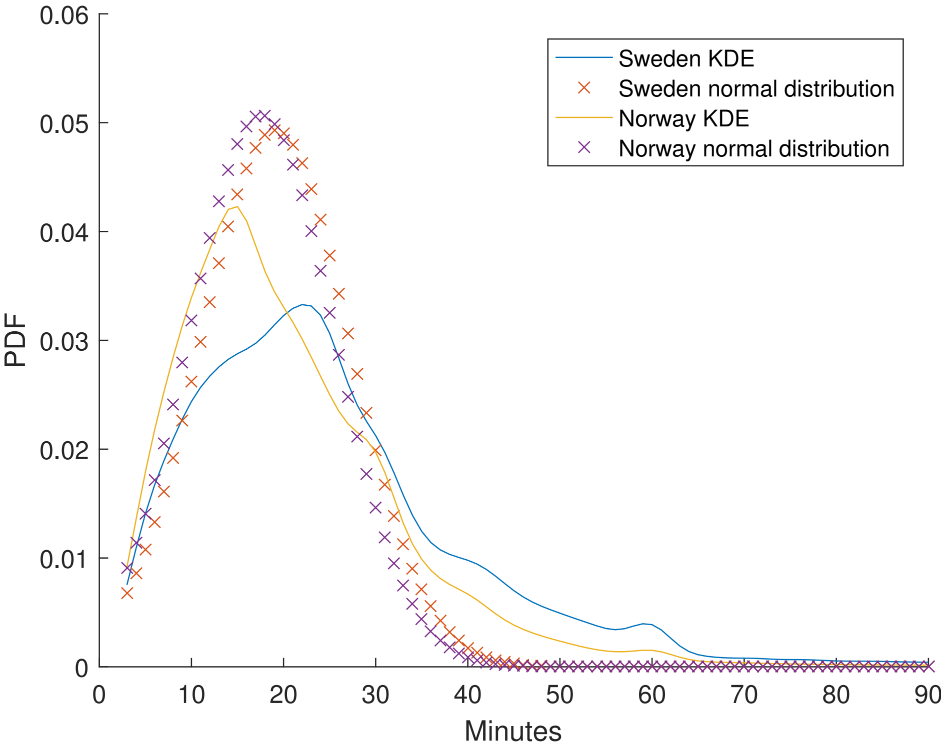

Figure 3.7: *Charging time distributions for Sweden and Norway. The solid lines are empirical KDEs. The crosses are the fitted Normal distribution where only data points below 35 minutes charging time have been included.*

car households, then this will not impact the two main conclusions of the paper: that second cars have fewer DRA, even at the same annual VKT, compared to first cars and to cars in one-car households; and that the second cars more often have a lower total cost of ownership as BEVs than as ICEVs compared to first cars and to cars in one-car households. However, modelling will be required to know if there is a relevant difference between the over-estimation of Log-Normal on the first cars, second cars and cars in one-car households. Note though, that for the SCMD1 data, probability distributions were not used in Paper 1, and this data also supports the conclusions of the paper.

In Section 2.2.2 I describe how Paper 1 and Paper 4 are closely connected. With the results from Paper 1 alone, we do not know what reasonable acceptance levels for DRA are, but we can observe in a medium-sized sample how many DRA different cars have. In Paper 4 we have a much smaller sample, but we

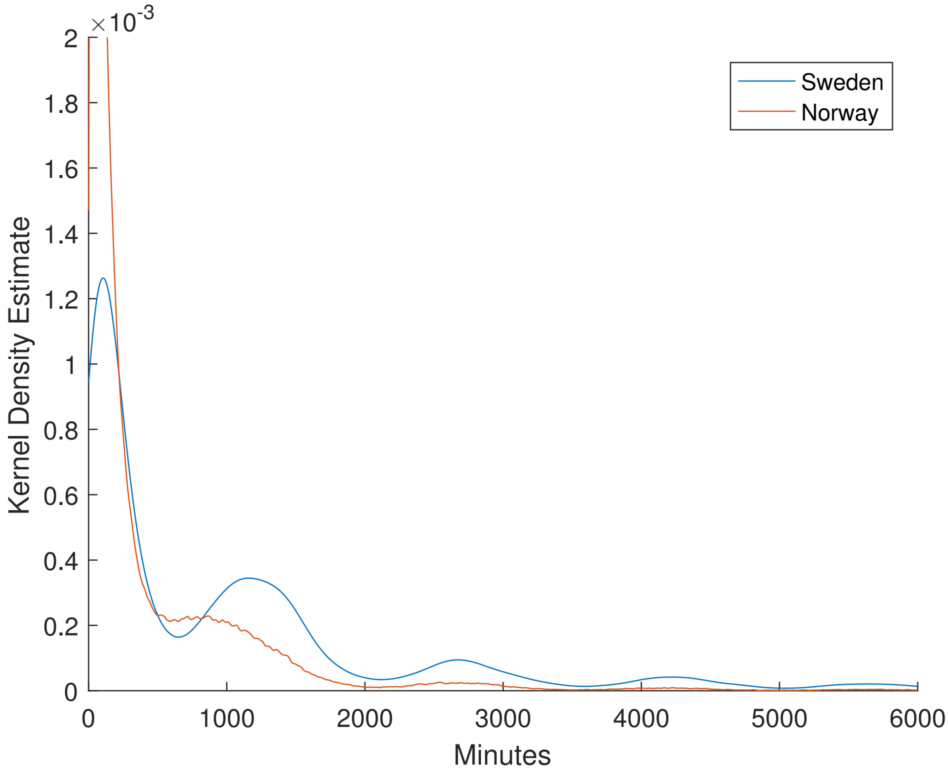

Figure 3.8: *Kernel density estimate for inter-plug-in times for Sweden and Norway.*

know both the number of DRA for both cars prior to the BEV trial, and the experience of the effect of the range limitation on driving needs. From Paper 1 we can observe that the households included in Paper 4 have slightly fewer DRAs compared to the average in Paper 4 (Table 2, Paper 4). This may have made it easier for the households there to experience problems with the range limitation as little as they did, thus increasing their appreciation of the BEV compared to what users in another, or bigger, sample might have experienced. However, from Table 2 in the same paper, it is still clear that, on average, they are able to adapt to some number of DRA, as only 40% of the households have no DRA on the replaced car. A possible comparison may be that in SCMD1 between 50% and 60% of the users of second cars have less than 1 DRA per month (Paper 1, Figures 4-5), while in the SCMD3 interview data, 15 out of 25 households (i.e. 60%) think that the range limitation was a minor problem in practice. (With an additional 2 households thinking it was a minor problem, but speculated it may be more of a problem in winter) Thus these two data sets together suggest that short-range BEVs may be sufficient for a slight majority of the second cars in two-car households.

GoF	MoP			Winnipeg			SCMD1			PSRC		
	ln N	W.	Γ	ln N	W.	Γ	ln N	W.	Γ	ln N	W.	Γ
AIC	32.3%	**59.9%**	7.8%	**40%**	35%	25%	34.7%	**39.2%**	26.1%	14.8%	**72.9%**	12.4%
RMSE	**74.0%**	12.5%	13.5%	**36%**	35%	29%	**43.6%**	37.3%	19.1%	35.7%	**36.4%**	27.9%
χ^2	**88.2%**	9.1%	2.7%	17%	**41%**	**41%**	29.6%	33.8%	**36.6%**	**68.3%**	18.3%	13.3%
MAPE	**75.2%**	21.9%	2.9%	9%	**51%**	40%	19.8%	**44.5%**	35.7%	**64.3%**	24.3%	11.4%

Table 3.2: *Summary of goodness of fit statistics. The best distribution for most users in bold face.*

Chapter 4

Reflections on this work

This thesis has presented data-driven research that has been done in order to support an introduction of battery electric vehicles into the transportation system. We have focused on a possible wider introduction of BEVs, and thus mainly kept general users in mind.

The underlying motivation for academia to interest itself in electro-mobility, and the underlying reason for society to motivate incentives to electro-mobility, is that it may bring about a more sustainable mobility system. Sustainable mobility, as a broader concept, can be contributed to by e.g. public transport, car sharing, car pools and demand management through e.g. re-designing cities (Banister (2008)). Though all of these approaches may be employed in lieu of maintaining the current car-based society, the car, as well, has its own merits. One is simply that societal structure is well adapted to the car, which means there are stakeholders, such as industry, that can be employed in the service of facilitating the diffusion of the technology. Another is that the car offers a utility that none of the other solutions fully does, which is the possibility to live away from urban and sub-urban areas while maintaining access to these areas, and vice versa. Note though, that the fact that I recognize these merits of the car, does not mean I think the car is a perfect solution that should be defended in all cases. I do, for example, question the wide use of cars inside cities, and I believe much of today's travels, especially for commuting, could, and should, be replaced by public transport. However, given the present focus on electro-mobility, let us consider some of the sustainability implications of the technology.

The two most common environmental arguments for BEVs are that they have no local emissions, thus reducing urban pollution, and that they have lower overall CO_2 emissions compared to conventional cars. The counter-argument from an environmental perspective are usually two-fold, firstly that current battery production are energy intensive and dependent on rare earth minerals that are sometimes also mined under bad working conditions, and secondly, that the overall CO_2 emissions are highly dependent on the electricity system and may not even be lower in some circumstances, such as when having coal power on the margin (Nordelöf et al. (2014)). All of these points are valid, and with continuously increasing battery sizes, these points may become more acute. With the results from this thesis fresh in mind, it may thus be reasonable to promote low-cost low-range BEVs for those user-groups where this vehicle type is sufficient. The large effect of the electricity system on BEV CO_2 emissions performance should also not be considered as a fatal flaw of BEVs. What is relevant from an electricity system point of view is not only what system we have today, but more so what system we have in 30-40 years when electric cars may have a large market share. Though it must be kept in mind that the electricity system needs to be cleaned up in tandem with larger BEV penetration of the market, otherwise the efforts to introduce BEVs will, from an environmental perspective, have been in vain.

It should be emphasized that the electric car is a technical solution to an environmental problem. Compared to a large-scale increase of public transport or demand management, it is more of an end-of-pipe solution. This means that it will retain its own problems with material use, large energy use, and a lock-in in a car-based society (Urry (2004)). If a lock-in in a car-based society is good or bad is a matter of perspective, but when it comes to material use and scarce minerals we need to keep in mind that some of these are mined under circumstances giving rise to serious concerns. As an example, in some Congolese mines child workers are used. In 2015, at least 80 miners died in these mines (Amnesty (2016)). Given the large amounts of cell-phones and laptops produced, this should not all be attributed to the electric car, though.

The automotive industry is a significant part of the economy. It directly generates 6.3% of European GDP, and even more due to ripple effects in connected industries (ACEA (2016)). A fast decline in car use would reasonably have considerable negative consequences for society on both short and semi-long term. A transition to an electric car fleet would preserve this industry and its turnover, thus disrupting society a lot less than other ways to clean up the transport sector.

At the onset of this thesis work, I experienced that two views existed of the BEV range limitation. One was that the range is too short, and that it needed to increase for large-scale BEV adoption. The other view was that the range of the BEVs of the time was sufficient for a large part of the population, and that BEV adoption was a matter of education of the public. The early work produced in this thesis then supported the view that only a minority of the population would have few DRA with short-range BEVs. With the current, actually very recent, trend of increasing battery sizes in the BEV market, a relevant purpose of driving data analysis may be to focus on reasonable upper limits of battery sizes. Such analyses not only require distance-based driving data analyses but naturally need to be done in combination with charging infrastructure sizing and placement. This therefore motivates a further development of destination-based analysis, and a thorough analysis of which of the currently existing GPS-measured data sets that are of high enough quality to enable destination-based analysis.

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