

TamagoCar: Using a Simulation App to Explore Price Elasticity of Demand for Electricity of Electric Vehicle Users

Research-in-Progress

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Abstract

The integration of electric vehicles (EV) into the smart grid is bounded by high variability of demand for electricity, unwillingness of consumers to change behavior as well as low degree of product familiarity. Especially the absence of real-time energy tariffs constrains the widespread use of EVs as sustainable alternatives to a combustion engine. We propose to explore the behavior of EV users with a specifically designed application, TamagoCar, which combines the users' real world driving behavior with a simulated EV environment. We hypothesize that the EV users will adjust their demand for electricity as a function of uncertainty about future price, range anxiety, uncertainty about future travel and social influence. With our application we enable the end users to gain experience with using an EV as well as adjust their electricity demand in response to real-time price changes with respect to their individual preferences, social influence and macroeconomic conditions.

Keywords: sustainability, electric vehicles, demand-side management, pervasive computing/ubiquitous computing, user behavior.

Introduction

The demand for electricity is growing: worldwide, an increase of 49 percent is expected by 2035 compared to 2007 (EIA 2013). This cannot be sustained with fossil fuels alone and that is where the involvement of sustainable sources such as solar panels, wind turbines or electric vehicles becomes critical. Additionally, concerns over greenhouse emissions and climate change are accelerating the process of transition towards the use of renewable energy. For example, electric vehicles (EV) consume 50% less energy and reduce carbon emissions by up to 60% compared to gas-fuelled alternatives (Kromer and Heywood 2007). Although nowadays EV comprise a small fraction of all vehicles, by 2020 20 million EVs are expected on the roads corresponding to an annual growth rate of 48% (IEA 2013).

However, the integration of sustainable energy resources (such as solar, wind, etc.), their producers and consumers (which are often called ‘prosumers’) into the smart grid is bounded by several challenges: i) decentralized energy production; ii) high variability in demand; and iii) unwillingness of consumers to change behavior (Ketter et al. 2013). Especially the integration of a large number of EVs can exacerbate this problem if they are charged at peak times thus putting high additional pressure on the grid. A solution to this challenge is real time pricing which reflects a market price for energy, and thus provides an incentive for people to shave off the peak hours and redistribute the grid load. This strategy is known as Demand Response (DR): EVs can be charged when a large amount of renewable energy is available, and can store and even feed the energy back to the grid when demand levels increase drastically.

Additionally, the adoption of EVs is bounded by a low degree of ‘product familiarity’ (Deloitte 2010). The electric vehicle market is relatively new, the main player Tesla started selling EVs in 2008 and other major companies (e.g. BMW, Daimler, Ford) are becoming involved in the industry only recently. On the one hand, users do not have a lot of experience with EVs which require not only to evaluate the vehicle itself, but also the battery, the charging technology at home, and the availability of charging infrastructure away from home (Anderson et al. 2011). On the other hand, companies need more insight into user behavior to be able to propose efficient tariffs and to adjust the vehicles according to customer’s needs.

In our study, we aim to explore how EV users adjust their demand for electricity given different pricing schemes (such as flat, time of use and real time pricing). We propose that as expected value maximizers they will try to charge their vehicles at a lower price, however this will be bounded by specific macroeconomic conditions as well as individual preferences and behaviors. Our research question is:

- *What factors and how impact the price elasticity of demand for electricity of EV users?*

The research question we pose is very difficult to answer without having real access to EV drivers and options to change their tariff schemes. Our study proposes to analyze the determinants of charging EVs with a specifically designed smartphone application. Due to the absence of real time pricing as well as scarcity of studies on the behavior of EV users (Duetschke and Paetz 2013), our experimental approach seems to be the best possible today. Authors call for the need to determine the factors that affect the intention to use information systems for environmental sustainability (Melville 2010). Inspired by the Tamagotchi of the late 1990s, and following the general idea of pervasive computing, we provide users with a possibility to interact with the app as if it was an EV. The application tracks real movement of the person and combines it a simulated EV environment. In the experiment people are offered different tariffs and are asked to adjust their charging behavior conditioned on their individual preferences, macroeconomic conditions as well as social influence. As such, we will be able not only to explore how these different factors impact the price elasticity of demand for electricity, but also allow users to gain experience in using an EV and possibly switching to that mode of transportation in the future.

The paper is structured as follows: first, we provide an overview of studies on demand side management. Based on the literature review, we propose a conceptual model which explores the factors that impact the price elasticity of demand for electricity of EV users. Third, we describe our experimental design. Fourth, we provide background on the development and design of the TamagoCar application which is being finalized at the moment. We conclude with a discussion of next steps and aspired contributions.

Theoretical Background

At the moment, the global EV stock comprises 180,000 vehicles, which corresponds only to 0.02% of total passenger cars, however is expected to increase to 20 mio by 2020 (IEA 2013). The advantages of EV over internal combustion engine (ICE) vehicles include more efficient motors, low emissions, low noise levels, and little to zero reliance on fossil fuels (Masoum et al. 2010). EV's are especially suited for urban driving, where they can achieve relatively large CO₂ reductions of 25% to 40% (Smith 2010). Additionally, EVs can be used as energy storage to support the grid during peak times (Masoum et al. 2010). As such, EVs can feed the energy back to the grid instead of starting extra production facilities (also known as Vehicle-to-Grid). The limitations for EV adoption, however, are significant costs, range limitations caused by the limited battery and the lack of adequate smart grid infrastructure (Masoum et al. 2010). Compared to ICE, electricity as fuel has two main disadvantages: storing is more bulky and expensive and refueling is slow (Pearre et al. 2010).

We propose to explore EV adoption in light of demand side management – which we identify as an essential prerequisite to integrate EVs into the smart grid. Nowadays, even though wholesale prices on the energy market fluctuate a lot, the complexity and volatility are hidden for customers since they are charged at a flat rate (Li et al. 2011). Flat pricing might be simple to understand and predictable, but results in demand peaks which are detrimental for the grid. Demand Side Management (DSM) allows to change the patterns of energy consumption in order to achieve more efficient energy demand (Palensky and Dietrich 2011). Two possible DSM strategies are Time of Use tariffs and Demand Response (DR) to Real Time Energy Tariffs. DR programs include tariffs to reflect the real cost of electricity and thus redistribute the risks between energy providers and consumers. By charging higher prices in times of high demand, people will tend to shift their consumption to other times and thus flatten the demand curve (Albadi and El-Saadany 2008). Thus, users can save on energy bills, energy network can be used more efficiently, the infrastructure becomes more reliable and hence, the overall market performance increases. It is estimated that already a small reduction in demand results in a bigger reduction in energy costs (Albadi and El-Saadany 2008).

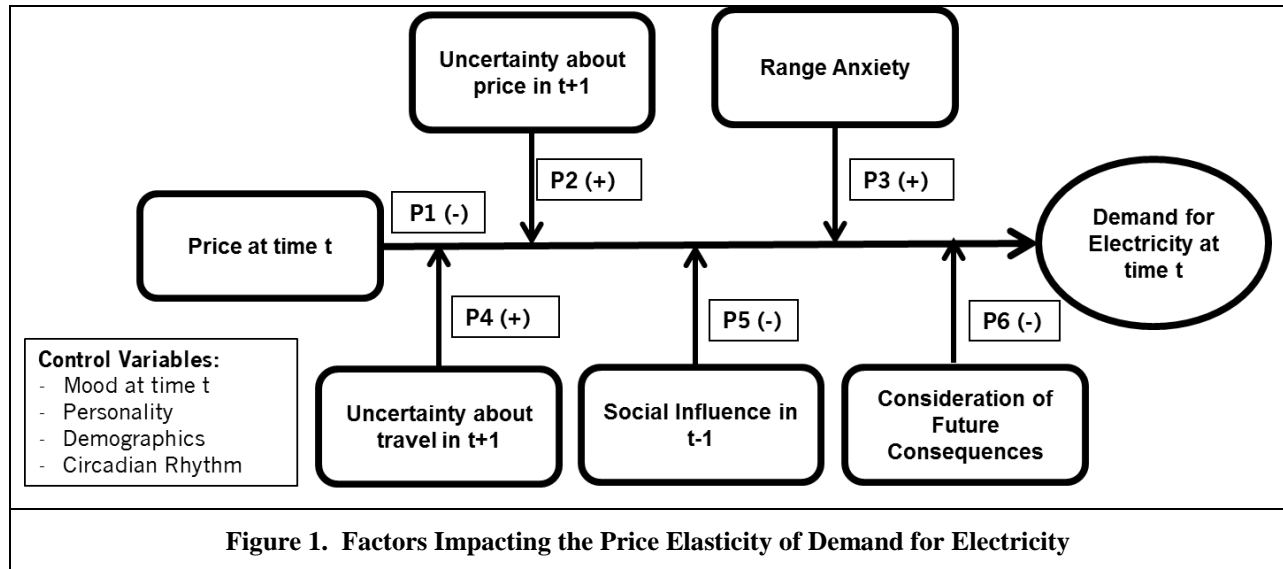
Demand response is recognized as the most effective strategy to redistribute the grid load and a large amount of load is available for shifting (Gottwald et al. 2011). However, so far not much research has been done on the effects of customer response to variable prices (Cappers et al. 2010; Duetschke and Paetz 2013). In fact, the existing studies show that it is hard for people to understand variable pricing schemes without actually trying them out (Verhagen et al. 2012). Energy users are in general open to dynamic pricing, but prefer simple programs to highly complex ones (Duetschke and Paetz 2013). In fact, DR is more risky as the customer is not sure about the future prices and risks paying the highest price for electricity. Moreover, the customer has to undertake more effort to plan consumption and to monitor the prices. This problem, however, can be alleviated by developing smart charging algorithms that learn customer's preferences and act on the behalf of the customer (Valogianni et al. 2014; Duetschke and Paetz 2014). These, however, require initial insights into customer response to DR which we aim to provide in this study.

Research Model and Hypotheses

The main aim of this study is to explore demand response, i.e. charging behavior of EV users in response to different tariffs. The decision when to charge the EV is not a trivial one as people have to deal with a certain amount of uncertainty. For their charging decision users do not possess complete information and as such, their decisions are in line with the concepts of bounded rationality (Simon 1979). People face – irrespective of their cognitive capabilities – three major constraints when making a decision: (i) the availability of limited information; (ii) the limited cognitive capacity of the humans mind in order to process and evaluate all decision alternatives; and (iii) limited time available in order to make a decision. The charging decision is especially complex in case of real-time-pricing: users can only forecast the possible future prices and thus do not possess complete information at time t . At the same time, they also can not foresee all of their future driving needs. Moreover individual perceptions of potential risk and levels of range anxiety can lead to sub-optimal decisions about when to charge.

In our model depicted in Figure 1 we propose that the demand for electricity is related to the price for electricity, moderated by several factors. We differentiate between: (i) the macroeconomic factors, such as

the uncertainty about future electricity prices (especially characteristic of the real time tariff); (ii) individual factors, such as the level of range anxiety, the proneness to consider future consequences of their decisions as well as driving needs that are specific to each participant, and (iii) social influence reflected in the actions of other participants of the study. All these factors are assumed to have an impact on the price elasticity of demand for electricity – the proposed relationships are discussed below. At the same time, these relationships are moderated by the control variables: mood, personality characteristics, demographics and circadian rhythm.



Price Elasticity of Demand for Electricity

We define price elasticity of demand for electricity as the responsiveness of the quantity demanded of electricity to a change in its price. In economics, numerous studies have shown that price is negatively related to demand. At the moment, the end-user price of electricity does not reflect the market price for electricity and is mainly stable at all times. However, in Netherlands end-users are offered Time of Use Tariffs, whereas real time pricing is only used on the wholesale market. We propose to explore the price elasticity of demand for electricity by comparing the demand response of users to several tariffs: i) flat tariff where the price of electricity is the same at all times; ii) Time-of-Use tariff, where the price is higher in peak hours, usually during the day; iii) Real-Time tariff where the price changes every hour and reflects the market price for energy. As such, for the flat tariff the demand will be stable. For the other two tariffs, we propose that as the expected value maximizers, users will reduce their demand if the price is high. At the same time, the small changes in prices that are characteristic of the electricity market could lead to no changes in demand. However, we propose that if participants are exposed to this information, it will lead them to adjust their demand. Authors find that people are looking for feedback on their energy consumption and use it to adjust their decisions (Hargreaves et al. 2010). We propose:

Proposition 1: Price will be negatively related to the demand for electricity of EV users (negative price elasticity of demand).

Macroeconomic Factors: Uncertainty about Price

However, in the case of real time tariffs users do not possess complete information about future prices and as such are constrained to make an optimal charging decision. Although real-time pricing is a prerequisite for an efficient energy market, the availability of information about the price is the main deterrent of tariff acceptance by users (Bloustein 2005). As such, the uncertainty about the future price will tend to diminish the price sensitivity of demand. However, this effect is likely to decrease once people gain experience with the tariff and learn the dynamics of price changes over the day. We propose:

Proposition 2: The higher the uncertainty about the future price, the lower the price elasticity of demand

for electricity, however this effect exhibits diminishing returns.

Individual Factors

Range Anxiety

Range is the distance that a person can travel with a vehicle in one charge. At the moment, an average capacity of an EV is 16 kWh which allows to drive about 100 km in one charge. The range problem thus occurs only in 5% of situations, because 95% of the daily driving can be done under this barrier (Gondor et al. 2007). Range anxiety refers to the phenomenon where a driver experiences stress as a result of uncertainty regarding the range capacity of the vehicle (Tate et al. 2009). Range Anxiety is a highly subjective perception, which is influenced by driving schedules, driving knowledge, motivations, habits, as well as personal risk levels (Franke et al. 2012). In a recent study of the EV drivers it has been shown that most users do not even know what the range of their current vehicle is and tend to fall back to the gasoline range for reference (Turrentine 1992). Most, however, have indicated that a twenty miles safety buffer is the desired amount they want to have in the car for emergency situations (Turrentine 1992; Franke et al. 2011).

However, research on range anxiety is scarce, focusing mainly on technical aspects (Francfort et al. 1998). Even though Range Anxiety has been heavily discussed in public media, scientific knowledge of range experience is scarce and little has been published about how real users experience EV range and how they deal with it (Franke et al. 2012). Prior research focused on field experiments, but few have examined behavior in relation to EV usage and range barriers (Francfort and Carroll 2001). Apart from the fact that range is often underutilized (Botsford and Szczepanek 2009) and the awareness of personal safety buffers are increasing in one's perceived range needs (Kurani et al. 1994), there have been no notable findings.

EV drivers engage in an essentially new behavior - charging their vehicle's batteries, either at home or on the way. Drivers report a lack of formal 'rules' to guide their behavior towards new social charging interactions in public or attitudes towards shared infrastructure (Caparello et al. 2013). Often users who score high on range anxiety feel the desire to charge even more or re-charge after completing even a short trip (Tate et al. 2009). The overall decision concerns either driving an EV with not fully charged battery and running the risk of getting stranded or to fully charge the battery and thus risk paying more for energy. We propose:

Proposition 3: Increased Range Anxiety will reduce price elasticity of demand for electricity of EV users.

Uncertainty about Travel

Mobility patterns reveal that users make an average of 3.4 trips per day and travel daily an average of 43km (IEA 2013). The capacity of EV's of approximately 100km is thus well suited for urban driving situations, in which also large CO₂ reductions up to 25% to 40% can be achieved (Smith 2010). A usual driving profile has a fixed component which can be well planned (like trips to work and home), but also a variable component when a user does not know when and for which purpose the car will be needed. A high variable component might increase the desire of EV user to charge once a trip has been completed consistent with the economics of immediate gratification (O'Donoghue and Rabin 2000). As future costs of charging are uncertain and in the future, whereas the reward of being able to drive now is certain and immediate, people tend to prefer immediate gratification. We propose:

Proposition 4: The uncertainty about future driving needs will reduce the price elasticity of demand for electricity of EV users.

Risk Attitude and Consideration of Future Consequences

An overall attitude towards risk will impact the decision making of individuals, in that it accelerates the feelings of range anxiety, travel uncertainty and price uncertainty in our model. However, as people are not consistently risk seeking or risk averse across all content domains (Weber et al. 2002), risk might have a differential impact on these uncertainties, which we aim to explore in the model.

Consideration of future consequences (CFC) refers to the individual assessment of the importance of one's actions in the future (Strathman et al. 1994). CFC is related to higher levels of concern about the environmental impact of cars (Van Vugt et al. 2004). As electric vehicles are better for the environment

than ICE cars, people who score high on CFC will have more positive attitudes towards EV in general, and in particular, would try to charge off peak hours, irrespective of the tariff, as it is best for the grid. As such, CFC moderate the impact of price on demand by increasing its sensitivity. We propose:

Proposition 5: Higher consideration for future consequences will increase the price elasticity of demand for electricity of EV users.

Social Influence

Consistent with the social influence theory, if people observe other's behavior which is regarded as more positive, they will tend to adjust their own behavior to match the observed norm (Cialdini and Goldstein 2004). Authors have found support for this theory when encouraging conservation behavior of hotel guests (Schultz et al. 2008) as well as households (Schultz 2007). If people are provided with the information about the behavior of others, especially in a situation which most closely matches their own, they tend to change their behavior to adhere to the social norm (Goldstein et al. 2008). Applied to our experiment, by exposing the participants to the performance of other users, we will provide them with an additional incentive to charge at a lower price in order to obtain a higher performance score. As such, we propose that if users are exposed to the performance of others which is better than their own, they will be prone to charge their EV at lower prices in order to improve their score.

Proposition 6: Increased social influence will increase the price elasticity of demand for electricity of EV users.

Control Variables

Different personality characteristics might also affect the charging behavior, either directly or indirectly, through one of the uncertainties identified in the model. First, demographics such as age might determine the overall desire to drive an EV as well as have an impact on range anxiety. Younger people are more risk-seeking, whereas older people are more risk-averse. For example, age has been found to have a negative impact on range anxiety (Turrentine 1992). Second, people are prone to different mood swings, so each day their mood might impact their charging decisions. In order to infer the mood of the person during the day, we use the Circumplex Model of Affect (Posner et al. 2005). Third, circadian rhythm might also have an impact on a person's driving and charging behavior. Authors have found important differences in morning and evening chronotypes (Carrier and Monk 2000). We will also explore the impact of the Big Five Personality traits on the dynamics of EV user behavior in the study.

Experimental Design

Application Design

The experiment combines real driving behavior with a simulated EV environment. To participate in the experiment, the users need to install the TamagoCar application on their smartphone. The application simulates the EV vehicle that needs to be actively taken to the real destinations the person travels to (the real part of the experiment). The EV is equipped with a battery with a certain range and that needs to be charged (the simulated part of the experiment).

Driving Mode

There is an EV the user can "drive" the TamagoCar to certain locations one needs to go to during the day which are more than 500 meter away from the home location (no matter whether on the bike, by car or public transport). A distance less than 500 meter is disregarded. A home location is specified as the place where the user spends most of the time (automatically). A user has to activate the car when leaving any location (check in), however once the user arrives at the destination, the application recognizes and deactivates the trip automatically (check out). If a user does not check in, but moves more than 500m from any location, the application detects the movement and sends a push notification that asks the user to take the TamagoCar (however, a user is able to refuse). The distance traveled for each trip and each day is recorded and shown to the user in statistics.

Charging Mode

In order to be able to “drive”, the TamagoCar needs to be charged. The average battery of the car has a capacity of 25 KWh which is comparable to a normal EV. However, if a user drives more (less) than average, a larger (smaller) battery will be given for the time of the experiment. EVs can be charged from regular plugs or public charging stations which spread rapidly. Already today there are almost 20,000 public charging stations available over Europe. For simplicity we assume that charging can be carried out at all times, except when a user is driving. In order to incentivize participants to drive (and charge) their car, they will be offered an unlimited budget for charging their EV.

Charging is carried out based on different tariffs as depicted in Figure 2. Flat tariff offers the same price all times. Time-of-Use tariff offers high prices in peak times between 7AM and 6PM. In the real-time tariff price changes every hour, reflecting the market price of energy. The prices are synchronized with the EPEX Spot prices from the European Energy Exchange. To ensure equal conditions for all participants, the price of the flat tariff and the average of the time of use as well as the real-time tariffs are equalized to the average EPEX price. The price that the user has to pay for a charging session is shown to the user. For the real-time tariff, forecast values of the next 12 hours are available. If the battery is out during travel, the car has to be towed, and the user has to pay a penalty. In order to avoid such situations, a planning tool is provided where a user can see which range one needs to reach a certain destination.

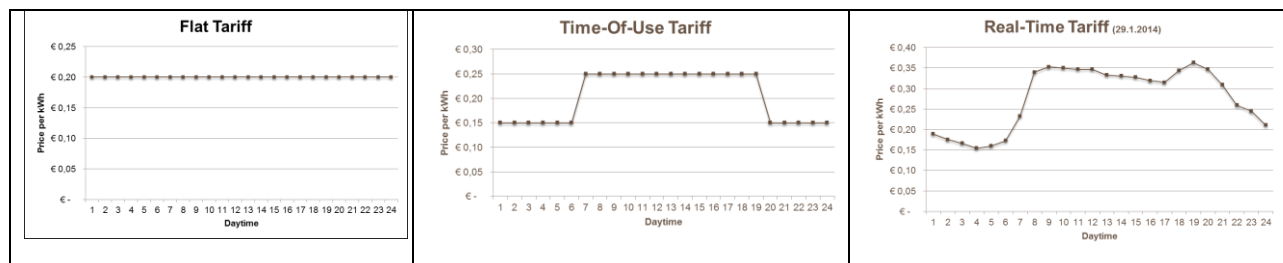


Figure 2. Tariffs Offered in the Experiment

Experimental Treatments

As depicted in Figure 3, we have a mixed design with one control group. The experiment lasts for 7 consecutive days. For the first three days the participants are offered a flat tariff where the price is constant. During this time the battery size can be adjusted for participants who drive a longer (shorter) daily distances than average. After the first three days, the two treatment groups are offered either a time of use tariff or a real-time tariff, whereas the control group stays with the flat tariff. Thus, by comparing the demand for electricity in of the control vs. the treatment groups we will be able to explore price elasticity of demand for electricity. For all groups, there will be a pre- as well as the post survey to evaluate differences in individual preferences and behaviors (moods, personality, range anxiety, etc).

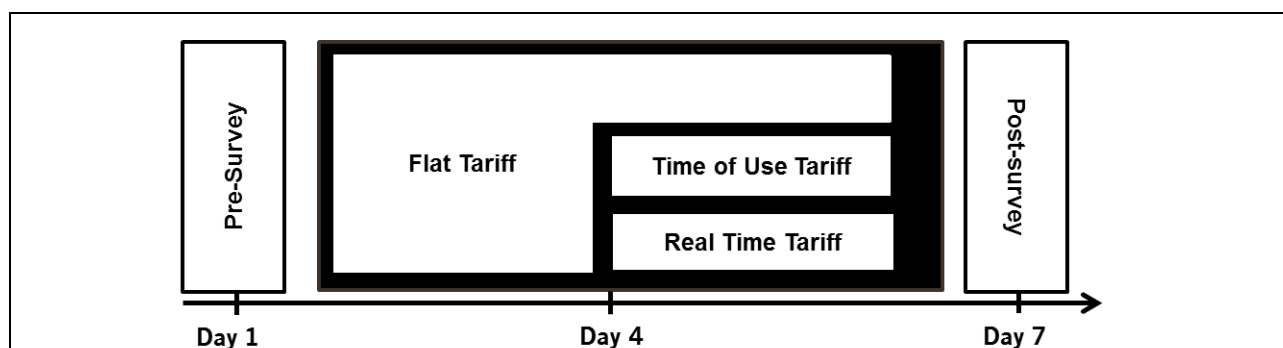


Figure 3. The Design of the Experiment

Incentives

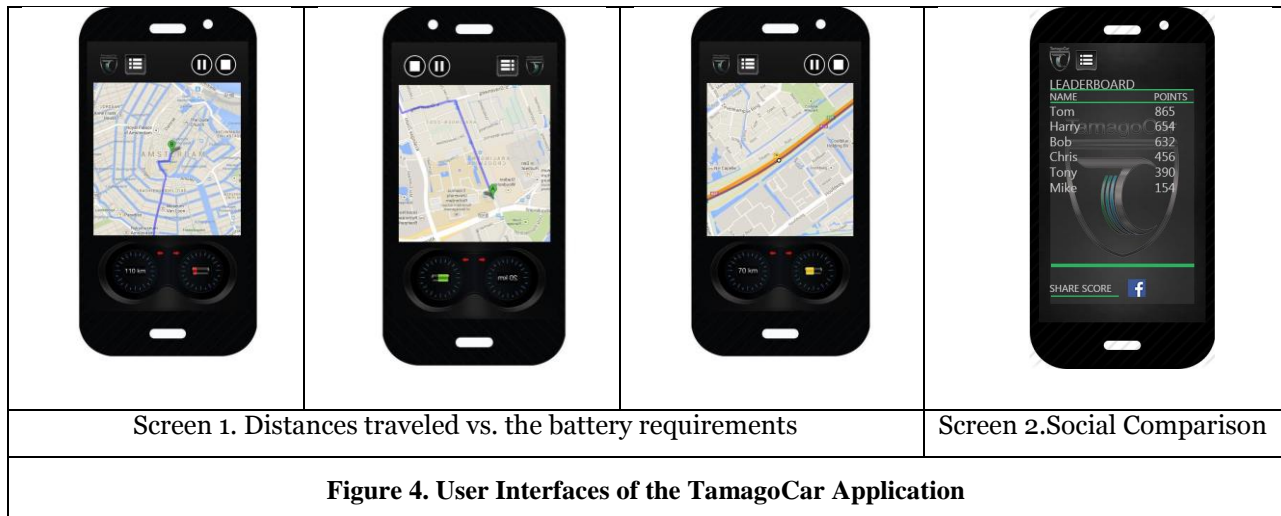
Each user is rewarded for participation in the experiment. The reward consists of the fixed fee for each day of participation (1EUR a day) and a variable fee based on the performance in the game. The Individual Performance Score is evaluated based on the distance driven l (in km) per trip i adjusted for the fuel efficiency ε (in kWh/km) relative to the cost of the energy that was charged P (in EUR/kWh). However, if the car is not charged enough and needs to be towed, a penalty is subtracted from the performance score over the towed distance τ (in km) adjusted for the fuel efficiency ε divided by the highest charging price \hat{P} (in EUR/kWh) plus a certain margin m (in EUR/kWh). The performance score for the driven and towed distance is weighted by the respective distances and summed over all trips I . See equation 1 for a formal notation.

$$\text{Individual Performance Score} = \sum_{i=1}^I \left(\frac{l_i}{l_i + \tau_i} \right) \frac{l_i * \varepsilon}{P_i} + \left(\frac{\tau_i}{l_i + \tau_i} \right) \frac{\tau_i * \varepsilon}{\hat{P} + m} \quad (1)$$

Considering the goals of the experiment it seems appropriate to incentivize people with the performance score only as it encourages people to drive and recharge in an effective way. An additional introduction of the budget would restrict the total range the participants would want to travel during the experiment. As already mentioned, in order to additionally incentivize the participants, users are exposed to the information about the performance of others. As such, the application represents a gaming environment, where people are motivated to compete with others by taking the car to the destinations they travel to and charging at lower prices.

Application Implementation

TamagoCar is a mobile application which is being developed within the Android Studio IDE (Integrated development environment) allowing us to make use of a variety of tools in the Android SDK (Software development Kit). The application as such is coded using the JavaScript programming language; JavaScript is a dynamic and multi-paradigm programming language that allows for client-sided scripts for user interaction. Furthermore, the application makes use of Google Play services to access the newest API's for popular Google services. In the specific case of TamagoCar perhaps the most important is the use of Location Services to track the commuting of the user. Lastly TamagoCar makes use of an external server to store the data generated from the application and to manage asynchronous communication with the users. The functionality of the app can be seen in the short video by following the link: <https://www.youtube.com/watch?v=PWUCKxoQDIQ>. In the figure 4 below we provide the preliminary screenshots of the application.



Conclusion and Next Steps

This study is a research in progress. So far, the application design has been finalized and the programming of the application has started. In the next steps, we are going to do the following: (i) finalize the programming and testing of the application (September); (ii) develop an application for the Iphone (October); (iii) pre-test with 70 subjects (October), results will be presented at ICIS in Auckland; (iv) main test with 300 subjects (December); (v) submit final results to a journal.

Our study will offer a number of theoretical and practical contributions. First of all, it will give insights into the driving patterns of users and their overall attitudes towards driving an EV. As such, the application can also be used for users to determine whether an EV is an option for their needs. Second, only limited number of studies exist that explore the demand response of users to real-time energy tariffs. By offering the people the possibility to charge at different tariffs, we will not only create the awareness of real world pricing and sustainability perceptions, but also let the users experience these tariffs for real and adjust their behavior in response. Demand response is the most effective strategy in redistributing the grid load, so the study will provide first insights into developing smart algorithms to advance in this direction. Third, we will explore the personal levels of range anxiety and other risks associated with driving an EV. Range anxiety is the main problem recognized in connection with the electric vehicles and determining personal levels thereof and their impact on price sensitivity is an important determinant of adoption of EVs. Finally, we will recognize the impact of personality characteristics, demographics and moods on charging and driving preferences. This, in turn, will help companies in differentiating between different types of EV users and providing them with specific recommendations.

Our study has several limitations. In the absence of real-time energy tariffs we cannot explore our research question in any other way. Additionally, using the application is quite a lot of effort to participants, as they have to use it for the consecutive 7 days and check in every time they travel. However, we believe that by providing specific motivation schemes, such as social information about performance of others along with monetary compensation, will allow to increase the motivation to participate in the experiment.

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