Final report

1.1 Project details

Project title	Consumer acceptance of intelligent charging
Project identification (program abbrev. and file)	Energinet.dk project no. 2012-1-10773
Name of the programme which has funded the project	ForskEL
Project managing company/institution (name and address)	DTU Management Engineering, Bygningstorvet 116, 2800 Lyngby
Project partners	DTU
CVR (central business register)	30060946
Date for submission	14-11-2016

1.2 Short description of project objective and results

Future growth in the number of electric vehicles (EVs) raises questions about the load these will have on the electric grid system. If no further solutions, incentives or regulations are introduced, charging occurrences might coincide with peak hours of electricity demand, which will contribute to a highly inefficient utilization of the electrical grid. On top of this, in order to comply with environmental goals, many governments try to increase their share of electricity produced from sustainable but highly unsteady sources such as wind and solar. A way to meet these challenges is to see EVs as a "Smart City" solution. With innovative solutions and careful planning, electric transport can contribute to smoothing the electricity consumption over different time periods of the day. In an even more advanced setting, the EV batteries could be used as buffers where the electricity produced when the supply is high is stored until it is needed in the grid. Postponing charging of the batteries to off-peak hours and vehicle to grid charging (V2G) are intelligent ways of ensuring a higher utilisation of renewable energy production and a more efficient utilization of the electrical grid. However, it is not obvious how potential customers will use their EVs and how they will react to different charging scenarios given that postponing charging and V2G charging may involve perceived or real mobility constraints.

In this project, we analyse how EV users react to various charging scenarios. This includes how EV users evaluate different contract agreements with the electricity supplier, which often will be a trade-off between charging costs and the flexibility that most users relate to car driving. Work in this project indicates that consumers show myopic loss aversion behaviour, which means that they show irrational behaviour when it comes to this trade off. In general, they are more sensitive to a reduction in flexibility than a corresponding reduction in price.

Furthermore, we investigate the travel behaviour of EV users as insights into their behaviour are necessary for a successful implementation of smart-grid solutions. To study the transport behaviour of EV users, we utilize a large and detailed set of data describing actual EV trips driven as part of a demonstration project conducted in Denmark from 2011 to 2014. In particular, the data contains information about how households will use an EV when it is available at the same time as their own conventional vehicle (CV). A specific feature of these data is that the trips have been joined with weather data from Danish Meteorological Institute so that it is possible to analyse the effect of the weather on behaviour. The project has resulted in various models covering many different aspects of the behaviour of EV users both when it comes to driving and charging. These models describe how the available variables have an effect on the electricity consumption, the daily choice between an electric car and a conventional car (when both types are available), the daily distance driven in both types of cars, and the routes that are chosen in both types of cars. The results indicate several examples of variables, especially weather variables that affect EV user behaviour differently than CV user behaviour.

Overall, the theories and results of this project contribute with useful insight of EV users' reaction to various contract agreements with electricity suppliers as well as the potential spatial and temporal EV usage from a large scale introduction of EVs which is highly relevant for both public and private actors in the EV market for identifying potential markets and for the planning of business solutions, the electric grid, and optimal charging infrastructure.

Den forventede fremtidige vækst i antallet af elbiler giver anledning til bekymring om, hvordan disse vil belaste elnettet. Uden nye løsninger, økonomiske tilskyndelser eller reguleringer, vil en stor del af elbilers opladning sandsynligvis ske på tidspunkter, hvor netværket allerede er hårdt belastet, hvilket vil bidrage til en dårligere udnyttelse af systemet. For at imødekomme forskellige målsætninger omkring klima og miljø, forsøger mange lande derudover at øge deres andel af elektricitet baseret på bæredygtige, men ustabile energiformer, såsom vind og sol. Et forslag til at løse ovenstående udfordringer omkring elnettet er at benytte elbiler som en "smart city" løsning. Ved hjælp af innovative løsninger og detaljeret planlægning, kan elektrisk transport bidrage til at balancere elforbruget, hvis opladning af elbiler udskydes til perioder, hvor det eksisterende elforbrug er lavt. I et udvidet løsningsforslag kan batterierne endda benyttes som midlertidige buffere, hvor overskudselektricitet fra perioder med høj kapacitet og lav efterspørgsel, bliver lagret til perioder, hvor der er lav kapacitet og høj efterspørgsel. Udskydelse af opladning samt "vehicle-to-grid" (V2G) opladning er intelligente måder for at opnå en bedre udnyttelse af bæredygtige energiformer, samt en mere effektiv anvendelse af elnettet. Det er imidlertid ikke åbenlyst, hvordan potentielle forbrugere vil benytte elbiler eller hvordan de vil acceptere forskellige scenarier for opladning, hvis man medtager at løsninger for udskudt opladning og V2G opladning vil kræve en direkte eller indirekte begrænsning i brugen af bilen.

Formålet med dette projekt er at give indsigt i, hvordan brugere af elbiler opfatter forskellige opladningsmuligheder. Dette inkluderer hvordan disse brugere vurderer forskellige kontrakter mellem dem og udbydere af elektricitet, hvilke ofte inkluderer en afvejning mellem prisen på opladning og den fleksibilitet, som de fleste bilejere forbinder med bilkørsel. Vores resultater indikerer, at forbrugerne udviser en irrationel skepsis mod en begrænsning af deres fleksibilitet. Generelt er de mere sensitive overfor en reduktion i fleksibilitet end en tilsvarende reduktion i pris.

Projektet bidrager derudover med viden omkring elbilisters adfærd, idet disse informationer er vigtige for en succesful implementering af intelligente løsninger til opladning af elbiler. Til dette formål, benytter vi et stort datasæt, der beskriver virkelige ture i elbil kørt i forbindelse med et større demonstrationsprojekt udført i Danmark mellem 2011 og 2014. Dette datasæt indeholder detaljerede informationer omkring, hvordan husstande ville benytte en elbil, hvis de fik den tilgængelig samtidig med deres egen konventionelle bil. Datasættet er beriget med vejrdata fra Danmarks Meteorologiske Institut, så det er muligt at analysere, hvordan bilisternes adfærd påvirkes af vejret. I forbindelse med projektet er der blevet udviklet et antal forskellige modeller, der dækker mange forskellige sider af bilisternes adfærd, både når det kommer til kørsel og opladning. Disse modeller beskriver, hvordan de tilgængelige variable påvirker elbilernes rækkevidde, det daglige valg imellem elbilen og den konventionelle bil, den daglige brug af bilerne samt bilernes rutevalg. Resultaterne giver adskillige eksempler på, hvordan faktorer (især vejret), påvirker brugere af elbiler anderledes end brugere af konventionelle biler.

Overordnet bidrager resultaterne og teorierne fra dette projekt med en bedre forståelse af elbilisters vurdering af forskellige forretningsmodeller for salg af elektricitet, samt en bedre forståelse af den forventede brug af elbiler ved et egentligt gennembrud af elbiler på markedet. Disse informationer er relevante, både for offentlige og private aktører på elbilsmarkedet, til at identificere potentielle servicer og til at planlægning af forretningsmodeller, elnettet og opladningsinfrastrukturen.

1.3 Executive summary

A future smart grid based on renewable energy, e.g. wind or solar, will need to store surplus energy from high supply periods to high demand periods. A possible storage consists of batteries in electric vehicles (EVs) connected to the grid through an in-home charger or a charging station. For the system to work, it is necessary to understand charging behaviour and driving behaviour of EV users. This project focuses on these important aspects of the smart grid. The focus has been formulated in two objectives.

The first objective of the project addresses EV owners' willingness to accept different arrangements concerning the price of vehicle/electricity use, control over the battery, and related elements that can be part of a contract with an energy or vehicle supplier.

This focus has been addressed through the following questions:

- What are the optimal contractual arrangements regarding the charging/de-charging of electric vehicle batteries?
- What are EV users' acceptance of buy/loan contracts in which they do not have full control over the vehicle's battery?
- How will costumers react to various prices for buying and selling electricity under the different contract forms?

These questions have been analysed in a PhD project. First, an analysis of the demand for and supply of charging facilities at a workplace show that even though the net private benefit could be positive, there is no contract that an employer is willing to offer and at the same time that the majority of the employees is willing to accept. If incentives for such a solution should be introduced, they should be put on the supply side rather than on the demand side, i.e. it is more promising to support employers in offering work-place-charging (WPC) contracts than to provide employees an incentive to accept WPC contracts. Second, results indicate that the consumers show myopic loss aversion behaviour, which means that they show irrational behaviour when it comes to the trade-off between price and flexibility. In general, they are more sensitive to a reduction in flexibility than a corresponding reduction in price. A treatment effect shows that presenting price discounts in terms of long-term contracts in an ultimatum game framework, instead of merely announcing discount prices, may reduce myopic loss aversion behaviour. Finally it was investigated whether individuals can be influenced by their peers to take decisions with higher risks, and thereby be influenced to postpone their charging. Results show that while individuals would like to see their peers' decisions, only few use this information to change their decisions.

The second main objective was to describe the general driving behaviour of EV users, as it is crucial for infrastructure developers to know as much as possible about the magnitude of electricity demand for transport and when and where charging will happen. Even if the users accept being involved in intelligent charging, this may be irrelevant if the driving behaviour of EV users necessitates a high share of charging away from their homes. This focus has been addressed through the following questions:

- What is the behavioural change due to the EVs' reduced range compared to conventional cars and the users' habits when using conventional cars?
- Are there changes in behaviour with eventually extra car kilometres for families getting the EV as car number two?
- What is the electricity consumption of EVs per kilometre under various driving conditions?
- What is the overall effect of EVs on the car kilometres and energy consumption? Special interest will be paid to possible reductions or whether they just add to the problem of congestion, increasing car kilometres and energy consumption.

First, descriptive analyses show that in general the EVs are used for a higher number of trips per day compared to the CVs, but when looking at the distances driven there is no large difference across the two technologies. Thus, as also expected, the CVs are used for the occasional longer trips. Second, an energy consumption model for was set up to investigate how the performance of electric vehicles fit to car owners travel behaviour. The results show that seen over a month, a very large share of the car owners would have to drive to the limits of the battery capacity, which can be stressful. Third, a model was set up to measure the effect of several variables on daily driving. The results indicate several examples of variables, especially weather variables, that affect daily driving in EVs differently than driving in CVs. Finally, a model was set up describing whether EV owners choose their EV or their CV for a home-based car journey (i.e. a chain of trips until home is reached again). The results show that there are several factors that affect the use of the two car technologies differently.

Looking particularly at applied utilization of the project results, relevant information for the planning of the electric grid, charging infrastructure and different business solutions for charging infrastructure has been provided. These activities are currently all in an initial phase as it is expected that the EV market will increase rapidly in the near future. Thus, the information generated can be important input for all areas of optimization, marketing and research on EV driving and charging.

1.4 Project objectives

A future smart grid based on renewable energy, e.g. wind or solar, will need to store surplus energy from high supply periods to high demand periods. A possible storage consists of batteries in electric vehicles (EVs) connected to the grid through an in-home charger or a charging station. For the system to work, it is necessary to understand charging behaviour and driving behaviour of EV users. This project focuses on these important aspects of the smart grid. The focus has been formulated in two main objectives.

The first main objective of the project is to address EV owners willingness to accept different arrangements concerning the price of vehicle/electricity use, control over the battery, and related elements that can be part of a contract with an energy or vehicle supplier. The main questions regarding this objective are:

- What are the optimal contractual arrangements regarding the charging/de-charging of electric vehicle batteries?
- What are EV users' acceptance of buy/loan contracts in which they do not have full control over the vehicle's battery?
- How will costumers react to various prices for buying and selling electricity under the different contract forms, and without any contract?

These questions have been analysed in a PhD project through the following activities.

1) A theoretical microeconomic model of the demand for and supply of charging facilities at a workplace.
2) A laboratory experiment used to test different contracts for EV charging giving insight about how to get individuals to charge their EVs in off-peak electricity consumption hours.
3) A laboratory experiment used to investigate whether and to what extent one can affect individuals' risk-taking decisions. Among others, this gives insight into how and what type of information that could be used to induce EV owners to postpone charging time towards off-peak periods of electricity consumption or to allow Vehicle-to-grid (V2G) charging.

The second main objective is to describe the general driving behaviour of EV users, as it is crucial for infrastructure developers to know as much as possible about the magnitude of electricity demand for transport and when and where charging will happen. Even if the users accept being involved in intelligent charging, this may be irrelevant if the driving behaviour of EV users necessitate a high share of charging away from their homes. Previous research on EV driving behaviour has mainly been based on data from conventional gasoline or diesel vehicles. In the current project, we have instead employed data from actual use of EVs obtained from a demonstration project about EVs. These data have been used to analyse the following questions.

- What is the behavioural change due to the EVs' reduced range compared to conventional cars and the users' habits when using conventional cars?
- Are there changes in behaviour with eventually extra car kilometres for families getting the EV as car number two?
- What is the electricity consumption of EVs per kilometre under various driving conditions?
- What is the overall effect of EVs on the car kilometres and energy consumption? Special interest will be paid to possible reductions or whether they just add to the problem of congestion, increasing car kilometres and energy consumption.

The main activities of this part of the project include:

1) Descriptive analyses of driving behaviour of EV users and comparison with the use of CVs in the same household before and after they received the EV.
2) A fixed effects econometrics model that is used to investigate the factors affecting the energy consumption rate of EVs under real-world driving patterns.

3) A regression model for energy consumption of EVs which is used to investigate how the performance of EVs fit the travel behaviour of car owners.
4) A mixed non-linear regression model that is used to investigate the distribution of daily travel in both the EV and the CV in the participating households.
5) A discrete choice model that is used to investigate the choice between the EV and the CV in the participating households.
6) A route choice model that is used to investigate the route patterns of EV users and a comparison with the route patterns when the participating households use their CV.

The objectives was implemented in the project through a partition of the project into two work packages (WPs). WP1 was set up as a PhD project based on the first main objective and the related questions. WP2 was set up as a combined work among various researchers addressing the second main objective and the related questions.

The project has seen some changes in active researchers throughout its lifetime as both the project manager, project participants, and PhD supervisors have changed with the current set up being established a year into the project. Given the high specialisation of researchers this has naturally lead to alternative approaches to address the two main objectives. Looking at the final project output, we believe that we have overall addressed the main objectives while we note that the emphasis on specific issues has evolved given the research expertise of the researchers involved in the project.

1.5 Project results and dissemination of results

This section presents a more detailed description of the activities related to the two main objectives together with a description of results and dissemination of the project. The project is an applied research project with a view to obtain new knowledge about electric vehicle usage and charging behaviour. The results can be used when developing new services and charging schemes related to a future smart grid.

The activities related to the first main objective are presented in section 1.5.1-1.5.3. They have been successfully carried out by PhD student Gebeyehu Fetene under supervision of Professor Carlo Prato and Associate Professor Sigal Kaplan. Overall, the PhD study has been very successful both from an academic point of view and with respect to methodological outcome. All activities related to the second main objective are presented in section 1.5.4 – 1.5.9. These are mainly carried out by Assistant Professor Anders Fjendbo Jensen and Associate Professor Stefan Lindhard Mabit, but there are also contributions from PhD student Gebeyehu Fetene, Assistant Professor Thomas Kjær Rasmussen, and Senior Researcher Linda Christensen.

1.5.1: Work place charging

While EVs offer new opportunities in the transport system in terms of reducing pollution and balancing the electric grid, the technology also presents new challenges. One of the main concerns about EVs is that recharging takes long time, from about 20 minutes to hours depending on the type of the recharging tool and on the battery type. Added to this is that the driving range of currently available (and affordable by a representative car buyer) EVs is limited. This result in driving-range anxiety (Franke & Krems 2013), making recharging time and place decisive issues (Bonges & Lusk 2016; Lieven 2015). The long recharging time makes on-the-road recharging costly because of the value of time (of the EV user(s)), the parking fee associated with the long recharging time and of the distaste of waiting long time in the car while recharging the EV in the middle of the trip . Certainly, EVs can be recharged at residence while the EV user is doing household activities without almost any waste of valuable time for recharging. However, not all individuals have private parking and even those who have private parking may need to recharge at non-residential areas to extend the driving range for planned and unplanned trips and when there are technical problems to recharge at the residence. One suggested means of addressing the recharging problem particularly for individuals without private parking is to provide recharging service at their workplace, which is considered as the second major recharging option next to residential charging (Neubauer & Wood 2014). However, this requires agreements at least between employers and employees about having a charging facility at the workplace denoted as workplace charging (WPC). There is a literature gap that systematically analyses the economics of the demand for and supply of WPC which is addressed in this activity.

WPC may have benefits for employees, employers, electricity suppliers and even for the society at large. For example, WPC could be an ideal recharging option for employees without private parking. It is also expected to be the favourite alternative to public and commercial recharging stations for individuals having private parking but who need to extend the driving range of their EVs recharged at residential areas. For employers, WPC can be a recruitment and retention tool and may attract more productive employees. For electricity suppliers, WPC has a potential for balancing the electricity grid system by recharging/de-recharging the batteries of EVs according to the electricity balance condition during the working hours. However, there might also be social costs because employer-provided fringe benefits favouring car use may increase travel demand and so traffic congestion. By increasing electricity consumption during peak-periods the electricity overload problem could be aggravated and cause an increase in electricity prices and inefficiency.

However, WPC related research is still in its infancy and to the best of our knowledge there is currently no systematic assessment of the economic rationale of WPC demand and supply. We propose a microeconomic model of WPC and use the approach to shed light on the incentives and barriers employees and employers face when deciding on the demand for and supply of WPC. In the model, we show the determinants of WPC demand and supply as well as the role that the electricity supplier (via electricity tariffs for companies and for recharging fees at residential and commercial sites) and the government (via income and energy taxes) play in affecting WPC provision. In addition to this, using the model and data calibration, we examine the existence of a WPC market without governments' or other agents' intervention.

The simulation results show that under the current market conditions, there is no WPC contract that an employer is willing to offer and at the same time that the majority of employees are willing to accept. To overcome the lack of demand for or underprovision of WPC we discuss various solutions, involving subsidies to recharging facility costs and adjustments in electricity tariffs or loading technologies. The results concerning remedies show that while incentives for the supply side of WPC are promising, incentives that aim at boosting the demand side of WPC are less feasible. A pure (non-distortionary) redistribution from employees to the employer may also help to overcome WPC underprovision since WPC generates private net-benefits when there is employer-paid recharging in that employees benefit from WPC but the employer does not.

1.5.2: Smart grid charging: Consumer responses to scheduling and pricing

Upward expectations of future EV growth pose the question about the future load on the electric grid system. This EV growth is expected to load significantly the electric power grid system. Charging times are expected to coincide with peak hours of electricity demand for household consumption and industrial use. Demand side management (DSM) of EV charging, by encouraging EV owners to change their charging patterns in response to changes in electricity prices, is viewed as a possible solution to reduce grid overload at peak hours and to reduce investments in grid capacity expansion (Finn et al. 2012; Flath et al. 2013). Economic evaluations have shown that DSM of EV charging has positive welfare effects. For example, smart charging grids in Finland could produce benefits of 227 EUR per vehicle per year (Kiviluoma & Meibom 2010).

While existing literature on EV charging DSM has focused on technical aspects and considered EV owners as utility maximisers, this study proposes a behavioural model incorporating behavioural and psychological aspects relevant to EV owners facing charging decisions and interacting with the supplier. The behavioural model represents utility maximization under myopic loss aversion (MLA) behaviour in an ultimatum game (UG) framework with two players: EV owner and the electricity supplier. We test the validity of the behavioural model by designing 3x2 laboratory experiments (there are treatments with two groups of participants for each treatment).

In one of the treatments, the electricity supplier (simulated in the experimental design) asks EV users (experiment participants) to choose between recharging upon arrival at home paying the highest fee when electricity consumption is at its peak or postponing the recharging to off-peak hours at night. EV users who choose the latter are asked to propose a recharging time to be eligible to the discounted fee where the later the chosen recharging time, the higher is the probability of being eligible to the discount and also the higher is the risk that an unplanned trip may occur. In other words, the EV users who proposed longer deferred time of recharging has a higher chance of being eligible to be offered discounted recharging fee. However, the longer the deferred time, the higher the probability of an unplanned trip occurrence where the EV user will not be able to use the uncharged car. In the second treatment, the EV users are asked to propose the amount of compensation they demand for postponing recharging fixed by the supplier. They are informed that the higher the requested compensation amount, the less likely is the supplier to offer the requested compensation; whereas, the lower the requested compensation amount, the less likely is the amount to cover losses associated with postponing recharging. The third treatment is similar to the second except the EV users are requested to ask for compensation for letting the electricity supplier control the recharging, where they are guaranteed to get the EV recharged for the next planned trip they have, but not for unforeseen trips that may occur before the planned trip. The three treatments were conducted each with two groups of participants: one group making decisions on daily bases and the other group engaging in weekly contracts. Each of the three treatments are incentive compatible, i.e. the EV users will likely reveal their true preferences to the supplier since the amount of threshold that the supplier accepts is concealed.

Findings from the experiment show that individuals reveal MLA behaviour when taking EV charging decisions, which means that they show irrational behaviour when it comes to this trade off. In general, they are more sensitive to a reduction in flexibility than a corresponding reduction in price. However, presenting long-term EV charging contracts within an UG framework can curtail MLA behaviour and help EV owners to choose cost-minimizing charging times in discounted off-peak charging hours.

1.5.3: Smart grid charging: Inducing risk taking behaviour with peer information

Numerous theoretical studies (e.g. Banerjee 1992; Bikhchandani et al. 1992; Lieven 2015) and empirical studies (e.g. Avery & Zemsky 1998; Bursztyn et al. 2014; Olaussen 2009; Weizsäcker 2010) have found that individuals are influenced by the choices and behaviour of others. The insights into the effects of peer information on choice and on behaviour have been used to guide individuals to take one choice or another (Hoff & Stiglitz 2016). Peer effects play a significant and lasting role in societies political, socio-economic and demographic aspects (Akerlof 1997; Ellison & Fudenberg 1995; Hoff & Stiglitz 2016). We design a laboratory experiment mimicking the real world situation where EV users may experience a trade-off between the cost saving from postponing recharging towards off-peak electricity consumption hours and the risk of the current battery power not being enough for unforeseen trip occurrence. The standard economic theory prediction in this case is that individuals will make choices according to their risk preference without being influenced by peers' choices. This is so because observing peers' choices does not convey new information as the electricity tariff and the distribution of the unforeseen trip distance are common knowledge. Recent field and laboratory studies find, however, that the choices of individuals are affected by peers' choices even when the peers' choices do not convey new information and when there is no payoff commonality (Cooper and Rege, 2011; Chung et al. 2015; Gioia 2016). For example, Allcott (2011) and Schultz et al. (2007) have found from field experiments that households decreased (increased) energy consumption after learning that their consumption was higher (lower) than their neighbours' consumption.

This study aims to shed light on whether and how peer effect may be used for policy-making in areas involving uncertainty in general and, in particular, about smooth integration of EVs in to the electricity grid system. By providing for the current EV users attractive incentives and tips that helps to reduce the psychological barrier of postponing recharging and then, by sharing the charging experience and cost of these customers, electricity suppliers may induce the current and future EV users to postpone recharging towards off-peak electricity consumption hours.

The study investigates whether individuals want to see the choices of others, if observing peers' choices influences own choices, to what extent the peer effect is pervasive and who are being influenced by peers' choices as well as the role the type of peer information plays on peer effects. We conducted five treatments tailoring peer information. In one treatment, risk-averse and risk-seeking participants received each other's choice. In the second treatment, each participant received the mean of the choices of all other participants excluding the recipient's own choice. In the third treatment, each participant received the same information as in the second treatment but framed as the choice of a peer instead of mean choice of all participants. In the fourth treatment, each participant received the choices of two other participants while the choice of a randomly chosen participant is for the fifth treatment.

The result shows that a lion share of individuals want to see peers' choices. However, only a moderate percentage of them, mostly those with relatively lower scores in our math test and lacking self-confidence, use the peers' choices to revise their intrinsic choices, implying that social learning is the main reason for peer effect. Accordingly, the use of a peer effect in inducing individuals to choose one action or the other depends largely on the decision-making ability and the self-confidence the decision problem under consideration. The results reveal also that the type of peer information plays a significant role in the measured peer effects.

1.5.4: Electric vehicle user behaviour

In the remaining main objectives we focus on driving behaviour of EV users. Growing literature shows an increasing interest in EVs and their market, but current EV travel demand studies are usually based on data collected from users of CVs (see e.g. Pearre et al. 2011; Greaves et al. 2014). EVs are however different from CVs in a number of ways, in particular when it comes to the driving range and the refuelling/recharging which can lead to behavioural changes (Jensen & Mabit n.d.). EV users might avoid longer and less-planned trips and, when deciding on a route, they might select roads where the general speed is lower, the trip length is shorter, or the charging facilities are better. On the other hand, over a longer period of time, most users do not need charging other than overnight charging at home in order to keep up with their current behaviour (Christensen 2011). Thus, the impact on traffic of a large scale EV adoption is not obvious, as it cannot be assumed that CVs currently on the road are simply replaced by EVs and individual behaviour otherwise stays constant.

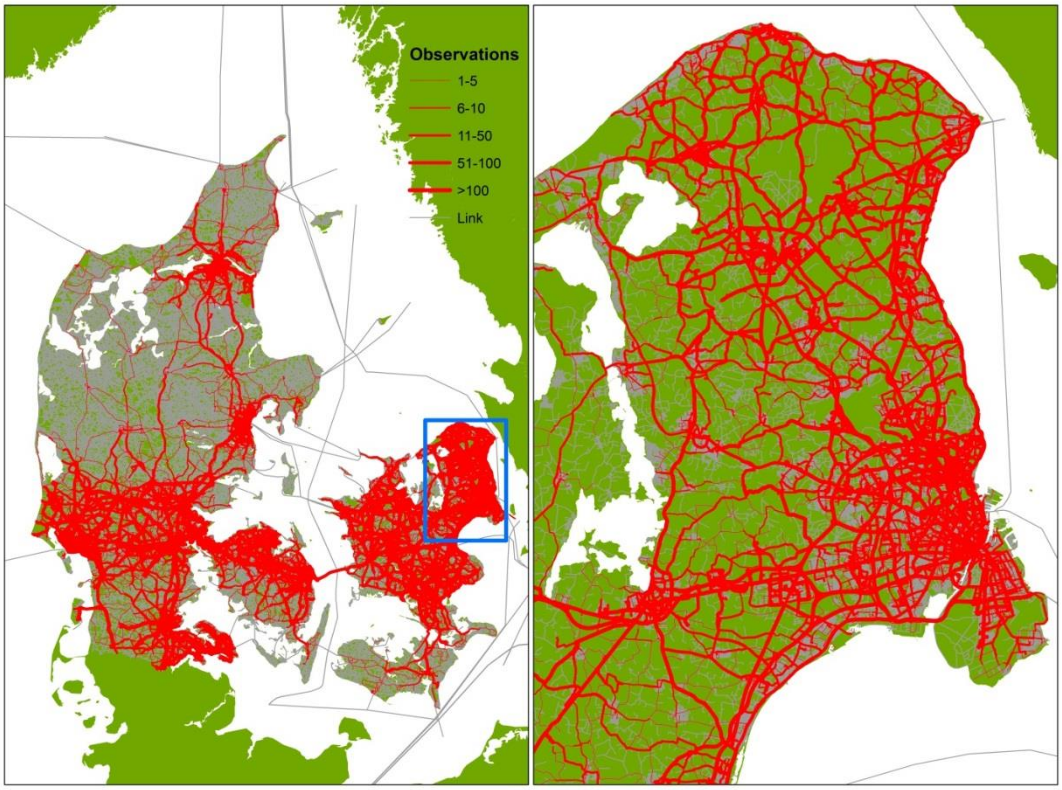


Figure 1: Spatial distribution of observations. Amount of observations (EV or CV) on links

We utilise a unique and vast dataset consisting of GPS records from EVs driven during a large demonstration project about EVs conducted in Denmark during the period 2011-2013. Households participating in the trial had an EV available for a period of three months during which all trips were GPS logged. Additionally, some of the households GPS logged trips by their CV in the month before and the month after the EV was received. With GPS data collected before and after the beginning of the trial period, we are able to analyse how an additional EV in the household affects daily car use. Each of a total of 198 EVs was distributed to several households over a period of three years, i.e. when a three month trial period finished in one household, the car was distributed to the next household. The sample of households was based on voluntary participation, but the household needed to already own at least one car and have a dedicated parking space where the EV could be charged with a home charging station. Furthermore, the participating household should belong to one of the 27 participating municipalities. From those who successfully fulfilled these criteria, the project managers selected the test households based on age, gender, demography, level of education, profession and driving needs, with the clear intention of representing a broad range of the Danish population.

The data is extremely useful for studying EV behaviour as it is most probably currently the largest existing dataset with revealed EV trips and a high level of detail and furthermore it offers comparison with trips in CVs in the houseshold. In the current literature on EV usage, it is often assumed that the travel behaviour of car users does not change whether they use an ICV or a EV. A large range of studies have analysed the potential use of EVs for everyday travel in households based on data on ICV journeys obtained from odometer reading at refuelling (see e.g. Greene 1985), from national travel surveys (see e.g. Christensen 2011), or from ICV journeys measured with GPS (see e.g. Christensen 2011; Pearre et al. 2011; Greaves et al. 2014). The two latter of these studies find that with the driving distances possible with the EVs currently available, a large share of the households would be able to maintain their current way of travel with only a minor level of adaption. However, GPS-based data collected over a longer period of time, Christensen (2011) find that such conclusions are problematic as several households occasionally have longer trips that cannot be covered by a EV. In the same manner, consumer choice studies have shown that the driving distance covered on a fully charged battery has great importance for potential customers (see e.g. Jensen et al. 2012; Dimitropoulos et al. 2013; Mabit & Fosgerau 2011; Bunch et al. 1993). Similarly, Franke & Krems (2013)found driving range preferences for potential customers to be substantially higher than their average daily driving needs.

In the following analysis we consider the trips conducted by the 100 households where the ICV trips were registered, for comparison. This leaves us with 29,242 EV trips and 14,573 ICV trips distributed on respectively 6102 and 3017 household days. For the description and the analysis of the data we define period 1 as the month before the EV was received by the household (i.e. only ICV is available and trips are registered), period 2 as the first month after the EV was received (in which both ICV and EV are available and trips from both alternatives are registered) whereas period 3 is defined as the last two months where the EV was available (i.e. both alternatives were available but only the EV trips were registered). The trips conducted in period 1 should give a good indication about the travel needs of the households in the trial. On average, including days with no travel, the daily distance travelled in the CV is 41.6km (25.8miles), which is slightly below the national average in 2013 which based on numbers from Statistics Denmark is 43.5km (27.0miles).

Regarding the charging behaviour of the EV users, each household charged their EV 67 times during the test period, which approximately accounts for 5.6 times per week. This is much more than the 3 times per week reported in Franke and Krems (2013). Similar to this study, however, we found that the users typically charge their car when there is plenty of energy left in the battery. On average there was 51% energy left on the battery when a charge was initiated. 65% of the charges were conducted when the state of charge (SOC) was more than 40% (In Franke and Krems (2013) they found that 66% of the charges were conducted when the SOC was more than 40%). On average we found that the SOC after a charge was 92% which means that many users disrupt the charging before the battery has been fully charged.

In order to analyse how the extra car in the household affects travel in the household, for each period we calculated the average number of trips per day, the average number of journeys per day, the average number of kilometres per day and the share of days where each car was used. To be able to analyse differences between weekdays and weekends, we calculated different means for these. Furthermore, we split period 2 so that period 2.1 is the first two weeks of period 2 and period 2.2 covers the remainder of period 2. This description of the data is found in Figure 2.

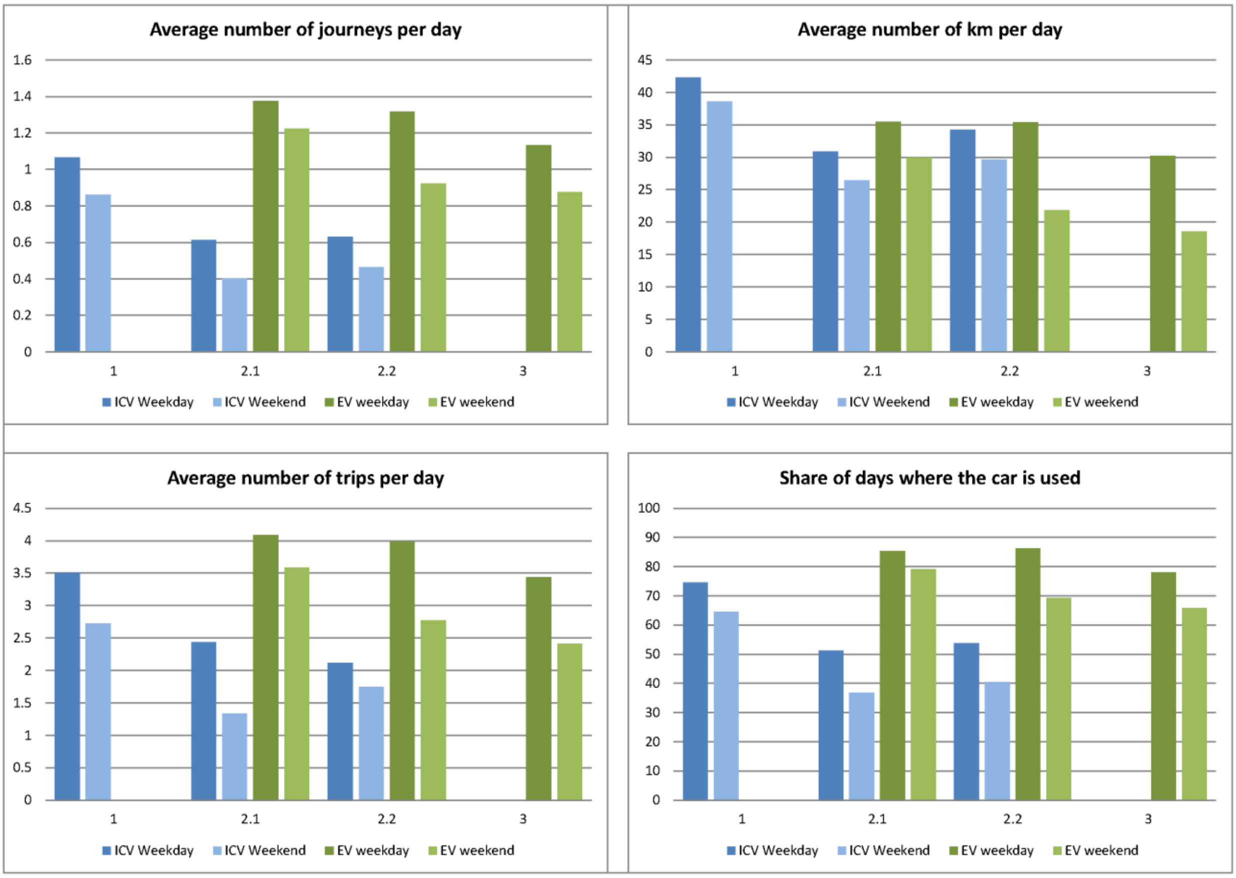


Figure 2: Travel comparisons across the various periods.

As expected, it is seen that the number of journeys conducted in the ICV decreases when the EV becomes available. However, it is also clear that the households still use the ICV for a large share of their journeys. In fact, the total household car travel seems to increase drastically, which means that the households make use of the extra mobility that an extra car in the household offers. In general there is more travel on weekdays compared to weekends. The number of EV journeys in period 2 is higher than the number of ICV journeys, whereas the number of kilometres driven is about the same. This indicates that the ICV is used for longer trips. Initially, the number of EV journeys and the number of days where the EV is used is higher than the comparable numbers for the ICV in period 1, but with time it seems that, both in terms of number of trips and in terms of kilometres, the EV usage decreases. One reason for this could be that many households in the beginning make 'presentation' journeys to show and give trials to friends and family. Unfortunately we do not have information on the journey types, so that this can be analysed further. However, Golob & Gould (1998) report that for their EV trial including households in Southern California, such journeys accounted for approximately 11% of the total number of trips in a two week trail and that correcting for the days where such trips have been conducted reduces the daily vehicle km travelled from 64.5km (39.8 miles) to 62.6km (38.9 miles).

1.5.5: Factors affecting energy consumption of electric vehicles under real driving conditions

Uncertainty about the energy consumption rate (ECR) and its sensitivity to the various driving environments is problematic for the uptake of EVs. Providing accurate information to people about the energy consumption rate of EVs using real-world data where the drivers are the people themselves is crucial for individuals to make informed decisions and to build trust about EVs, particularly in the current situation where big car manufacturers have been mistrusted after they have been found providing incorrect information about fuel efficiency (Kubota 2016; Randazzo & Boston 2016). Analyses of the factors affecting ECR of EVs are also relevant to figure out the ways to improve the electricity efficiency of EVs (analogous to fuel efficiency to CVs).

Insights into the factors that influence the ECR of EVs are scarce. Most studies include technical analyses that investigate the effects of car components on the ECR (see e.g. Duke et al. 2009) and studies using either only few EVs or drivers and without full account of the weather condition (Birrell et al. 2014; Wu et al. 2015) mostly by stakeholders in EVs. Large differences about fuel consumption of passenger cars are usually observed between the results of car manufacturers and the results observed in real-world driving (Huo et al. 2011).

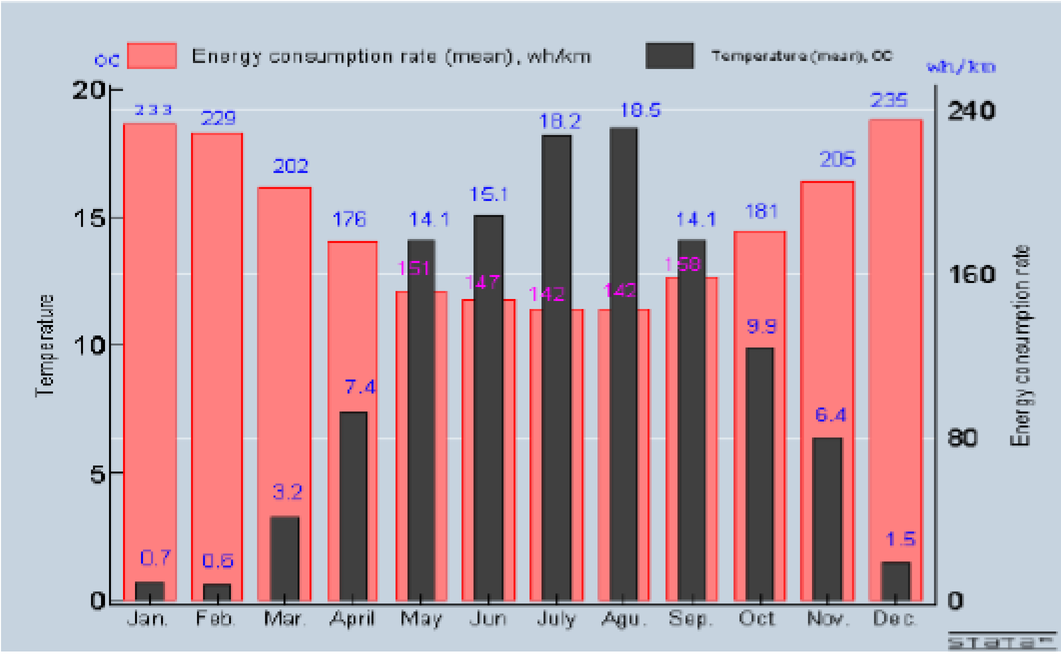


Figure 3: Mean ECR (wh/km) and the mean temperature (Degree Celcius) by month.

This study analyzes the electricity consumption of EVs and its sensitivity to the various driving environments in the hands of customers. Analyzing the factors that affect the energy efficiency of vehicles is crucial to the overall efficiency improvement in the transport sector, one of the top polluting sectors at the global level. This may help individuals to make informed decisions about EV choice, manufacturers to build trust with customers by provide more accurate information, and governments to design policies based on reliable information.

The results of the analysis measure the (unweighted) mean ECR of EVs at about 0.183 kWh/km. The ECR of EVs is highly sensitive to the various driving environments. Particularly, the weather effect is strong with the energy consumption rate in December being higher by about 65 %, on average, than the consumption rate in July or August. Moreover, the results of the analysis show that driving speed, acceleration and temperature have non-linear effects.

1.5.6 Driving patterns and the need of the users

The purpose of this sub-project is to investigate how the performance of modern electric vehicles fit to the needs of car owners and their travel behaviour. From different sources we know how cars are actually used, how far they are driving, how often they are parked at different destinations, etc. What we are interested in is if this known driving pattern can be covered by an electric vehicle in case the actual car is replaced by an electric vehicle. Is the driving range far enough to cover the daily travel activity and if not how often will it have to be charge during the day? Furthermore, is the parking period during the night long enough to get charged and be ready for the following day? Or would it be possible to charge during the day and in this way get enough power to overcome the daily activity.

Method

Based on combined GPS data and energy data collected from the large trial ‘Test en elbil’ several authors have shown that the travel range of electric vehicles is not as long as the producers declare from the official driving test circle. Especially during the winter period the driving range of a 'triplet' (Citroën C1, Peugeot iOn or Mitsubishi iMiev) which is declared to have a range at 130 km is only 77 km. In the summer it is 115 km (Fetene et al. 2015). Fetene et al. have developed a model which shows how the energy consumption depends on the driving style (speed, acceleration and distance), the battery's state of charge (SOC), and weather (temperature, precipitation, sunshine and wind).

The model developed in Fetene et al. (2015) is a fixed effect panel data model which is developed to assess the effect of each variable affecting the energy (electricity for EVs) consumption rate (ECR), i.e. the amount of electricity consumption per unit distance. It cannot be used directly for making predictions of the ECR from other data sources. Instead a more suitable model had to be developed.

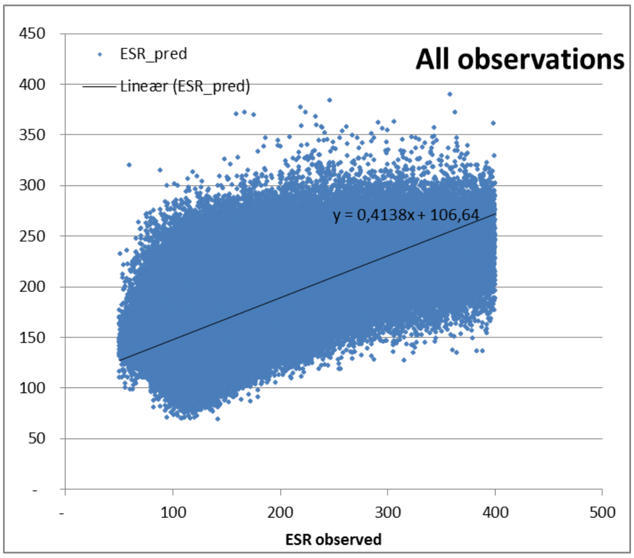
When the developed model is used for prediction of the energy consumption, it is assumed that the driving style, travel behaviour and weather situation is exactly the same as combustion engine cars have in the trials at which they are measured.

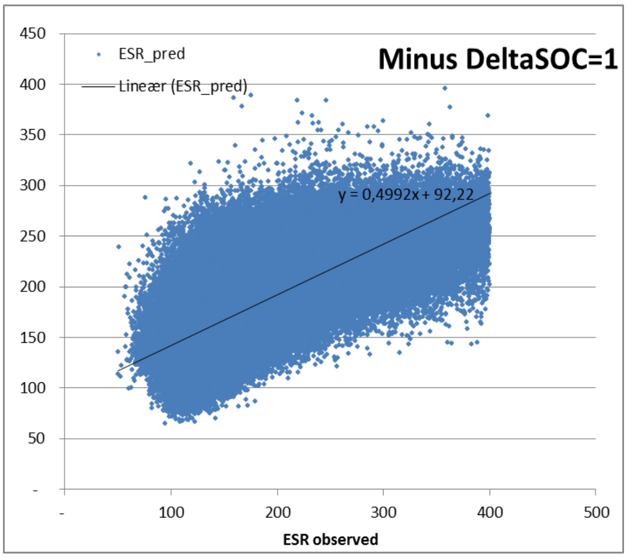
For each car it is investigated if it is possible to fulfil the daily travel pattern with the energy it is possible to charge during the night and how often it is not possible during a fortnight, a month or a longer period. Furthermore, different scenarios for charging during the day are introduced (at home, at a working place or at a fast charging station close to the actual destinations). The effect of range anxiety of the drivers is tested too. This analysis uses results by (Sun et al. 2015) who have modelled the distribution of anxiety by EV drivers using fast charging data from Japan.

The data were collected from 741 EVs in the 'Test en elbil' trial during 2012-14 and included both information about location from a GPS logger and information about SOC from the Canbus. Out of these, 111 drivers had a GPS logger installed in their own car in a 2-4 weeks period before they received the EV. They kept the logger during the EV period but for this sub-project we only use data for the period before they received the EV and thereby an extra car in the household.

The energy consumption model

For the purpose of prediction of energy consumption, it was found suitable to use a linear regression model. This model is used to predict the ECR of the EVs in the trial and the mean value of the predicted ECR and the real mean are compared. The predicted value is 6% higher. Furthermore, when plotting the predicted observations against the observed values these are not following a tendency-line crossing through zero which it ought to if the model is fitting well. We have tried different solutions to develop a prediction model closer to the observed values.





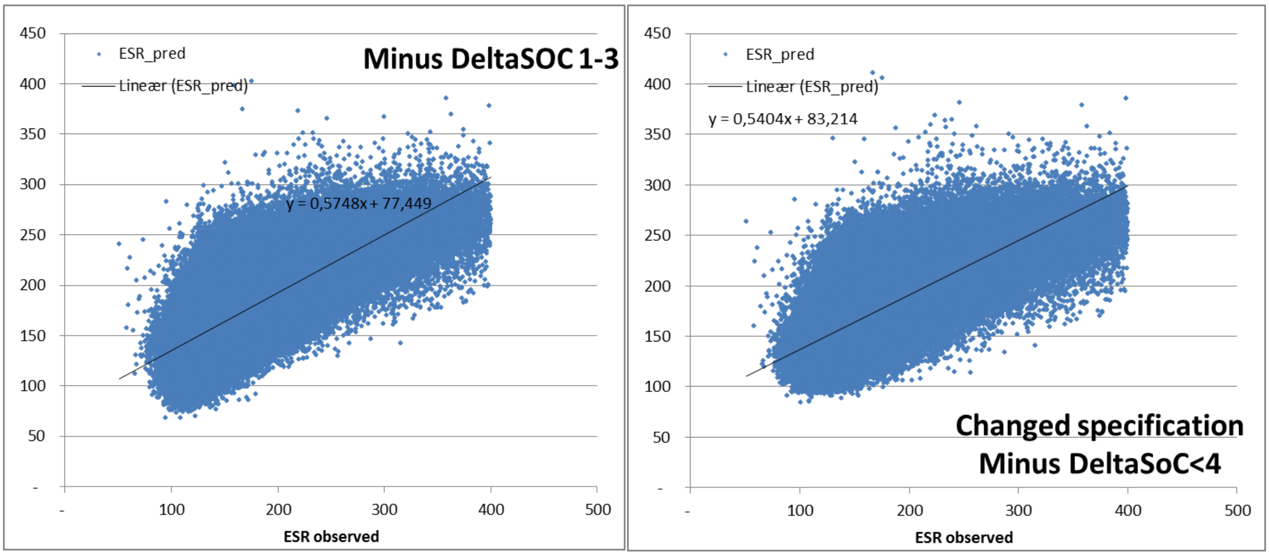


Figure 4: Plots of observed vs. predicted ECR.

One solution has been to remove observations for which the change in SOC (DeltaSOC) is very small (SOC is measured as percent without decimal). With DeltaSOC=1 the real value of the SOC is lying in the interval +/- 100% of the reported value of the ECR. With DeltaSOC=2 the uncertainty is +/- 50%, with DeltaSOC=3 the uncertainly is +/- 1/3 etc. By using the original specification and removing the uncertain observations with DeltaSOC in the interval 1-3 the tendency line gets closer to passing through zero, but the deviation is still large.

Another way to go has been to change the specification of the model wrt. travel speed. In the actual model, ECR is specified as K1*Speed + K2*$Speed^2$ +… A more correct form will be to develop ECR from the energy balance and therefore use K1*Speed + K2*$Speed^3$ +… (Duke et al. 2009). This again improves the results. A final conclusion on the best model is not yet found. However, it is important to observe that the influence from the SOC at the beginning of the trip and of weather data is very robust in the different models with close to similar coefficients. Only the effect of the driving data and the intercept is changing.

Table 1 shows the model that is used in the following and an example of alternative specification.

	Fixed effect model	Linear regression model used	Linear regression with Delta SOC>3	Changed specification with Delta SOC>3
Intercept	135.489	253.922	262.7589	224.429
Mean driving speed (m/s)	-19.000	-19.406	-20.0267	-10.4591
Mean driving speed squared	0.761	0.8269	0.8191	
				0.0177
Median acceleration (m/s2)	55.521	103.298	121.0087	157.3917
Median acceleration square	27.828	-20.33	-22.6636	-30.6533
Trip distance (km)	-1.11	-1.2099	-2.1775	
Distance squared	0.01	0.0075	0.0206	
Rush hour (dummy: 1 = trip during rush-hours of traffic)	-1.926	-1.1307	0.7403	2.3077
Highway (dummy: 1 = trip on highway) (left out in other models)	0.534			
Battery level at trip start (%)	3.401	2.9032	3.2359	2.5151
Battery level at trip start squared	-0.056	-0.0466	-0.0502	-0.0396
Battery level at trip start cubed	0.0003	0.0002	0.0002	0.0002
Winter (dummy: winter ==1)	14.687	22.3256	19.3105	19.6215

Temperature (0C)	-4.807	-4.7057	-4.4719	-4.5487
Temperature square	0.081	0.0754	0.0687	0.0674
Precipitation (mm)	5.287	5.5934	5.3146	5.2707
Wind speed (m/s)	0.695	0.387	0.5506	0.6474
Sunshine (minutes)	-0.118	-0.1723	-0.1706	-0.1689

Table 1 Coefficients estimated for different model specifications.

Need to charge

The model is used to calculate the share of the driving days it is needed to charge depending on the demand for rest-power on the battery. According to (Sun et al. 2015) only a few travellers risk to drive the EV down to 10% rest-power. Half of the drivers want to charge by fast charging when 25% of the power is left. Table 2 shows the resulting need to charge in the summer part and winter part of the year. The results are furthermore differentiated according to the length of the period the GPS has been available to measure the travel activity of the conventional vehicle.

			Driving to 0	10% anxiety	25% anxiety
Share of days with need to charge	April-October	15-30 days	11%	16%	18%
		1-14 days	10%	15%	18%
	November-March	15-30 days	13%	20%	22%
		1-14 days	18%	24%	27%
Share of families who need to charge	April-October	15-30 days	78%	86%	87%
		1-14 days	45%	55%	58%
	November-March	15-30 days	75%	92%	92%
		1-14 days	63%	71%	74%

Table 2 Number of days where additional charging is necessary to complete daily travel.

It can be seen that even though it is only needed to charge in a minor share of days, a very high share of the drivers need to charge once or more times .

Further analyses

The results are for the moment only calculated for the model using the specification of Fetene et al. (2016) removing the most uncertain part of data. Different specifications will be analysed in the future. The same will be the case for charging at home, at work and at holiday stays.

1.5.7: Factors affecting daily travel in electric vehicles

Daily usage of EVs has related consequences on both the transport network and the electricity network. Within this main objective we seek to investigate the factors that affect daily usage of EVs and how the effects of each factor differ from the effect on CV usage. Specifically, we use a mixed non-linear regression model that can be used to analyse the daily distances travelled (DDT). With panel data available it is possible to use an error specification taking into account household heterogeneity. With the suggested model we demonstrate how DDT for both EV and ICV is affected by household characteristics (e.g. area population density and the number of driving licenses), weather characteristics (e.g. temperature and wind speed) and trip time characteristics (e.g. weekday vs. weekend) and show that several of the mentioned types of characteristics affect travel behaviour and that there are differences across EV and ICV.

Previously, Greene (1985) and Lin et al. (2012) specifically investigated the distributions of daily vehicle usage for ICVs in order to study the implications for respectively EV and hybrid EV use. They suggested the gamma distribution to be best at representing vehicle use in households, but to our knowledge, similar analyses have not been conducted on actual EV data to investigate whether the daily vehicle usage is different when using a EV compared to an ICV.

For both ICV and EV, across all periods, a higher population density in the area of the household leads to a significantly lower DDT. In the same way, households located in city areas drive significantly less in the ICV compared to other households. However, such an effect was not found for EV. A large difference in behaviour appears during weekends. In period 1, we did not find a difference in DDT across weekdays and weekends for ICV and thus the dummy parameter for period 2 was taken out. However, in period 2, the ICV is used significantly more in weekends than weekdays. For EV, the picture is opposite. The reason is most likely, that weekend trips usually are longer and less scheduled which means that the EV is less convenient to use during weekends compared to ICV. Furthermore, the effect is significantly higher in period 3 than period 2, which indicate that the effect is even stronger with more experience (or less enthusiasm with trying to use the EV as much as possible).

For ICV, none of the weather variables affect the DDT in either of the two periods. However, and as also expected, high wind speed and cold temperature has a negative effect on the DDT for EV. As with the rest of the variables it was interesting to analyse, whether there was a learning effect on the weather variables so that, e.g. the users with more experience would avoid the EV more as they found out that high wind speed and cold weather significantly reduces the driving distance of the EV. However, we did not find any such effects. Furthermore, we did not find any effects from rain or sunshine.

Unfortunately, the data does not include information on trip purpose, as it would have been interesting to extend the analysis to different trip types. This would also allow for filtering out trips that are not related to actual household mobility needs but rather relates to transitory needs to show off the EV to e.g. neighbours and family. This effect was instead, to some extent, taken into account by including a dummy for the first week of the trial and one for the first two weeks of the trial. According to the model, this effect is only significant for the first week and as expected the parameter sign is positive.

1.5.8: Factors affecting the choice between electric vehicles and conventional vehicles for household journeys

The next model estimation goes further by investigating the factors relevant for the decision of using the EV or the ICV for a specific journey, using a discrete choice model. For total journey time, net driving time and number of trip-legs, we did not find any difference in preferences between the alternatives. As expected, these all have negative signs, but it does not seem that the total journey time affects the choice between ICV and EV. As discussed earlier, EV trial participants often use the early trial period to present the EV to friends and neighbours. As we do not have information on trip purpose, we tried to take this into account by other available information. In the first week of the trial there is a higher preference for the EV compared to the rest of the trial, which could be due to a higher enthusiasm for using the EVs but also due to presentation of the EV to friends and neighbours. Furthermore, we tested if there is a difference in preference during the morning peak, where most car users are going to work and found a positive preference for EV. Home-work trips are easy to plan and a lower level of flexibility is often needed, which means that the EV is very suitable for this. On the other hand, there is a lower preference for the EV during weekends compared to weekdays. The parameter for the first week interacted with the number of trip legs in each journey for EV is positive and almost cancels out the negative preference for the number of trip-legs. This indicates that individuals do not have a preference for this factor until they reach one week of experience. The parameter for EV journey time interacted with first week is negative and significant which indicates that individuals have a lower preference for using the EV for journeys conducted over longer time in the beginning of the trial. We furthermore tested whether the number of necessary charges has an effect on the choice and found that taking the log to the number of charges explained the choice better. This makes sense as it is expected that the first necessary charge has a higher marginal disutility than the following charges.

Including information about the weather highly improved the model which we to some extent also expected and in line with the work presented in 1.5.5. Lohse-Busch et al. (2013) found that the impact of temperature on vehicle efficiency was higher for EVs than for CVs. In fact they found a 100% increase in energy consumption for a Nissan Leaf EV, when the temperature drops to 20 degrees Fahrenheit (about -7 degrees Celsius) from 70 degrees Fahrenheit (about 21 degrees Celsius). The corresponding drop in efficiency for ICVs was only 20%. Similar results for EV efficiency are found in Zahabi et al. (2014) and Fetene et al. (2015). Inevitably, such a drop in efficiency will have a great effect on the driving distance it is possible to drive on a fully charged battery which again should have an effect on EV travel behaviour. Hence, we expected that a lower temperature would have a negative effect on the EV preferences. We tested several specifications for temperature, but surprisingly we were not able to find a strong effect of temperature on the choice. Instead, wind speed seem to explain the preferences much better, as more individuals are avoiding the EV when there is much wind and this effect is even stronger in the first week of the trial. This might partly be due to the fact that the EVs available in the trial were mini class cars, which probably feels less stable in strong wind. Unfortunately, we do not know whether this effect would be the same if the EV would have been the same car class as the ICV in the household. The effect of the wind is also due to a much higher energy need when the wind speed is high as found in Fetene et al. (2015). Furthermore, precipitation had an effect on preferences, and here it seems that individuals have stronger preferences for the EV if there is more precipitation. We believe that this result represents a weakness of the data, as we do not have information about the full choice set of the household transport options. Thus, when it is raining, we believe that many bike trips are replaced by the EV.

1.5.9: EV route choice model

Understanding the behaviour of EV users is important in a number of ways. Beside potential environmental effects, there is a need to understand other related effects, such as effects on the electricity network and the transport network. The objective of this study is to use revealed preferences (RP) data to investigate differences in route choice behaviour between CV and EV users. To our knowledge, this is the first time that a state-of-the-art route choice model has been estimated on RP EV data. In addition, the level of detail in the data allows for accounting for congestion, reliability, topology, weather and socioeconomic background.

The GPS traces were matched to the very detailed NAVTEQ street network (NAVTEQ 2010). The high level of detail of the network is crucial, as EV users might use smaller roads with lower speeds in order to save energy due to current technological restrictions on driving distances. Following the procedure in Prato et al. (2014), route choice behaviour is modelled with a two-stage approach consisting of choice set generation and model estimation. The first stage used a doubly stochastic generation process to generate a choice set consisting of a maximum of 100 unique alternatives for each observed route. Subsequently, the observations were filtered to exclude observations for which the choice set contained only one alternative route or did not contain any alternative reasonably similar to the observed route. In the second stage, a mixed path size correction logit model was estimated for modelling route choice behaviour (Bovy et al. 2008). Comparison of EV and ICV preferences is made possible by estimating jointly across data from each technology using a logit scaling approach with at least one generic parameter across data (Bradley & Daly 1997).

A route choice model has been estimated jointly on EV and CV data with parameters for free-flow travel time, trip-length, number of left turns and number of right turns. The parameters have expected signs and indicate that there is a difference between EV and CV when it comes to trip-length but not number of left- and right turns. This result seems plausible and it is very relevant to address and quantify such differences in the transport network. We see a great potential in continuing our research in this direction. Indeed, with this data it is possible to investigate the EV users charging behaviour in great detail. In particular we would with this model be able to model the demand side aspects of EV usage and model both impacts on the transport and the electrical network and considering congestion, vehicle storage and smart-grid aspects like vehicle-to-grid strategies.

1.5.10 Discussion

This section discusses the results and relates them to the research questions stated in the project proposal. The overall background for submitting this proposal was to support the ambition to increase the share of renewable energy technologies in the electric power system and to balance the system when these fluctuating energy production technologies have large variations. A more recent idea to meet this environmental challenge is to combine the need for storage of electricity to balance the electric power system with a large scale introduction of electric vehicles. However, such a setup quickly raises a number of questions which need further research. Overall we wanted to provide relevant information for the following two questions about intelligent charging to be answered:

- Will EV owners accept an arrangement, where either delayed charging and/or potential de-charging can happen?
- How will the behaviour of EV drivers be with respect to driving and charging?

To give answers to these questions, it is necessary to look both at the supply side and the demand side of the electricity network. This project has focused on providing information related to the demand side only. The two questions have been treated separately in separate work packages where the objective of the first work package was to investigate consumers' willingness to accept different contractual agreements with the electricity provider and the objective of the second work package was to describe driving behaviour of electric car users. We believe that the project has successfully lived up to the expectations in terms of contributing to the political climate and energy objectives as several results and advise is provided with regard to smart charging and behaviour of EV users.

Throughout the project, several theories have been tested and models have been developed, which all contribute to a much more detailed understanding of the demand for electricity used for private EVs. The models have been based a dataset which is probably currently the largest and most detailed data available from EV usage and the results provided are therefore providing a great step forward for a better understanding of EV user behaviour which leads to the demand. In fact, the scale and the detail of the data provided more possibilities for research than we initially had hoped and we look forward to continue this direction of research in the future. The level of detail provided can be used for both spatial and temporal analyses of electricity demand for individual transport. The next step would be to integrate the models provided in this project with models for electricity supply. Thus, smart charging and EV behaviour will be a future research area for our group, not least due to the activities taken place in this project.

1.5.11 Dissemination activities

The findings throughout this project have so far resulted in 11 presentations in conferences of which 8 are international. Furthermore, the findings have resulted in a publication in an international ISI journal while 3 more papers are under review, also in international ISI journals. We furthermore expect that 3 more papers will be submitted to international ISI journals within a year. A general overview of the written dissemination activities is presented in Table 3, while a general overview of the conference dissemination activities is presented in Table 4.

Papers/Reports			
Authors	Title	Journal	Status
Gebeyehu M. Fetene, Georg Hirte, Sigal Kaplan, Carlo G. Prato and Stefan Tscharaktschiew	The Economics of Workplace Recharging	Transportation Research Part B	Published

Gebeyehu M. Fetene, Sigal Kaplan, Alexander C. Sebald and Carlo G. Prato	Myopic Loss Aversion Behavior under Ultimatum Game Framework in the Scheduling and Pricing of Electric Vehicle Recharging	Transportation Research Part D	Re-submitted
Gebeyehu M. Fetene	Using the Peer Effect in Scheduling and Pricing Electric Vehicles Recharging: Laboratory Evidence about Peer Effect in Risk-Taking'		Work in progress
Gebeyehu M. Fetene, Carlo G. Prato, Sigal Kaplan, Stefan L. Mabit and Anders F. Jensen	Harnessing Big-Data for Estimating the Energy Consumption and Driving Range of Electric Vehicles	Transportation Research Part D	Under review
Anders Fjendbo Jensen, Stefan Mabit	The use of electric cars in multi-car households	Transportation Research Part A	Under review
Anders Fjendbo Jensen, Thomas Kjær Rasmussen	A joint route choice model for electric and conventional car users		Work in Progress
Linda Christensen	Daily need for recharging of Evs		Work in Progress

Tabel 3: General overview of written dissemination activities.

Author(s)	Title	Venue
Min Wen; Stefan Røpke	A combined station location and vehicle recharging problem	Invited presentation at the third meeting of the EURO working Group on Vehicle Routing and Logistics Optimization (VeRoLog), June 22-25, Oslo
Fetene, Gebeyehu Manie; Kaplan, Sigal; Sebald, Alexander Christopher; Prato, Carlo Giacomo	Smart Grid Charging of Electric Vehicles: EV-Owner Response to Scheduling and Pricing under Myopic Loss Aversion in an Ultimatum Two-Player Game	Transportation Research Board (TRB) 94th Annual Meeting
Gebeyehu M. Fetene	Electric Car Users' Time of Charging Decision Problem and Its Implications for the Electricity Supplier	Kuhmo NECTAR International Transport Economics Association (ITEA) conference
Fetene, Gebeyehu; Hirte, Georg; Tscharaktschiew, Stefan; Kaplan, Sigal; Prato, Carlo Giacomo	Three Players Nash Equilibrium Game Concerning the Charging Time and Place of Employee Electric Vehicles	the 14th International Conference on Travel Behavior Research (IATBR)
Anders Fjendbo Jensen, Stefan Mabit	Modelling real choices between conventional and electric cars for home-based journeys	the 14th International Conference on Travel Behavior Research (IATBR)
Anders Fjendbo Jensen, Stefan Mabit	Modellering af observerede valg imellem en elbil og en konventionel bil for bilrejser	Trafikdage 2015
Morten Aabrink, Stefan L. Mabit	Analyser af GPS-data fra "Test en elbil" og TU-data	Trafikdage, 2015
Gebeyehu Fetene, Stefan L. Mabit	En model for elbilers energiforbrug baseret på GPS-data fra "Test en elbil"	Trafikdage, 2015
Fetene, Gebeyehu; Hirte, Georg; Tscharaktschiew, Stefan; Kaplan, Sigal; Prato, Carlo Giacomo	Three Players Nash Equilibrium Game Concerning the Charging Time and Place of Employee Electric Vehicles	the 4th symposium arranged by European Association for Research in Transportation (hEART).
Fetene, Gebeyehu Manie; Prato, Carlo Giacomo; Kaplan, Sigal; Mabit, Stefan Lindhard; Jensen, Anders Fjendbo	Harnessing Big-Data for Estimating the Energy Consumption and Driving Range of Electric Vehicles	Transportation Research Board (TRB) 95th Annual Meeting
Gebeyehu M. Fetene	Consumer's behavior towards scheduling and pricing of electric cars recharging: theoretical and experimental analysis	Ph.D. defence, DTU

Tabel 4: General overview of conference activities.

1.6 Utilization of project results

Worldwide, researchers and electric grid operators focus more and more on the interaction between the transport network and the electric grid network, which will be more and more relevant as the share of EVs increases. Thus, initial models for how the electric grid is affected by a higher demand for EVs are currently being developed. Common to these is that they rely on information on the demand for charging. This is the kind of information the results from this project and the continuation of the work will provide. The project has resulted in various models covering many different aspects of the behaviour of EV users both when it comes to driving and charging. In general these models contribute with insight into the potential EV usage which is highly relevant for both public and private actors in the EV market for identifying potential markets and for the planning of business solutions, the electric grid, and optimal charging infrastructure.

In this project, we focus on EV users' behaviour and in particular the users' reaction to different contractual agreements with the electricity supplier. The activities related to objective 1 in this project, focus particularly on elements relevant to such contracts between car users and energy or vehicle suppliers. Information provided from these activities can especially be utilized by energy suppliers when designing potential business solutions and when planning their electricity supply. Furthermore, it is relevant for policy makers when designing a potential incentive strategy.

The first activity in objective 1 focuses on workplace charging (WPC) as a solution that can have benefits for employees, employers and electricity suppliers. This would especially be relevant for employees without private parking at home and it could be a recruitment and retention tool for employers, particularly when working sites are located in areas where public/commercial recharging sites are limited. For electricity suppliers, such a solution could have a potential for balancing the electricity grid using V2G charging during office hours. The results show that even though the net private benefit could be positive, there is no contract that an employer is willing to offer and at the same time that the majority of the employees is willing to accept. If incentives for such a solution should be introduced, they should be put on the supply side rather on the demand side, i.e. it is more promising to support employers in offering WPC contracts than to provide employees an incentive to accept WPC contracts. Policy makers should be aware of possible negative effects of benefits favouring car use and that office hours are usually during time periods where the electricity consumption is high which means that WPC could in fact cause a less optimal use of the electric grid.

The second and third activity of objective 1 focus on consumer responses to scheduling and pricing of recharging. This is a main element of the concept of smart grid charging as the most efficient system is obtained if electricity consumption is smoothed over different time periods of the day. In this context, the supplier needs to know consumers trade-off between price and flexibility. The results of the second activity indicate that the consumers show myopic loss aversion behaviour, which means that they show irrational behaviour when it comes to this trade off. In general, they are more sensitive to a reduction in flexibility than a corresponding reduction in price. A treatment effect shows that presenting price discounts in terms of long-term contracts in an ultimatum game framework, instead of merely announcing discount prices, may reduce myopic loss aversion behaviour. Results of the third activity investigate whether individuals can be influenced by their peers to take decisions with higher risks, and thereby be influenced to postpone their charging. Results show that while individuals would like to see their peers' decisions, only few use this information to change their decisions. Whether to change or not depends on the customer's self-confidence and decision-making abilities. This opens for the possibility that peer effects could play a substantial effect in inducing customers to choose specific charging options to support the smart grid. Electricity suppliers can use this information when designing their business strategies. Policy makers should be aware of behaviour at the individual level as incentives might be necessary for successful smart grid solutions where societal benefits are obtained from a more efficient use of the electricity grid.

In objective 2 we focus on several aspects of EV user behaviour. Current EV travel demand studies are usually based on data collected from users of CVs, but we utilize a unique dataset from a large number of real EV trips to obtain much better information about EV user behaviour. In particular, the data provides information about car use (both CV and EV) behaviour for households with a CV in a period where they furthermore had access to an EV. Furthermore, a particular feature of the utilized data is that it has been merged with information about weather, geographical information, and socio-economic information about the household.

The focus of all activities in objective 2, except for activity 2, is to provide detailed analysis of the driving behaviour of EV users and compare this with the use of CVs. This is relevant as the particular characteristics of EVs compared to CVs, i.e. shorter driving range and longer refuelling times, might lead to different usage. The descriptive analyses in activity 1 show that in general the EVs are used for a higher number of trips per day compared to the CVs, but when looking at the distances driven there is no large difference across the two technologies. Thus, as also expected, the CVs are used for the occasional longer trips. In the third activity, an energy consumption model for EVs (similar to the one in activity 2 described below), was set up to investigate how the performance of EVs fit to car owners travel behaviour. The results show that seen over a month, a very large share of the car owners would have to drive to the limits of the battery capacity, which can be stressful. In the fourth activity, a model was set up to measure the effect of several variables on daily driving. The results indicate several examples of variables, especially weather variables, that affect daily driving in EVs differently than driving in CVs. Activity 5 furthermore included a model for whether the users choose the EV or the CV for a home-based car journey (i.e. a chain of trips until home is reached again) and this model shows similarly that there are several factors that affect the use of the two car technologies differently. Finally, activity 6 included a route choice model which again finds that there are differences in the routes chosen across EVs and CVs. Such models are interesting from a research perspective and furthermore they are relevant for energy suppliers and infrastructure providers as they can improve their products with the information such models can provide.

Activity 2 in objective 2 deals with a model for the energy consumption of EVs and especially how different factors, such as weather and driving style affect electricity consumption and thereby the distance that it is possible to drive on a fully charged battery. The model has received great attention from the conferences where it has been presented. Such a model is relevant from a consumer perspective as the driver experience can be enhanced with better information about how far it is possible to drive. Furthermore, such a model is important from a planning and research perspective as it can be used for socio-economic energy calculations in various future scenarios.

While the project participants do not expect to utilize the project results commercially or to take out patents, the results and the generated data provide an important basis for future research on EV behaviour both with respect to driving and charging. Several projects that are currently running or being initiated are dependent on data and models generated in this project. Many of the outcomes of the projects were recently presented at a workshop for future collaboration on Smart Cities between Nanyang Technological University, Singapore (NTU) and the Technical University of Denmark (DTU). NTU is one of the leading research universities in the world and has a strong focus on research and innovations within electric grids. In many discussions, the NTU researches requested more knowledge about the behaviour of EV users. Thus, the collaboration will take advantage of strong capacities within electricity research at both DTU and NTU and our strong capacities within research on travel behaviour at the Transport Modelling division at DTU. Results from the PhD project related to this project has not yet been directly included in teaching, but the data and results in the project have given input that will be used in future master thesis proposals.

Looking particularly at applied utilization of the project results, relevant information for the planning of the electric grid, charging infrastructure, and different business solutions for charging infrastructure has been provided. These activities are currently all in an initial phase as it is expected that the market of EVs will increase rapidly in the near future. Thus, the information generated can be important input for all areas of optimization, marketing and research on EV driving and charging.

1.7 Project conclusion and perspective

The project has been divided in two separate objectives where we have worked to provide a better understanding of electric vehicle charging behaviour which is important for understanding the future electricity demand from the transport sector.

Within the first objective, we have examined EV consumers' willingness to accept different contractual agreements with electricity suppliers with a specific focus on intelligent charging solutions, i.e. postponing charging or allowing electricity to be charged from the car back to the grid in periods where this can contribute to a more efficient use of the electrical system. Such contracts will most often include a trade-off between charging costs and the flexibility that most users relate to car driving. The results show that users show irrational behaviour when it comes to this trade-off. In particular, they are more sensitive to a reduction in flexibility than a reduction in costs. However, we show that this behaviour can be reduced using long-term contracts. In another study, we examined, whether better information about other consumer choices regarding contractual agreements with the electricity suppliers can help reduce the psychological barrier of postponing recharging and in general if such information can be used for policy making in areas involving uncertainty for the users. In general we found that while most consumers were interested in this information, only those with low math scores in a pre-test, used this information to revise their initial choices.

Within the second objective, we examined EV driving behaviour in general, as this has a large influence on both the geographical and the temporal demand for electricity. Using a unique and large set of data on real EV trips, we have developed detailed models for EVs regarding their electricity consumption, daily usage, the choice between EVs and CVs, and route choice, and found that in several circumstances, the behaviour of EV users deviate from that of CV users. Thus, besides providing information within several of these areas, we conclude that it is highly relevant to study EV users transport behaviour further, as this has an influence on both general transport demand (e.g. congestion in the road network) as well as the electricity demand (e.g. electric grid utilization).

The information generated can be important input for all areas of optimization, marketing and research on EV driving and charging. However, besides providing results directly relevant for the implementation of different intelligent charging business solutions, this project has contributed to the research literature within behavioural economics, optimisation, and transport modelling.

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