THESIS FOR THE DEGREE OF LICENTIATE OF ENGINEERING

On Battery Electric Vehicles

Driving Patterns, Multi-Car Households and Infrastructure

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CHALMERS

Department of Energy and Environment

Division of Physical Resource Theory

Chalmers University of Technology

Göteborg, Sweden 2016

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ABSTRACT

The transportation sector is responsible for a quarter of all greenhouse gas emissions in Europe. Though the transport system may be difficult to change into a less polluting system, electric vehicles may be a possible approach. For personal use, there are today different models of battery electric vehicles, and plug-in hybrid electric vehicles available. Though battery electric vehicles have the bigger potential for reducing emissions, they also have the biggest hurdle in terms of range limitation and investment cost.

In this thesis we have assessed battery electric vehicles performance as replacements for conventional cars using GPS-based driving pattern analysis. We have found that for common battery electric vehicle ranges of 120 km, a noteworthy adaptation is required for the average user. However, it is possible to specifically adopt battery electric vehicles within multi-car households to significantly reduce the need for adaptation. When applying a cost, resembling that of a rental car, for the days that the battery electric vehicle cannot fulfill the driving need of the user, close to 14% of the second cars in multi-car households would have a lower total cost of ownership as a battery electric vehicle compared to a conventional car in Sweden. We have also assessed the degree of adaptation in a small set of Swedish two-car households who adopted a battery electric vehicle for 3-4 months. Though the data set is small, it displays a large degree of heterogeneity in behavior, with some households increasing the use of the battery electric vehicle compared to the replaced car, while some decrease it, and others make virtually no change in travel behavior. Overall, we do not see a large increase in driving of the battery electric vehicle compared to the replaced car.

We have also done methodological development by analyzing 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. Additionally, for electric vehicles there are specific applications that are interesting, for battery electric vehicles: estimating the frequency of long-distance driving above the range limitation; and for plug-in hybrids, estimating the frequency of short-distance driving that may give rise to a high electric drive fraction. With regards to these applications, we find that the distributions systematically give different estimates, and that a researcher may choose distribution according to the chosen research question.

Finally, we have analyzed the usage of fast charging infra-structure in Sweden to support assumptions made for a queueing model of charging infra-structure usage developed at Fraunhofer ISI, in Karlsruhe, Germany.

Keywords: Electro-mobility, BEV, battery size, GPS-logging, individual movement pattern.

LIST OF PUBLICATIONS

I. Niklas Jakobsson, Till Gnann, Patrick Plötz, Frances Sprei, 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*, Volume 65, April 2016, Pages 1-15, ISSN 0968-090X, http://dx.doi.org/10.1016/j.trc.2016.01.018.
FS, PP and SK suggested the idea, NJ developed the research question, NJ developed the methodology with contributions from TG, PP, SK and FS, and NJ implemented the analysis on the Swedish data, TG on the German data. NJ wrote the paper with contributions from TG, FS, PP, and comments from SK. SK collected the original data.

II. Patrick Plötz, Niklas Jakobsson and Frances Sprei, On the distribution of individual daily driving distances. Working paper (2016).
PP suggested the idea, PP, FS and NJ developed the research question, PP developed the methodology with contributions from NJ and FS, NJ implemented the analysis on the Swedish and American data, PP implemented the analysis on the German and Canadian data, NJ and PP wrote the paper with comments from FS.

III. Niklas Jakobsson, Sten Karlsson and Frances Sprei, "How are driving patterns adjusted to the use of a battery electric vehicle in two-car households?". In proceedings to EVS29 Montréal, Canada, June 19-22, 2016.
SK and FS suggested the idea, NJ, SK and FS developed the research question, NJ developed the methodology with contributions from SK, NJ implemented the daily analysis, SK implemented the trip analysis, and NJ wrote the paper with contributions from SK and comments from FS.

IV. Till Gnann, Daniel Goldbach, Niklas Jakobsson, Patrick Plötz, Anders Bennehag and Frances Sprei. "A Model for Public Fast Charging Infrastructure Needs". In proceedings to EVS29 Montréal, Canada, June 19-22, 2016.
TG, DG and PP did all the work with the model, including writing the model parts of the paper with contributions from NJ and comments from FS on the writing. NJ did all the work with the charging data, including methodology, analysis and writing. AB collected the original charging data.

Relevant Publications not included in this Thesis

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

II. Patrick Plötz, Niklas Jakobsson, Frances Sprei and Sten Karlsson, "On the distribution of individual daily vehicle driving distances". In proceedings to European Electric Vehicle Congress, Brussels, Belgium, December 3-5, 2014.

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Niklas Jakobsson

Göteborg, April 2016

CONTENTS

1 INTRODUCTION

Climate change is one of the most difficult issues facing humanity. The Intergovernmental Panel on Climate Change project that global mean temperatures are likely to exceed 2 degrees Celsius by 2100 in most scenarios due to anthropogenic greenhouse gas emissions (GHG) [1]. A reduction of greenhouse gas emissions (GHG) will affect all aspects of society, one that may be more difficult to change is transport and mobility. Transport accounts for a quarter of all GHG emissions in Europe [2], in Sweden it is 30% [3]. The reasons that it may be difficult to change the transport sector is partly due to decentralized decision-making in the sense that many individuals need to collectively transition to more sustainable solutions such as electric vehicle usage and biofuels, and partly due to strong lock-in of gasoline and diesel. Besides GHG, conventional cars have local emissions that cause urban pollution. In 2012, urban pollution caused 3.7 million premature deaths according to the OECD and World Health Organisation [4]. A way to reduce, or remove, these two problems is to change the engine, and fuel, 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 dependent on the electricity system within which it operates. 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, causing the investment cost to be much higher than for a conventional car. The drawback of a limited driving range has prompted the development of PHEVs that combine an electric engine with a conventional engine. This type of vehicle has very different properties compared to a BEV from a user's perspective, and will not be analysed in depth here.

As of today (April 2016), there are different models of both BEVs and PHEVs on the market. Most BEVs on the market up until today have had driving ranges around 130 km according to the EPA driving cycle, this is the case for e.g. the Nissan Leaf and Volkswagen e-Golf [5]. The cars obtain this range using a battery size of 24 kWh, however, these batteries can be increased in size. The model of Nissan Leaf for 2016 has a battery of 30 kWh, and towards the end of 2016 Chevrolet plans to release the Bolt which will have a 60 kWh battery and a real world driving range of around 300 km. Tesla, which will release its Tesla Model 3 the following year has a similar range and similar price. The much higher range of these cars has prompted the electric vehicle community to consider them next generation BEVs with the potential for mass-market adoption. The Tesla Model 3 has received close to 400000 reservations (as of end of April 2016) one year ahead of its scheduled release [6]. This number should be compared to the most sold electric car until today, which is the Nissan Leaf with 200000 sold cars from 2011-2015 [7].

Though electricity is available almost everywhere, there are not charging points for BEVs everywhere, and especially not 'fast chargers'. Fast chargers usually refer to chargers that output 50 kW of power, and thus charge a 24 kWh battery from 0-80% in half an hour. As a comparison, the slowest chargers would require 12 hours for a full charge, and most public chargers fall somewhere in-between these two extremes. This means that fast chargers would be required to extend travel distance for long driving days, while the slower chargers could be used at workplaces, homes, or inside cities. One way to mitigate the effect of BEVs is to extend the charging infra-structure.

Given the range limitation of BEVs, it is important to understand to what extent peoples driving needs are fulfilled. And, if they are not fulfilled, can this be mitigated by focussing on certain usage scenarios until the technology is further developed? In this thesis I utilize GPS measured driving data to analyse three topics:

- How well driving is fulfilled by BEVs with common range limitations, and if they, given the low cost of operation, can have a lower TCO than conventional cars. A special focus here is on multi-car households, where we identify different usage patterns for different vehicles in the household. This topic is further extended into analysing how households adapt to the use of a real electric car.
- What is the consequence of using three common probability distributions to analyse driving data with respect to two important measures, being the days requiring adaptation for BEVs, and electric drive fraction, for PHEVs?
- How is existing charging infra-structure in Sweden used?

Throughout the analysis, I take a user's perspective in the sense that I analyse the driving need and economics of the user of a BEV, rather than optimizing average battery sizes for the whole car fleet.

2 ON THE SUSTAINABILITY OF ELECTRO-MOBILITY

The underlying motivation for academia to interest itself in electro-mobility, and the underlying reason for society to motivate subsidies to electro-mobility is that it may bring about a more sustainable mobility system. Sustainable mobility, as a broader concept, can be visualised in ways such as public transport, car sharing, car pools and demand management through e.g. re-designing cities. 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 CO2 emissions compared to conventional cars. The counter-argument from an environmental perspective are usually two-fold, firstly that current batteries are dependent on rare earth minerals that are sometimes also mined under bad working conditions, and secondly, that the overall CO2 emissions are highly dependent on the energy system and may not be lower in some circumstances, such as having coal on the margin. All of these points are valid, though especially the later one can be discussed since many electricity systems are not pure coal, and there may be other energy sources than coal on the margin. Furthermore, what is relevant from an energy system point of view, is what energy system we have in 30-40 years when electric cars may have a large market share, and not what energy system we have today.

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 thus 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. 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 in Congolese mines using child workers. In 2015, at least 80 miners died in these mines [8]. Given the large amounts of cell-phones and laptops produced, this should not all be attributed to the electric car though.

The automotive industry directly generates 6.3% of European GDP, and even more due to ripple effects in connected industries [9]. This means it is a significant part of the economy a strong decline in car use would have 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.

3 Data and methodological background

This research is based on real-world data sets. Throughout the papers, we use seven data sets, of which I am the main analyst of four. Five of the seven data sets consist of GPS measured driving data, one of surveyed driving data, and one of charging infra-structure data. Table 1 contains an overview of the driving data sets used, and Table 2 an overview of the charging data used. Especially the Swedish Car Movement Data (SCMD) should be highlighted, this data set consist 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. Discourse concerning BEVs in electro-mobility conferences and workshops tend to focus on trip distances rather than daily distances and are occasionally based on survey data that systematically under-count total driving distance [10]. 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 enables us to make statements about how often individual drivers will be limited by the range of a BEV instead of national or fleet averages of the same measure, in the context of driving data, this is what we call user's perspective. The present research draws its main value from this data and our focus on individual driving patterns.

Table 1 Description of driving data sets

	Location	Collection Method	Sample Size	Avg. Observation period	Extra information	Ref.
SCMD1	Sweden	GPS	429	58 days		[11]
SCMD2	Sweden	GPS	130	74 days	Contain 65 two-car households with both cars measured.	N/A
SCMD3	Sweden	GPS	50	106[1]days	Subset of SCMD2, one car replaced by a BEV in each household.	N/A
MoP	Germany	Survey	6339	7 days		[12]
PSRC	USA	GPS	484	251 days		[13]
Winnipeg data	Canada	GPS	72	216 days		[14]

[1] The full data set contain 25 households, however as of the writing of this thesis, only 10 households have finished their measurements and been pre-processed enough for analysis. The average observation period reflects these 10 households.

Table 2 Description of charging data set

	Location	Number of 50 kW chargers	Avg. Number of charging events	Extra information	Ref.
Charging data	Sweden	43	812	Licensed under CC3.0, attributed to Nobil, Enova, Norway[2].	[15]

Like all data sets, GPS measurements have limitations. 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 [16] for details). However, this leads to a lower accuracy when it comes to single trip analysis and location analysis. In all the results presented here, we have aggregated trips to daily distances, this 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). A key quantity is the number of days that a user drives longer than the range limitation, we call this quantity 'days requiring adaptation' (DRA), this measure is directly obtained from the daily driving distances for each user. 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).

In the German data which has a short measurement period of seven days we have assumed that daily driving distances follow a Log-Normal distribution:

$$f(r) = \exp[-(\ln r - \mu)^2/(2\sigma^2)]\,/(r\sqrt{2\pi}\sigma)$$

From this, the probability for a DRA can be calculated as the integral summed from the range limitation to infinity: $\int_L^\infty f(r)\mathrm{d}r = 1 - F(L)$. The annual number of DRA can then be scaled up as $D(L) = 365\left(\frac{n}{N}\right)[1 - F(L)]$ where $\frac{n}{N}$ is the share of driving days in the measurement period. Further methodology relating to the different parts of my research follow in each part in the research summary below.

[2] CC3.0 License: https://creativecommons.org/licenses/by/3.0/legalcode, Nobil, Enova, Norway: http://info.nobil.no/index.php/api/66-api-informasjon

4 RESEARCH SUMMARY

4.1 BATTERY ELECTRIC VEHICLES IN MULTI-CAR HOUSEHOLDS

Given no adaptation compared to conventional car usage, a large fraction of users will have problems fulfilling their driving need. Figure 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, adding another two percentage units per extra 10 km of range. Specifically, a BEV with 230 km of range would be needed for half 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 more easily be fulfilled.

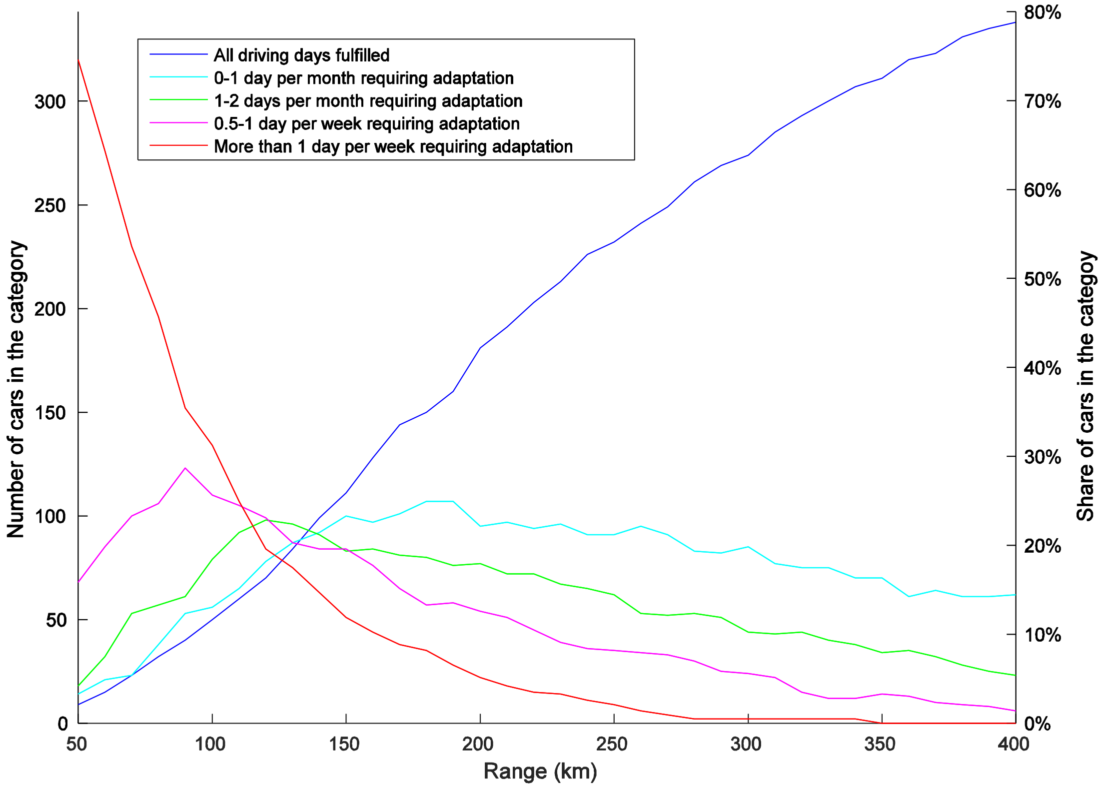

Figure 1 Share of cars with different number of DRA as a function of range in the SCMD1 data. The categories are: cars that fulfil all driving (blue), cars with 0-1 DRA per month (cyan), cars with 1-2 DRAs per month (green), cars with 0.5-1 DRA per week (magenta), and cars with more than 1 DRA per week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

One way to circumvent the range limitation of BEVs is to adopt them in multi-car households. The line of argumentation for BEVs in multi-car households builds on two assumptions. The first assumption is that 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 be satisfied by a 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. In Paper 1, we focus on the first assumption.

Specifically, in Paper 1 we address the following two questions: Are the second cars in a multi-car household better suited as BEVs from a driving pattern point of view? And taking into consideration total cost of ownership, are these BEVs economical compared to conventional vehicles? Here we define a first car as the car in a household that has the highest annual VKT, while the second car is the car with a lower annual VKT.

Figure 2 shows the share of users with no DRA, and with 12 DRA per year separated on first car, second car, and all cars 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 adapted 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, while having this user group accept adaptation for 12 days per year, or once a month.

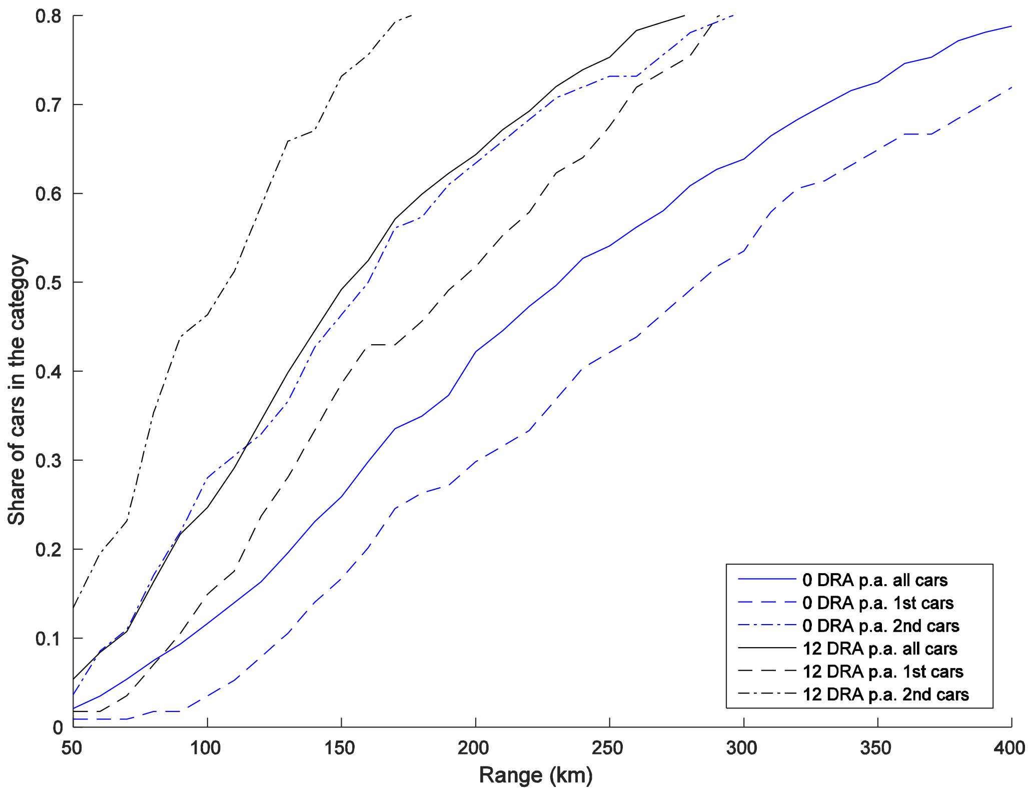

Figure 2 Share of vehicles w.r.t. range for an adaptation acceptance level of zero days, as well as maximally 12 days per annum (blue lines, black lines, respectively) for first cars, second cars and all cars (dashed line, dashed-dotted line, and full line, respectively), SCMD1 data.

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 be an as good, or better, group for adopting BEVs. This is undesirable, as a BEV has a high investment cost and a low operational cost, thus you would want cars with a high annual VKT to 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. The full parameter list and the equations we use for the TCO calculation can be observed in Paper 1, however the important aspects 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 are projected by a national survey into clean transport in Sweden [3]. Our choice to include 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 we show 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 German data in the right sub-panel. In both cases the second car perform better than the first car, though in the German case both categories have very low number of economical cars due to the cheaper gas, 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. This share would have been higher with a milder cost for DRA, though then the gap between first and second cars would start to close as well.

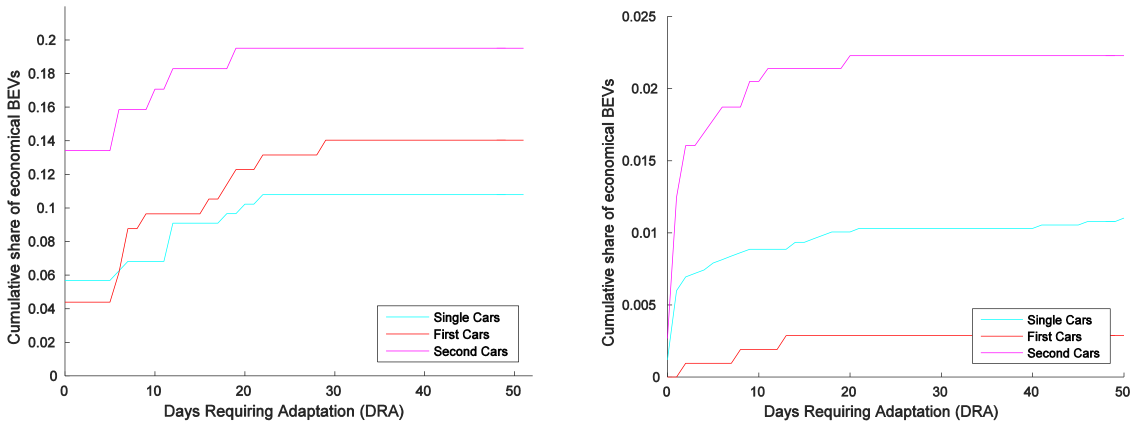

Figure 3 Share of economical BEVs w.r.t car category and less than specified number of DRA. The shares are calculated as quotients of all cars in a specific car category using a range of 120 km. SCMD1 results to the left, German results to the right.

The result from Paper 1 shows that in the general car fleet, a low percentage of cars would fulfil their driving need. However, if focussing on second cars in multi-car households, a more substantial share (30%) of cars fulfil all their driving. When imposing a high cost for DRAs, a rental car cost for these days, and demanding that the BEV have a lower TCO than a conventional car, almost 14% of second cars manages to achieve this. This means that given range limitations of around 120 km, a focus on multi-car households is warranted. This could be part of information campaigns from both industry and policy makers.

In Paper 3 we analyse one of the unanswered questions from Paper 1, that is, how much do households actually adapt their driving when adopting a BEV. In this study we first measured the driving of 65 two-car households in Western Sweden (SCMD2). These households were randomly selected from the vehicle registry for enquiry of participation with some selection criteria. These criteria were that the households should have two cars, both should be used for commuting, and the cars had to be restricted in terms of motor power, size and age. In the second data set (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. The marketed range of the car according to the NEDC driving cycle used in Europe is 190 km, however the EPA driving cycle used in North America rates it at 130 km, while our users has stated a usable range of up to 120 km during interviews. However daily variations in a number of factors, such as driving speed, temperature, and humidity, can vary the actual range from around 100 km to 140 km. For the comparisons made here, we have chosen to use a range of 120 km. As of the writing of this thesis, data collection is still ongoing for some of the 25 households, and some others need additional pre-processing of the data before analysis. So the results here refer to 10 households. These 10 were using their electric car for 3-4 months during the fall-winter of 2015. We use the terminology 'replaced car' for the conventional car in BRD2 that the households chose to not use during SCMD3, 'electric car' for the Volkswagen e-Gold, and 'persistent car' for the car that remained in the household over both measurement periods.

A key feature of the data used here is that they 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 be considered early adopters, but instead would represent an early majority, using the terminology of Rogers (2003) [17]. In this sense, our study differs from most other travel measurements of electric vehicle users. Note however, that since the sample size is very small in our study, the results should be considered as illustrative of possible behaviours rather than representative of car users in general.

Note that in some cases the households have acquired new cars in-between the two evaluation periods, thus the EV may have replaced a different car then the one actually driven in the comparison period, or the persistent car may have changed between the periods. In these cases, we have designated replaced and persistent car such that the person in the household who mostly (>90% according to interview results) drove the respective car in the comparison period would drive the corresponding car in the evaluation period. This also means that the commuting distances should be consistent for the replaced-EV and persistent-persistent cars in the two data sets, assuming no changed behaviour or optimization of EV usage. Thus, we attribute the changes in commuting distances, or total distances between the EV and the replaced car to adaptations the household has made given the new situation of having one EV and one conventional car.

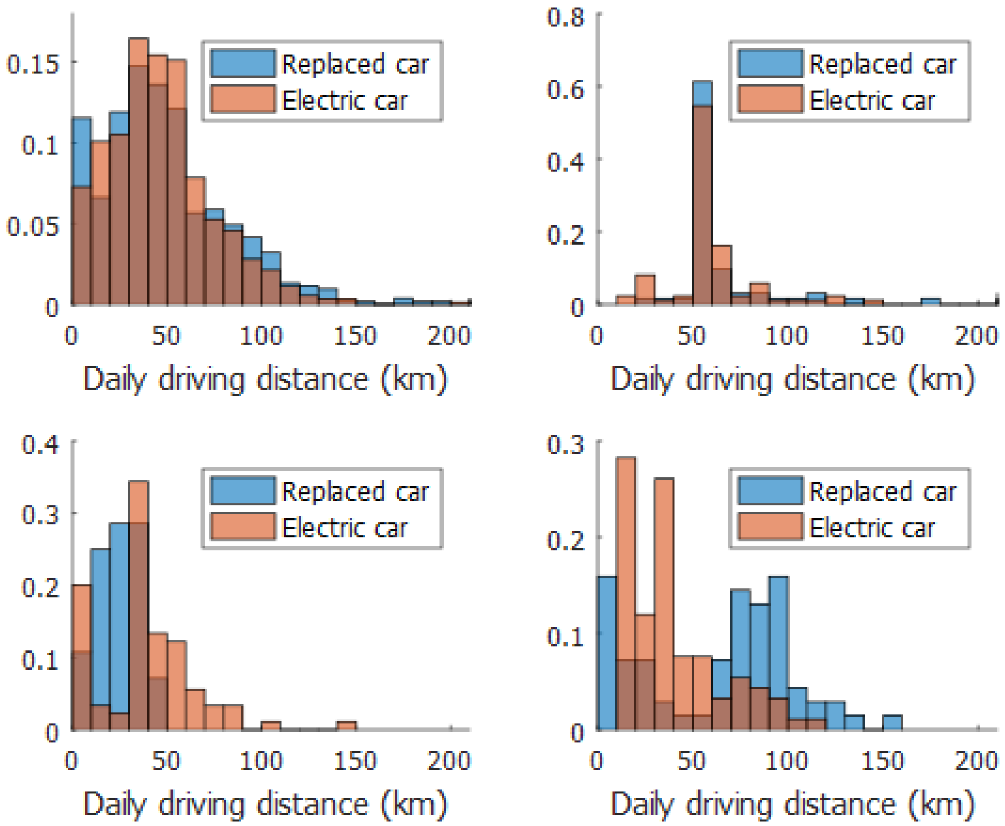

Figure 4 Distribution of daily driving distances for the EV and the replaced car. The top left figure displays the average of all ten households, the other three figures display some typical results. Blue colour marks the replaced car, light brown marks the electric car, and dark brown shows overlap between the two car types.

In order to judge how much, and in what way the households change their driving behaviour 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 4 show these distributions of daily driving distances as normalized histograms for the electric car, and the conventional car it has replaced. The top left sub-panel show 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 EV to take driving tasks within a fairly narrow range of around 40 km to 70 km, while the replaced car increases its driving in the other ranges. Thus the electric car both reduces the amount of long distance trips (70-140 km) of the replaced car, and increases the number of short distance trips (0-30 km) of the same. This might represent both an effect of range anxiety and a wish to utilize the EV more. The top right figure shows an example of a household that to a large extent keeps the same driving distances for the EV 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 have increased and decreased its 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 EV in the SCMD3 data, and the corresponding fraction for the replaced car in the SCMD2 data. This, as well as the fraction between them, are shown in Table 3. In most cases, the adjustments in driving due to the adoption of an EV is small, with three households lowering their driving of the EV compared to the replaced car. Among the others, there are two with low-moderate increase of driving distance (12%), and one with very large increase of driving distance (160%). In general, it cannot be said that households overall increase their driving of the EV compared to the replaced car.

Table 3: 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.

EV	Replaced car	Fractional increase
65%	63%	2%
32%	29%	12%
52%	20%	160%
59%	59%	-1%
45%	47%	-4%
45%	42%	7%
50%	48%	3%
35%	34%	4%
58%	52%	12%
57%	63%	-8%

When interpreting the results from Paper 3, we see that it is not unrealistic to assume a low degree of adaptation, this has implications for how to interpret the results of Paper 1, where we would focus more on the results relating to accepting few number of DRAs instead of many, it also motivates having a high cost for DRA. However, to make a refined statement about households' willingness to adapt, deeper analysis needs to be performed on trip level, this will be part of my upcoming research.

A reasonable criticism against Paper 1 is that 120 km is a quite low range to assume for EVs 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, and large batteries that can run car for 300 km 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 strong cold, where specific battery technologies could be desirable. In the case of cold it could be Ni-MH, which performs better in cold climate compared to Li-Ion, but is twice as heavy per kWh. In these cases, knowledge that low range is sufficient in some cases can enable the use of these alternative battery technologies.

4.2 On the distribution of daily travel distance

In the previous analysis we chose to model the German data with a Log-Normal probability distribution. As briefly outlined in Paper 1, this choice is not obvious, and there are several distributions that could be considered for modelling daily driving data. The choice of distribution may also have implications for results obtained. Especially when it comes to electric vehicles where a researcher could be interested in either days requiring adaptation for BEVs, or electric drive fraction for PHEVs. These measures are mainly influenced by, respectively, particularly long, or short, driving; and 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 [18] and Lin, et al., [19] analyse two data sets and argue that the Gamma distribution is the most suitable for driving data. However, there are other findings, such as that from Blum (2014) [20] and Plötz et al., (2012) [21] who argue that the Log-Normal distribution provides the best fit for most drivers. Thus, further research is required to judge not only the overall best distribution for driving data, but also to investigate the effect of choosing one distribution over another for common measures relating to electric vehicles.

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:

$$\text{Log-Normal } f(r) = \exp\left[-(\ln(r)-\mu)^2/(2\sigma^2)\right]/\left(r\sqrt{2\pi}\sigma\right)$$

$$\text{Gamma } f(r) = r^{k-1}\exp\left[-r/\theta\right]/\left(\Gamma(k)\theta^k\right)$$

$$\text{Weibull } f(r) = (k/\lambda)(r/\lambda)^{k-1}\exp[-(r/\lambda)^k]$$

The data sets used for analysis is SCMD1, PSRC, the Winnipeg data, and the German data. The data sets have complementary properties in that The German 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:

1. Which is the best overall distribution for daily driving data?
2. 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: (1) Akaike information criterion (AIC), a penalized log-likelihood where $\text{AIC} = -2\ \text{LL} + 2\ (p+1)$, p is the number of model parameters and LL the log-likelihood; (2) the root mean squared error $\text{RMSE} = \sum_i (y_i - f_i)^2\ /n$, (3) the mean average percentage error $\text{MAPE} = \sum_i |(y_i - f_i)/f_i|\ /n$, and (4) the χ^2 statistic $\chi^2 = \sum_i (y_i - f_i)^2\ /f_i$ 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 4 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.

Table 4 Summary of goodness of fit statistics. The best distribution for most users in bold face.

Goodness-of-fit	Mobility Panel			Winnipeg			Sweden			Seattle		
	ln N	Weib.	Γ	ln N	Weib.	Γ	ln N	Weib.	Γ	ln N	Weib.	Γ
AIC	32,3%	**59,9%**	7,8%	**40%**	35%	25%	34,7%	**39,2%**	26,1%	16,0%	**71,6%**	12,4%
RMSE	**74,0%**	12,5%	13,5%	**36%**	35%	29%	**43,6%**	37,3%	19,1%	**36,8%**	35,7%	27,5%
χ^2	**88,2%**	9,1%	2,7%	17%	**41%**	**41%**	29,6%	33,8%	**36,6%**	**68,9%**	18,3%	12,8%
MAPE	**75,2%**	21,9%	2,9%	9%	**51%**	40%	19,8%	**44,5%**	35,7%	**65,0%**	24,0%	11,0%

To analyse the second question above we calculate the number of DRA for each distribution equivalently to the description in Section 3. 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 50000 driving days for each user and distribution, this 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.

In Tables 5 and 6 we present estimates of DRA in the four data sets for the different distributions, and using three range limitations of 100 km, 150 km, and 200 km. Table 5 shows the percentage of users with number of DRA<1, DRA<12 and DRA<52 for three range limitations (100, 150, 200 km). Similarly, Table 6 shows the mean and median percentage of DRA for the same range limitations. Though there are differences among all three distributions, it is clear that Log-Normal differ more in prediction of share DRA from Weibull and Gamma, then Weibull and Gamma does from each other (especially for mean and median). What should especially be noted, is that Log-Normal estimate a higher fraction of DRAs than Weibull and Gamma. Consider, for example, the share of users with DRA<1 for a range of 150 km in the SCMD data. Log-Normal predicts 7.9% of the 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 fulfil their driving with a BEV, one might wish to choose to model driving data with the Log-Normal distribution. It should also be noted that the empirical values for mean and median in Table 6 to a larger extent agrees with the estimate from the Weibull and Gamma distributions.

Similarly, Tables 7 and 8 show the estimated electric drive fractions for the different data sets and distributions using common range limitations for PHEVs of 25 km, 50km, and 75 km. Table 7 show the fraction of users with an EDF above 50% and 80%, while Table 8 show the mean and median electric drive fraction. Again we see that Log-Normal differ more from the other results than Weibull, Gamma and the empirical calculations differ from each other. Log-Normal consistently estimate 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.

Table 5: Share of users with adaptation needs below 1 DRA, 12 DRA and above 52 DRA per year, for different the distributions, ranges and data.

DRA	L [km]	Mobility Panel			SCMD			Winnipeg			Puget sound		
		ln N	Weib.	Γ	ln N	Weib.	Γ	ln N	Weib.	Γ	ln N	Weib.	Γ
DRA<1	100	17.3±0.9	36.9±1.2	31.3±1.1	3±1.6	9.1±2.7	7.2±2.5%	3±2	36±5	32±5	1.2±1	9.8±2.8	7.4±2.5
[%]	150	28.5±1.0	53.0±1.2	48.0±1.2	7.9±2.6	21.2±3.9	17.5±3.6%	19±4	61±6	61±6	3.9±1.8	29.1±4.3	22.7±4
	200	37.0±1.2	64.2±1.2	62.3±1.2	11.4±3	34.7±4.5	30.8±4.4%	36±6	81±4	83±4	10.7±.2.9	51.3±4.7	46.8±4.7
DRA<12	100	37.4±1.2	51.7±1.2	48.8±1.2	15.6±3.4	24±4	22.4±3.9%	59±6	72±5	73±5	16.4±3.5	31.1±4.3	29,2±4.3
[%]	150	53.6±1.2	68.9±1.1	67.0±1.1	30.1±4.3	51.1±4.7	49.9±4.7%	87±4	92±3	92±3	38.9±4.6	62.9±4.5	64.3±4.5
	200	65.3±1.2	78.8±1.0	77.5±1.0	40.1±4.6	69.5±4.4	69.5±4.4%	89±4	99±1	97±2	60.9±4.6	84.7±3.4	85.5±3.4
DRA>52	100	32.1±1.1	29.4±1.1	30.1±1.1	45.9±4.7	38.5±4.6	39.2±4.6%	4±2	4±2	4±2	31.7±4.4	27.9±4.2	27.1±4.2
[%]	150	17.9±0.9	15.6±0.9	16.1±0.9	18.4±3.7	13.3±3.2	13.3±3.2%	0	0	0	10.2±2.9	6.2±2.3	5.3±2.1
	200	10.4±0.8	8.6±0.8	9.2±0.8	11.4±3	4.9±2	5.3±2.1	0	0	0	2.8±1.6	1.6±1.2	1.6±1.2

Table 6: Mean and median adaptation needs according to different distributions, ranges and data.

DRA	L [km]	Mobility Panel				SCMD				Winnipeg				Puget sound			
		ln N	Weib.	Γ	Empirical	ln N	Weib.	Γ	Empirical	ln N	Weib.	Γ	Empirical	ln N	Weib.	Γ	Empirical
Mean DRA	100	45.8±1.4	43.1±1.5	44.3±1.5	42.6±1.6	52.7±3.8	48.4±4.3	48.9±4.3	45.3±4.7	16.1±4.2	11.3±4.8	11.1±4.5	12±5	43±3.2	38.2±3.7	38±3.6	30.4±3.6
	150	25.5±0.9	21.1±1.0	22.2±1.0	22.0±1.1	32.4±2.7	22.6±2.7	23.2±2.7	22.4±2.7	7.2±2.1	3.2±1.8	3.2±1.8	5±2	22.5±2.1	14.3±2.1	14.5±2.1	12.6±1.9
	200	16.7±0.7	12.3±0.7	13.1±0.7	13.7±0.8	22.4±2.1	11.9±1.8	12.1±1.8	12.8±1.8	3.8±1.2	1.0±0.7	1.1±0.7	2±1	13.6±1.5	6.1±1.3	6.31.3	7.2±1.1
Median DRA	100	26.6±1.6	10.2±1.3	13.1±1.5	-	49.6±4.2	35.4±6.1	37.5±6.8	29.0±3.3	10.3±3.4	4.0±2.3	4.5±2.5	4±3	36.8±3.9	27.1±4.3	27.4±4.0	17.9±2,6
	150	9.4±0.7	0.4±0.1	1.3±0.2	-	27.3±3.5	11.2±2.7	12.2±2.7	12.2±2.1	4.2±1.6	0.2±0.4	0.5±0.5	1±2	16.5±2.0	4.6±1.4	5.9±1.4	6.6±1.3
	200	4.1±0.4	0.01±0.01	0.1±0.04	-	17.4±2.0	3.8±1.5	4.1±1.4	6.0±1.0	1.9±0.9	0.01±0.05	0.04±0.05	0±0	8.7±1.3	0.9±0.5	1.3±0.4	4.0±0.7

Table 7: Share of users with EDFs above 50% and 80% according to different distributions, ranges and data.

EDF	L	Mobility Panel				SCMD				Winnipeg				Puget sound			
		ln *N*	Weib.	Γ	Empirical	ln *N*	Weib.	Γ	Empirical	ln *N*	Weib.	Γ	Empirical	ln *N*	Weib.	Γ	Empirical
s>50%	25	42.9±1.0	51.2.0±0.8	51.0±0.8	29.7±1.1	18.4±0.2	24.9±0.2	24.9±0.2	26.8±0.2	63±7	76±4	79±4	77±9	23.6±0.2	33.0±0.1	33.6±0.1	36.8±0.1
[%]	50	70.9 ±0.4	80.6 ±0.3	80.5 ±0.3	50.6±1.2	46.6±0.0	76.0±0.2	77.6±0.2	76.5±0.2	91±2	99±1	99±1	97±3	70.3±0.1	90.0±0.3	90.0±0.3	90.2±0.3
	75	81.4±0.2	90.3±0.1	90.1±0.1	57.5±1.2	64.3±0.1	92.3±0.3	92.5±0.3	91.1±0.3	97±1	99±1	100±0	99±3	88.1±0.3	97.7±0.3	97.9±0.4	97.7±0.4
s>80%	25	14.5±1.3	20.7±1.3	20.6±1.3	10.1±0.7	28.0±0.3	4.6±0.3	4.0±0.3	4.2±0.3	1±9	21±13	21±13	23±9	1.8±0.4	4.6±0.3	3.5±0.3	5.7±0.3
[%]	50	37.2±1.1	50.5±0.9	49.9±0.9	29.2±1.1	12.1±0.3	21.0±0.2	20.3±0.2	20.3±0.2	37±11	67±6	71±5	67±11	14.4±0.2	28.1±0.1	28.0±0.2	31.6±0.1
	75	52.6±0.8	68.9±0.5	68.2±0.5	41.5±1.2	24.0±0.2	48.0±0.1	48.5±0.0	44.1±0.04	70±5	89±2	89±2	81±9	34.1±0.1	63.8±0.1	66.0±0.1	61.6±0.1

Table 8: Mean and average EDFs according to different distributions, ranges and data.

Electric drive fraction s	L	Mobility Panel				SCMD				Winnipeg				Puget sound			
		ln *N*	Weib.	Γ	Empirical	ln *N*	Weib.	Γ	Empirical	ln *N*	Weib.	Γ	Empirical	ln *N*	Weib.	Γ	Empirical
Mean	25	48.0±0.6	54.0±0.6	53.8±0.6	50.2±0.6	33.2±1.9	41.9±1.6	42.2±1.6	42.1±1.6	54±4	62±4	62±4	63±4	40.3±1.5	46.3±1.5	46.2±1.5	47.5±1.6
[%]	50	66.0±0.6	74.6±0.6	74.3±0.6	71.3±0.6	49.3±2.3	64.3±1.7	64.5±1.7	63.6±1.7	74±4	84±3	84±3	83±3	60.0±1.7	70.5±1.5	70.7±1.5	71.4±1.5
	75	74.7±0.6	83.9±0.5	83.7±0.5	81.3±0.6	58.6±2.4	76.9±1.5	77.1±1.5	75.5±1.6	83±3	92±2	93±2	90±2	70.8±1.7	83.3±1.2	83.3±1.2	82.6±1.2
Median	25	44.4±0.8	50.8±1.0	50.9±1.1	46.5±1.0	29.4±0.1	39.1±1.0	39.7±0.3	39.4±0.03	54±4	62±5	63±4	63±5	38.5±0.2	43.9±0.4	43.9±0.3	44.8±0.2
[%]	50	69.2±1.1	80.4±1.0	80.0±1.0	74.7±1.4	47.9±0.4	63.3±2.0	64.0±0.1	62.4±0.2	76±2	87±4	87±3	85±6	61.1±0.2	70.8±0.2	71.5±0.5	72.1±0.5
	75	81.9±0.9	94.0±0.6	93.0±0.6	91.6±1.0	59.6±0.3	78.9±2.4	79.0±0.4	76.9±0.3	87±2	96±2	96±2	94±4	73.6±0.4	86.4±0.4	85.6±0.2	84.8±0.3

4.3 Usage of charging infrastructure in Sweden

An alternative to focussing on multi-car households to deal with the range limitation, as suggested in Papers 1 and 3, is to extend the range by usage of charging infra-structure. As outlined in the introduction, 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. While the fast chargers best serve their purpose in situations where a user would not want to stay more than approximately half an hour, such as a diner or viewpoint along a highway, though not to say that fast chargers don't have a function inside cities as well. In Paper 4 which strictly analyse fast charging, my co-authors have developed a queueing model for estimating the needed number of fast chargers in Germany. This model is valuable because it estimates the number of chargers, rather than the position of chargers which most of earlier work has [22]–[24]. My contribution to the paper has been to analyse charging data from fast chargers in Sweden to verify some of the assumptions of the model, while also presenting general charging usage.

The total number of fast chargers in Sweden amounts to 121 Chademo chargers and 117 CCS chargers (some at the same charging site) [25] for a BEV fleet of 6600 cars [26], yielding 36 chargers per 1000 BEV, though less charging sites per BEV. Charging infrastructure in Sweden is either provided by the municipalities and is free of charge, or by one of the big power utilities where a user has to pay a fixed per-minute price for charging. The charging data we use here consists of 43 fast chargers (Chademo and CCS) and has been gathered over 14 months from 2014-12-30 to 2016-03-09 [15]. When the data has been cleaned by removing registered charging events that are shorter than 3 minutes or longer than 3 hours it contains 34,934 charging events. This equates to 1.9 charging events per charger and day. The results presented here are probability densities which have been calculated using kernel density estimates. The results further use all charging events for all chargers, so they are averages in a sample where there may be large heterogeneity in usage.

Figure 5 shows the distribution of charging time for a car standing by the charging station. The peak is around 25 minutes, which is below the expected time to charge from empty battery to 80% state of charge, and logically most cars would not arrive with completely empty battery, thus requiring a shorter time than 30 minutes at the station. After this point, the charging time has an approximate exponential decrease. The model in Paper 4 assumes an exponential distribution for the charging times and the empirical data do not support this assumption over the whole spectrum of charging times. It can however, be interpreted to support the assumption pf exponential distribution for charging times above 25 minutes. The model assumes a mean charging time of 30.3 minutes and this mean falls within the exponentially distributed part of the charging time spectrum.

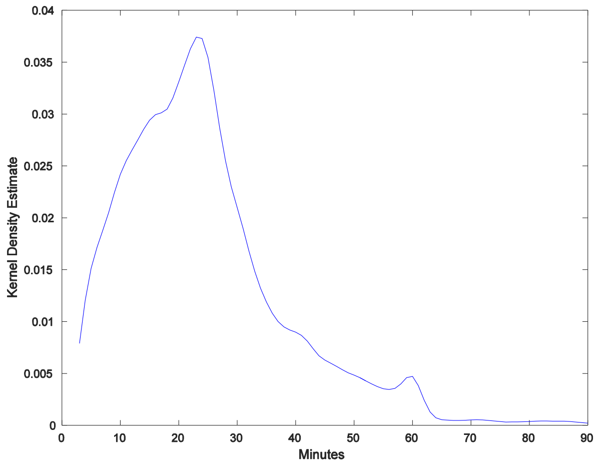

Figure 5 Distribution of duration of charging time (minutes)

Figure 6 shows the distribution of inter-arrival times for the fast chargers. That is, the time it takes from the arrival of one car, to the arrival of the second car to the charging station. The average behaviour resembles an exponential distribution, which the model also assumes, and thus the empirical data supports this assumption. We can also see tendencies to some inter-arrival times being more common than others, this is an effect of heterogeneity in how charging stations are used. A conclusion from this is that more thorough analysis of charging data should consider individual chargers rather than network averages, similar to how we analysed individual driving patterns rather than fleet averages in the multi-car household analysis.

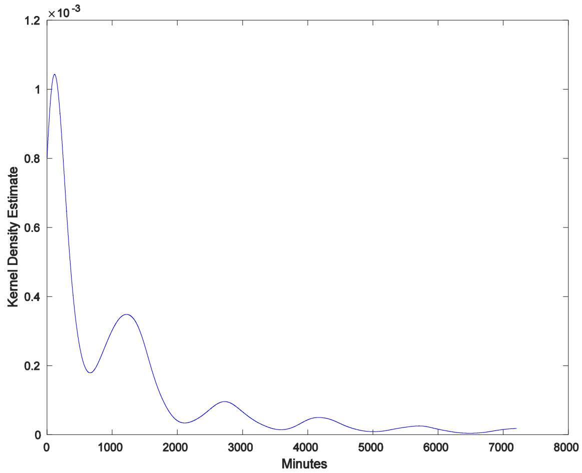

Figure 6 Distribution of inter-arrival time for the charging stations (minutes)

Figure 6 could also be interpreted as a measure of how much the charging infrastructure is used in Sweden, which is not very much, as idle times for the stations are in the order of dozens of hours. If Figure 6 is also interpreted in tandem with Figure 5, we see that the probability of having to wait at a charging station is low. Note that most charging events occur during the day (see Paper 4 for details) which slightly increases the probability of experiencing a queue. Another measure of how much the charging network is used, is the number charging events per car. Given 6600 BEVs in Sweden, and 34934 charging events on our 43 chargers out of the total 238 fast chargers in Sweden, we can crudely calculate the number of charging events per BEV per year to approximately 25. One can expect though, that this number is unevenly distributed among the BEVs.

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