Variable-rate Pricing of Electric Vehicle Charging; Exploring consumer behavior using TamagoCar app

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MASTER THESIS

Variable-rate Pricing of Electric Vehicle Charging;
Exploring consumer behavior using TamagoCar app

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Preface

Acknowledgements

This Master thesis was initiated by my profound interest in the field of Renewable Energy Business, which is explained by the great positive impact it can have on the everyday lives of each one of us. Electric Vehicles are a great example of how humanity can move from a state of resources consumption and polluting to a state of recycling and sustainability.

For the completion of this Master thesis, there are some people that I would really like to thank. First of all, I would like to thank Prof. Ketter for the opportunity he gave me to be involved with the topic of Electric Vehicles as well as for the trust in me to conduct a challenging experiment in a Master-student class. Also, I want to sincerely thank PhD candidate Konstantina Valogianni for her empowering stance and critical guidance throughout the whole thesis. Konstantina's insights and recommendations played a crucial role in the formation of this thesis and for that I am deeply grateful. In addition, I want to thank the scientific developers Govert Buijs and Erik Kemperman for their pivotal contribution in the development and modification of TamagoCar application and their constant availability to resolve problems throughout the experimental period. Finally, I want to thank Dr. Yashar Ghiassi Farrokhfal and PhD candidate Micha Kahlen for their enabling role in the execution of the experiment in the class of Designing Business Applications, where they were lecturers.

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Executive Summary

The continuous growth of global electricity demand is an issue that becomes more and more urgent these days. Although the revolution of renewable sources of energy has surpassed all expectations over the past decade, the existing static power grid has not yet been able to cope with the new dynamic electricity production pattern. Thus, innovative ways to balance the load and shift the demand are imperative in order to facilitate a sustaining electric power grid.

Electric Vehicles (EVs), which are rapidly gaining significant market shares across the globe, consist of a unique opportunity not only to move to a new low-carbon mobility era but also to balance the electricity grid. Although, many studies have focused on finding optimal pricing mechanisms and solutions to coordinate EV charging, they are based primarily on simulation results, which assume that EV drivers are represented by intelligent agents that are fully rational.

This study bridges the gap between theoretical approaches and real-world behavior by taking into account the behavioral aspect of the users. Specifically, a 21 days experiment is conducted where 154 users are provided with a smartphone application, the TamagoCar app, which simulates the operation and charging of an EV. Through TamagoCar app, two smart-charging pricing mechanisms are tested; 1) Real-Time pricing (RTP), where the prices presented to the users are related to the electricity retail-prices and 2) Variable-rate pricing, where pricing is also correlated with the energy capacity desired by the users.

Results reveal that Variable-rate pricing mechanism significantly improves the observed phenomenon of demand peaks when compared to the smart-pricing alternative of Real-Time Pricing and leads to an average Peak-to-Average ratio reduction of 80-87%. In addition, the study shows that users do not experience a significant difference in the cognitive load required to use the two different pricing mechanisms.

This finding implies that variable-rate pricing could be a viable alternative to RTP when it comes to EV smart-charging coordination and thus further examination with real EV drivers is proposed. In addition, the study presents a user-friendly and already applicable interface that can be used in reality in future research projects.

Table of contents

List of tables

List of figures

List of equations

1. Introduction

The demand for electricity is continuously increasing and will continue to increase over the next decades. It is projected that by 2040, global net electricity generation only from central producers will almost double to an amount of 39.034 billion kWh annually from an amount of 20.240 billion kWh in 2010 (EIA, 2013). In addition, world energy-related carbon dioxide emissions are expected to rise from 31,2 billion metric tons in 2010 to 36,4 billion metric tons in 2020 and 45,5 billion metric tons in 2040 according to IEO2013 Reference case (EIA, 2013). Policy makers, understanding the direct climate implication of an increased energy demand, have already established strict policy regulations that set specific greenhouse gases (GHG) emission limits for the foreseeable future. Specifically, the European Union, being responsible for around 10% of GHG emissions in 2012, made a unilateral commitment to reduce overall greenhouse gas emissions from its 28 Member States by 20% in 2020 compared to 1990 (EU-Commission, 2014). This policy has already resulted in a notable 19% decrease of EU's total GHG emissions in 2012 compared to 1990 (EU-Commission, 2014).

Even though the overall aggregated energy industry efficiency has improved in terms of GHG emissions, road transport, with a share of 22% of EU's total CO_2 emissions, has increased its emissions at a total rate of 27% between 1990 and 2009 (Vicente, 2011). It is argued that technological progress in increasing the fuel efficiency of Internal Combustion Engine (ICE) vehicles over the last decade has not been able to keep pace with the increasing demand of mobility (Kihm & Trommer, 2014). On the other hand, Electric Vehicles (EVs), which consume 50% less energy on average and can reduce carbon emissions by 60-100% compared to gas fuel vehicles seem like a viable alternative over ICE (Koroleva et al.,2014).

1.1 Electric Vehicles

Many governments, such as Norway, the Netherlands, the USA et al., seem to have also realized the potential societal benefits of an EV policy adaption and have invested heavily in R&D, infrastructure as well as in fiscal motives in order to further incentivize customers and render EVs commercially attractive. Specifically, total EV spending by EVI (Electric Vehicles Initiative) countries has already reached the amount of $16 billion between 2008 and 2014 resulting in a global EV fleet consisting of more than 665.000 vehicles in stock and representing almost 1% of total passenger cars in 2014 (EIA, 2015). Norway plays the leading role in terms of EV market penetration, which accounts for an astonishing 12,5%, with Netherlands, the USA and Sweden following at a rate of 3,9, 1,5 and 1,4% respectively. Sales of EVs in California already exceeded 100.000 in 2014, and the state is well on its way to doubling that figure (Hant, 2014). It is also estimated that in less than 5 years the amount of EVs will increase by 20 times, resulting in more than 20 million EVs on a global scale (Trigg et al., 2013). Assuming a global average of 12.000 km per car driven annually and efficiency of 0,2kWh/km, the total energy consumption surplus will be more than Portugal's total electricity net generation (43 billion kWh/ year). This fact that will pose several challenges in the way the electricity industry is currently operating.

One of the direct implications of the aforementioned potential fast adoption of EVs is that it will add an additional burden to the grid and further sharpen the problem of demand peaks. The existing power grid was originally designed to distribute electricity from large, constantly generating producers to individual consumers. On the other hand, renewable sources of energy, such as photovoltaic panels, characterized by Schleicher-Tappeser (2012) as the most disruptive energy technology, have already enabled consumers of all sizes to produce power themselves (prosumers) operating with a new bottom-up control logic and creating new innovative business models (e.g. cloud solar initiatives[1]). The combination of both top-down grid structure and increasing bottom-up decentralized production will result in conflicts with the current power grid control infrastructure and render the electricity supply highly uncertain and unreliable.

On the demand side, EVs, during charging time, have the capability to almost double the average household load and exacerbate the already high Peak to Average Ratio (PAR) (Mohsenian-Rad, 2010). In addition, they can also result in degradation of the power quality, voltage problems and potential utility's and consumer's equipment damage. Hence, methods for balancing the increasing demand are imperative to facilitate a safe transition to the new decentralized environment.

[1] http://www.gocloudsolar.com/

1.2 Research Question

As discussed, the fast penetration of renewable energy sources, such as wind and solar, in the global energy mix already necessitates new ways of load balancing and demand reshaping. Electric Vehicles are a great opportunity for the electric grid to be more stable due to their availability that enables the redistribution of their charging throughout the day.

In theory, there are many models that describe through simulations how EV charging can be optimally coordinated in order to achieve a more balanced electrical grid (Clement-Nyns et al., 2010; Rotering & Ilic, 2011; Moura et al., 2011; Vandael et al.,2013). However, these studies assume that EV drivers are represented by intelligent agents that are fully rational and do not account for the actual human behavior. In addition, according to Maes (1994), the actual users tend not to trust the intelligent agents, a fact that creates an additional gap between theoretical approaches and reality.

In this study, we try to bridge this gap by conducting a real-world experiment and providing the users with an intelligent agent (a smartphone application), so that they are enabled to intervene and interact with the agent when they think this is appropriate.

Through this prism the research question of this study is the following:

i. How can EV charging be better organized so that all stakeholders (drivers, grid operators) are enabled to reap the benefits of moving to an electric mobility economy?

Based on this fundamental question, a series of important sub-questions arise:

a. Which smart-charging mechanism can better serve this purpose?
b. What is the role of Information Technology in this quest and what is the role of the EV driver? How can they optimally be combined?

2. Theoretical background

2.1 Literature Review

The literature review will initially address how the topic of demand side management evolved over the last 30 years and gradually focus more on the literature of EV charging and coordination. The latter is a field that was introduced and popularized in the 90's (Kempton&Letendre, 1997) and has since then gained a lot of scientific attraction due to its increasingly significant societal relevance.

2.1.1 Demand Side Management

Traditionally, electric utilities[2] used to invest in capital intensive methods, such us pumped storage water plants, flywheels, compressed air etc. in order to store energy in times where the supply exceeded the demand. In the late 1980's utilities began recognizing that energy conservation could also take the form of a provided service that can lead to similar levels of energy service with fewer kilowatt-hours and at a lower cost (Masters, 2013). What emerged was a process called integrated resource planning (IRP) or least cost planning (LCP) (Masters, 2013), which consisted of utilities' programs that targeted at controlling energy consumption on the consumer's side of the electric meter. These programs are also known as Demand Side Management (DSM) programs. In their initial implementation DSM programs included conservation and energy efficiency programs, fuel substitution programs and load management programs (Masters, 2013). Regarding the latter category, the programs usually aimed at either reducing consumption or shifting consumption.

According to Mohsenian-Rad (2010), shifting residential consumption can be achieved mainly through two methods; Direct Load Control (DLC) (Top down-control approach) and Smart Pricing (bottom-up control). Direct Load Control allows utilities to remotely control certain appliances of a household, such as lighting, HVAC, refrigerators etc., in order to provide balancing power. Recently, the concept of Smart Home Appliances and its impact on load shifting constituted a central point of interest for different research communities such as Computer and Natural Scientists

[2] An electric utility is an electric power company (often a public utility) that engages in the generation, transmission, and distribution of electricity for sale generally in a regulated market- Wikipedia

(Stamminger, 2008; Son, 2010; Gottwalt, 2011). However, concerns regarding private privacy still act as a barrier in the rapid development and adaption of DLC initiatives.

On the other hand, Smart Pricing targets at reducing load peaks by giving to consumers price incentives to switch consumption when demand is high. A commonly used residential peak reduction strategy is Time-of-Use (ToU) pricing. Typical ToU tariffs signal high prices during work-hours while offering lower prices at late-night hours. According to Faruqui & Sergici (2010), the adaption of a ToU tariff system can yield reductions of 3-6% in peak demand. Another smart pricing alternative is Critical Peak Pricing (CPP), which can take a time-invariant or ToU rate structure with a dispatchable high or "critical" price during periods of system stress (Herter, 2007). Again, empirical evidence revealed that when CPP is implemented and accompanied with several enabling technologies, it can also lead to reductions of peak demand at an impressive rate of 27-44% (Faruqui & Sergici, 2010). Finally, Real Time Pricing (RTP) is one of the most popular but also controversial alternatives of smart pricing. In the US, more than 70 utilities offered voluntary RTP tariffs from mid-1980s till 2004 with a motive to achieve better customer satisfaction rates, reduce load peaks, shift load but also encourage load growth (Barbose et al, 2004). While these programs revealed moderate load reductions, they did not provide enough evidence on the potential positive implications they could have on the wholesale market performance and the utility resource planning. Newer studies also highlight the consumers' lack of awareness about their electricity consumption as an important factor of the preference of traditional pricing schemes over RTP (Dütschke & Paett, 2013). In contrast, Borenstein (2005) argues that RTP can lead to large long-term societal and economic gains that can by far outweigh the cost for the largest consumers. In his paper he estimates that ToU schemes capture only a mere 20% of the efficiency gains that can be achieved through RTP.

2.1.2 Related Work on EV Smart Charging

Smart pricing in the smart grid era and instant forecasting is becoming increasingly important in a variety of complex and dynamic markets (Ketter et al., 2012; Ketter et al., 2015). Specifically on EV charging, the literature covers a wide range of scientific fields. In their majority, researchers have focused on the technical challenges of introducing EVs to the existing grid by recognizing new opportunities, such as using the EVs’ batteries as a storage source for balancing the load curve (V2G) (Kempton& Letendre, 1997; Peterson et al., 2010), and proposing coordinated charging control mechanisms (Clement-Nyns et al., 2010; Rotering & Ilic, 2011; Moura et al., 2011). Vandael et al. (2013) describe a three-step top-down approach to coordinate the EV charging, while Kahlen et al. (2012) develop a centrally coordinated fleet operator business model that yields significant profits for the fleet aggregator. Many companies have also realized the added value of EVs in the future energy scheme, most notable of which being the collaboration of Enel, Endesa and Nissan that jointly developed a two-way charger capable of supporting a V2G initiative (Enel, 2015). The municipality of Utrecht has also already installed 20 bidirectional charging stations, co-developed by Stedin and a conglomerate of partner companies and institutions (Van Jaarsveldt, 2015).

Regarding smart pricing, Lyon et al. (2012) evaluate the feasibility of shifting charging demand by using ToU and RTP schemes, proposing that ToU pricing is worthwhile under all evaluated scenarios, while RTP, although better in terms of expected returns, is still not able to justify the additional investment in smart grid infrastructure needed. In addition, in order to reduce the common observed phenomenon of herding, when a RTP tariff is applied, Valogianni et al. (2015) propose a mutliagent approach that applies a hybrid pricing mechanism to coordinate charging. According to this approach, which is defined as Variable-Rate pricing, prices are signaled to EV users as a function of charging rate (KW) resulting in a notable average Peak Reduction of 9,61% when compared to a Real-world scenario and 16% when compared to a rate-independent scenario where day-ahead prices are signaled that vary during the 24 hour-period but are static and do not change dynamically (Similar to RTP).

However, EV users’ actual response and behavior to smart pricing mechanisms are difficult to be estimated just based on theoretical assumptions. Rathnayaka et al. (2011) identify and comprehensively analyze prosumer behavioral patterns in order to propose an optimal multi-agent architecture. In an effort to understand, which factors can influence consumers’ decisions to charge their EVs at different times, Koroleva et al. (2014) developed a smartphone application, the TamagoCar app (See paragraph 3.1), which simulates the experience of owning and charging an EV. By altering the pricing mechanisms that are signaled to the end-users (Flat Tariff, ToU, RTP), it is observed that they are willing to redistribute their charging behavior.

2.2 Variable-rate pricing

Building on the work of Koroleva et al. (2014) and Valogianni et al. (2015), this thesis will explore the impact of variable-rate charging in load curve balancing through TamagoCar app with the aim to measure the users' actual behavior when compared to the behavior of intelligent EV agents.

According to the model of Valogianni et al. (2015), EV users are represented by an intelligent agent, who is responsible for charging the EV. The grid operator is then represented by a control agent, who broadcasts price signals to the EV agents and is responsible for monitoring their aggregate consumption taking into account the existing production level. The proposed price function that is broadcasted every time-step t by the control operator and is dependent on the charging rate has the following form:

$$P_t\,(r_t) = P_{0,t} + a_t r_t$$

Equation 1 Variable –rate pricing formula

where r_t is the charging rate in time step t, a_t is the slope of the price curve with respect to charging rate and $P_{0,t}$ is the price for zero demand, which can be determined as a percentage of the wholesale price of electricity at time t. As previously stated, Valogianni et al. proved that the introduction of a variable rate charging mechanism through intelligent EV agents led to significant balancing of the demand when compared to the rate-independent pricing mechanism and a Real World scenario. However, these outcomes are purely based on simulations results assuming cost minimizing intelligence agents. We are taking this work to the next level by putting the mechanism in practice. We provide the EV owners with an intelligent agent (smart-phone application) and let them decide on how to use it.

2.3 Conceptual Framework formulation

The main objective of the current thesis is to test the boundaries of variable-rate charging mechanism in the real world through TamagoCar app and assess the behavior of EV users when compared to the intelligent EV agents.

In addition this thesis aims:

1. At measuring the impact of cognitive load required for this method to be implemented directly to end EV users and comparing their results with the ones of the intelligent EV agents
2. At providing recommendations about improving the method so that is directly applicable to real experiments
3. At analyzing the managerial implications stemming from a successful implementation of variable-rate pricing and the shared value that can be created among multiple stakeholders (EV users, grid operator, society)

As previously mentioned, Valogianni et al (2014) found that the introduction of variable-rate pricing led to 9,61% PARP reduction when compared to a real-world charging scenario and 16% when compared to rate-independent pricing. Based on the latter finding and not having any additional evidence that contradicts it, it is expected that variable-rate pricing will lead to significant balancing of the demand when compared to rate-independent pricing (RTP).

H1: Variable–rate pricing mechanism will lead to significant balancing of the demand as compared to rate-independent pricing (RTP)

In addition, Valogianni et al (2014) observed that when selecting a variable a_t that is correlated with the Retail price, the EV agents adjust this value in order to reach the desired load profile. This leads to an even better aggregate demand curve than with constant a_t. Accordingly, we expect that a similar pattern will be observed in the present thesis.

H2: Inserting a variable a_t that depends on the Retail Price each time period t will result in better balancing results than having a constant a_t

Finally, it is expected that variable-rate pricing modelling will increase the amount of decision-making time required. This fact will most probably lead to additonal cognitive loading of the users.

H3: Variable-rate pricing will present higher values of cognitive load

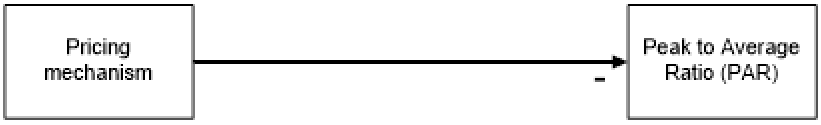

Figure 1 Conceptual Model

Peak to average ratio (PARP)

The balancing of the demand will be measured primarily through PARP. The PARP is a measurement of the highest peak of a load curve divided by the average. The more efficient the grid, the fewer the demand peaks. The formula that calculates the PARP is the following:

$$\mathbf{PARP} = \frac{|\mathbf{x}|^2_{\mathbf{Peak}}}{\mathbf{x}^2_{\mathbf{RMS}}}$$

Equation 2 Peak to Average Ratio (PARP)

Pricing mechanism

The pricing mechanism variable will represent different experimental conditions that will be described in the next chapter. To illustrate the hypothesis that a change in the pricing mechanism will lead to a differentiation of the Peak to Average Ratio, the pricing mechanisms under examination will be defined as nominal variables expressing different experimental treatments.

0: Rate-independent pricing (RTP)

1: Variable-rate pricing with constant a

2: Variable-rate pricing with variable a

Cognitive load

According to Simon (1996), people are not totally rational and do not always respond in a perfect cost minimizing manner. Most of the times they can be influenced by the cognitive load which can result in them taking sub-optimal solutions. Thus, this thesis will measure the amount of cognitive load of each user to confirm if there were significant differences among the three pricing shemes.

According to Pass and Merrienborer (1994), Cognitive Load (CL) is imposed on the cognitive system during the completion of a task. There are three types of cognitive load: intrisic, extraneous and germane CL. The former refers to the intrinsic nature of the material and cannot be easily altered (e.g., the calculation of 1+1 versus solving a differential equation). The extraneous CL is induced by inadequate instructional design. The latter, germane CL, directly reflects learners' efforts to construct and store schemas during learning (Sweller, Van Merrienboer, & Paas, 1998). For this thesis, the level of intrisic CL will be measured in order to assess if high levels of smart charging complexity led to unexpected decisions.

3. Methodology

3.1 Introduction

In order to measure the actual behavior of the EV users under different pricing schemes, a mobile application that simulates the EV usage was employed. TamagoCar app, developed by RSM in collaboration with TU Delft, consists of an innovative and well suited platform to explore the objective of this thesis. In particular, TamagoCar app provides the users with the experience of operating and charging a car while commuting on foot, by bike, by car or by train/bus (Koroleva et al., 2015). The app uses GPS services to measure the distances covered by the users and discharges the EV battery accordingly. The users have to manually start/end their commutes through the “Commute Now” functionality and recharge their batteries using the “Charge” functionality. In addition, the users can monitor their charging and commuting history using the “History” button and compare their aggregated scores to their fellow users through the “Leaderboard” functionality (See Figure 2). The application was developed both in Android and iOS environments.

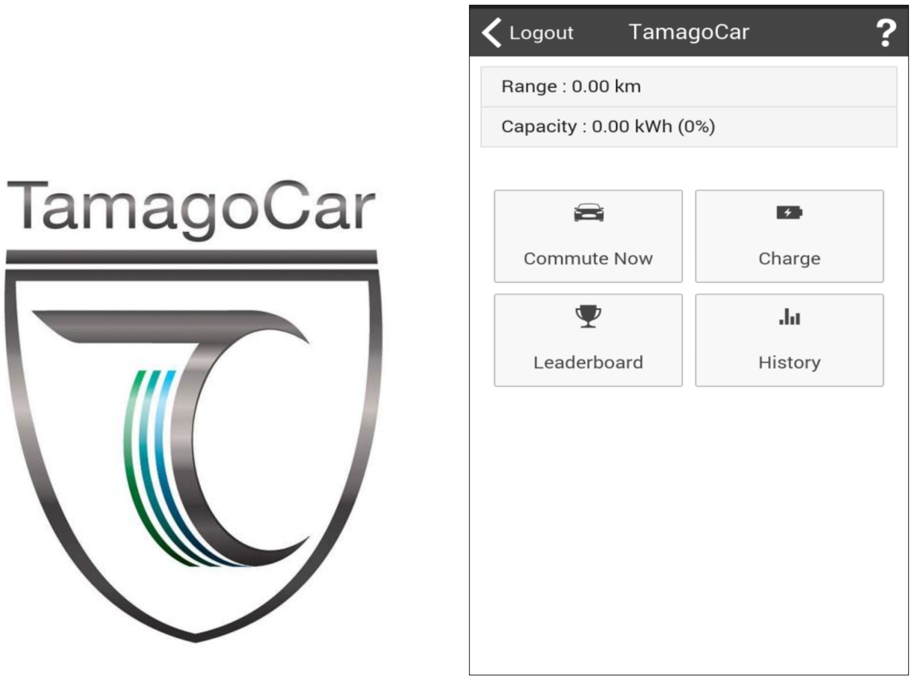

Figure 2 TamagoCar application main page

3.2 Experimental Group

The experiment was conducted among students of the Master in Business Information Management at Rotterdam School of Management. The students were urged to use the app during their daily commutes from or to the university regardless of the transportation mode (bike, bus, bike etc.). The participation in the experiment was optional but secured bonus grades to the participants. Specifically 0,2 points were awarded to all participants provided that they will commute once per day on average and another 0,2 were awarded to the top 30 most efficient drivers based on their leaderboard score. This way the students were motivated not only to participate in the experiment but also to optimize their charging profile as efficient as possible.

3.3 Pre-experiment survey: Battery Design

In order to decide the size of the simulated battery, an initial questionnaire was distributed that asked the participants to specify how many kilometers they commute on average every day. In addition, the questionnaire asked the participants to specify the transportation mode they intended to use in their daily commutes as well as which operation system they had in their mobile phones. The specific questions as well as the descriptive statistics are presented below:

1. How do you commute on your daily transportation?
2. Can you give an approximation of the total distance you travel every day (back and forth)
3. What is the operation system of your mobile phone?

Transportation mode frequencies				
	Frequency	Percent	Valid Percent	Cumulative Percent
Train/tram/bus	45	28,7	28,7	28,7
Bike	97	61,8	61,8	90,4
Car/motorcycle	8	5,1	5,1	95,5
Foot	7	4,5	4,5	100
Total	157	100	100	

Table 1 Transportation mode

Average daily commute estimation					
	N	Minimum	Maximum	Mean	Std. Deviation
Distance	157	1	170	22,97	27,56

Table 2 Descriptive statistics for average daily commute distance (in km)

Operating system				
	Frequency	Percent	Valid Percent	Cumulative Percent
android	70	44,6	44,6	44,6
iOS	87	55,4	55,4	100
Total	157	100	100	

Table 3 Operating system

From Table 2, it can be observed that the average daily commute of the students spanned from 1 to 170 km with an average of 22,97 km. Thus a range of 24 km was decided for the battery of the app which corresponds to an equivalent energy capacity of 4kWh assuming EV efficiency of 6 km/kWh.

3.4 Experimental design

The experiment took place from the 28th of September 2015 until the 21st of October 2015. To validate the hypotheses that were described in the previous chapter, three experimental conditions were formed throughout the three weeks of the experiment. During the first week the students were tasked to charge their EVs through a RTP mechanism, while during the second and third week they were given a variable-rate charging mechanism (one week with constant a_t and one week with variable a_t).

3.4.1 Week 1: RTP

Throughout the first week, the participants were experiencing a Real Time Pricing mechanism. The application provided a user with a price forecast for the next 12 hours. The participants could then decide if they wanted to charge immediately or schedule the charging for the time that the price was lower. The charging rate in this case was constant at a rate of 3,6kW. The following figure depicts the 24-h price curve that was used during the first week.

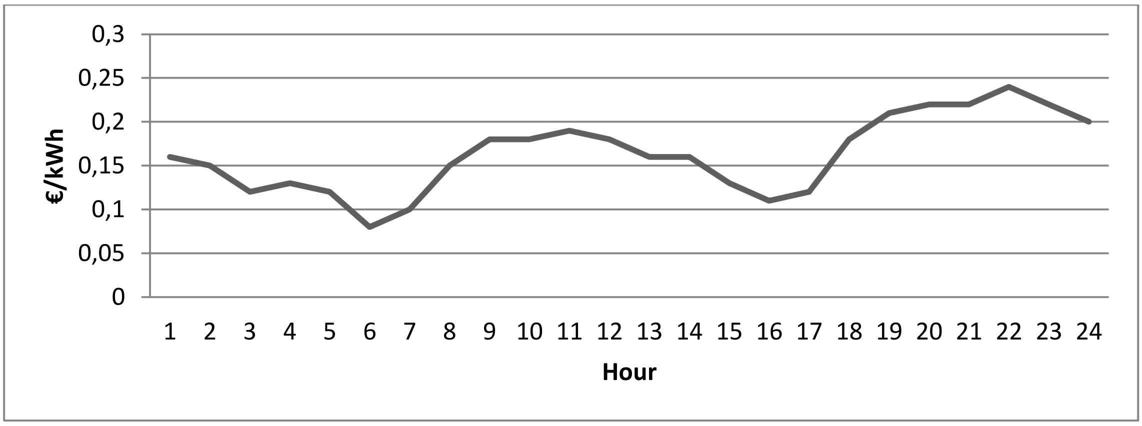

Figure 3 Retail Prices during the 24-h

3.4.2 Week 2: Variable rate with constant a

In order to experiment with the variable-rate pricing mechanism, a new module had to be introduced to the existing version of the app. For this, a cost minimization algorithm was developed and inserted in the app. The users had to select their desired battery capacity and time availability (h) through the sliding bars of the application. Then, the cost minimization algorithm returned the total charging price to the user (See Figure 4).

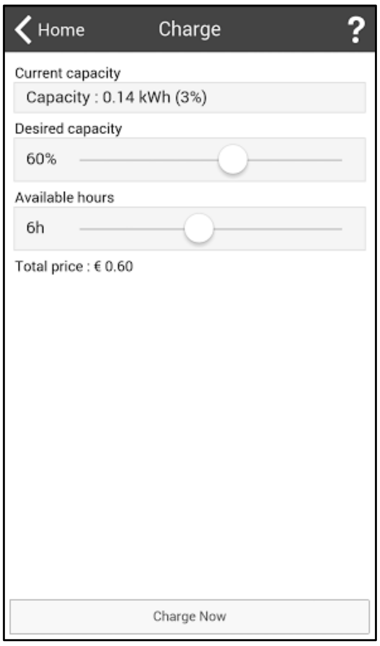

Figure 4 Screenshot from variable-rate pricing mechanism charging

The objective function of the minimization algorithm is calculated by first multiplying Equation 1with r_t to find the total price for time period t and then replacing $P_{0,t}$ with the Retail Price (R_t) for time t. The sum of all the prices between the current hour, n, and the availability period n+h is the objective function. The goal of the algorithm is to calculate the optimal charging schedule that would minimize the total cost of charging for the user.

$$min \sum_{t=n}^{n+h} R_t r_t + a_t * r_t^2$$

Equation 3 Objective function

The Retail prices that were used for this experimental setting were the same as with those of week 1 for comparison purposes. Also, throughout week 2 α_t had a constant value of 0,2 for all time periods t.

3.4.3 Week 3: Variable rate with variable a

In order to examine the validity of H2, a_t was correlated with the Retail Price. To better observe the difference between the results of Week 2 and Week 3, it was decided to correlate a_t with R_t but keep always a minimum a_t of 0,2.

$$a_t = 0{,}2 + R_t - 0{,}08$$

Equation 4 a_t depending on the retail price

3.5 Leaderboard functionality

As previously described, in order to add the social element to the application and incentivize the participants to charge as efficiently as possible, a leaderboard functionality was designed. The score of the users depended on their average cost paid per kWh. In addition, a penalty was given when the users were commuting without having enough battery. The equation for the score was calculated as follows:

Score = (Total cost spent for charging + towing cost) / Total kWh charged

Equation 5 Score formula

Where,

Towing cost = (towed distance/6)*0.37

Equation 6 Towing cost

3.6 Post-experiment survey: Cognitive Load

Finally, to assess the level of mental effort that every experimental condition required from the participants, a post-experiment survey was handed. Based on the self-rating measurement scale of cognitive load proposed by Bratfish et al. (1971), the questions for the three weeks were structured in the following way:

"During the … week, when you were deciding on how to charge your Electric Vehicle more efficiently, did you feel that you made a great deal of mental effort?

Please rate your effort on the 5-point scale".

3.7 Example of using the app (Week 2)

Before moving to the results of the experiment, a real case example of using the app will be described. This way the reader will have the opportunity to easily understand how the participants experienced the simulated ownership and operation of the EV.

On the 7th of October, user 83 had to go from his house to Erasmus University by bike in order to attend the class of Designing Business Applications. At 7:48, he logged in TamagoCar app and pressed the commute button. After 9 minutes, he ended his 1,7 km commute. During this time he consumed 0,28 kWh of his simulated EVs battery that left him with 1,39 kWh from a total battery capacity of 4kWh (as explained in paragraph 3.3).

In order to recharge his battery for future usage, he decided to use the charging functionality of the app at 8:00. As shown in Figure 4, the user after experimenting with different availability hours and desired capacity values, he selected to charge his EV for 1 hour to a total capacity of 1,77 kWh. This choice signaled a total cost of 0,045 € or 0,118€/kWh, which resulted from the cost-minimization routine as described in paragraph 3.4.2.

4. Results

4.1 Introduction

In the first chapter the subject under examination was introduced and the research question of the study was specified (Paragraph 1.2). In the second and third chapter the study focused on the specific smart charging mechanisms that would be examined and formulated the proposed framework under which the developed hypotheses would be tested. This chapter will evaluate whether the developed hypotheses are supported. The chapter starts with the analysis of the sample and continues with the experimental treatment of the data. Finally, the post-experimental survey on cognitive load is analyzed. The conclusions of the results are presented in the following chapter.

4.2 Sample

The total number of students that took part in the experiment was 154. Of those 59,7% were male and 36,4% female (Table 4). The average age of the sample was 23,22 years old, which can be considered as a rather young and tech-savvy sample (Table 5). The age distribution of the sample is depicted in Figure 5.

The average distance covered throughout the three weeks of the experiment was 117.571 km or 19,60 kWh when converted to energy-equivalent units (See Paragraph 3.3). To account for location mistakes in the commute functionality, all commutes that had an average speed of more than 34km/s (or 122,4 km/h) were deleted. The average capacity charged per user was 23,54 kWh, which implies that the users were charging considerably more than they actually needed for their commutes.

Gender				
	Frequency	Percent	Valid Percent	Cumulative Percent
Female	56	36,4	36,4	40,3
Male	92	59,7	59,7	100,0
Not Mentioned	6	3,9	3,9	3,9
Total	154	100,0	100,0	

Table 4 Gender distribution

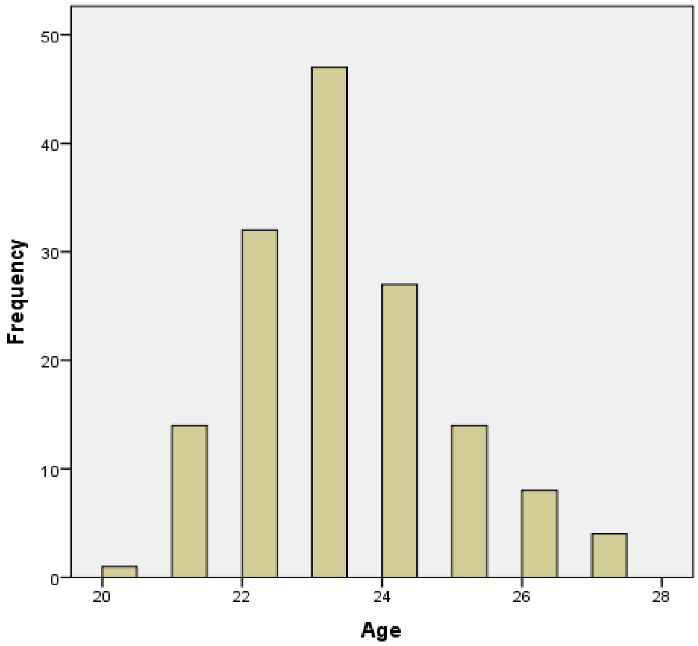

Figure 5 Age distribution

Descriptive Statistics					
	N	Minimum	Maximum	Mean	Std. Deviation
Age	147	20	27	23,22	1,46
Distance	154	0	862422	118334,88	118569,53
Charges	154	2,64	94,84	23,54	15,06

Table 5 Descriptive Statistics of the experiment

The driving behavior in terms of km at each hour of the day between the different pricing schemes (RTP, Variable-rate pricing with constant a, Variable-rate pricing with variable a) is depicted in Figure 6. The driving was done primarily during the day (6-19) whereas there were only small amounts of commutes covered during the night hours (21-5). In addition, there was a commonly observed driving peak between 3-6 PM and at 7-8 AM, which could be explained by commutes of the students from and to the university. However the total distance covered during the first week was much higher: 8900,72 km when compared to 5056,10 and 4266,76 km of week 2 and week 3 accordingly. This fact is attributed to the rules of the experiment that required one commute per day on average from the participants. This means that some students may did complete their required commutes already from the first and second week. In addition, the decline in the distance commuted can be explained by the accumulated cognitive load that was required by the participants in the time horizon of the experiment. To counterbalance this effect and to secure the validity of the result, a standardized evaluation of the charging patterns will be proposed in the next paragraph.

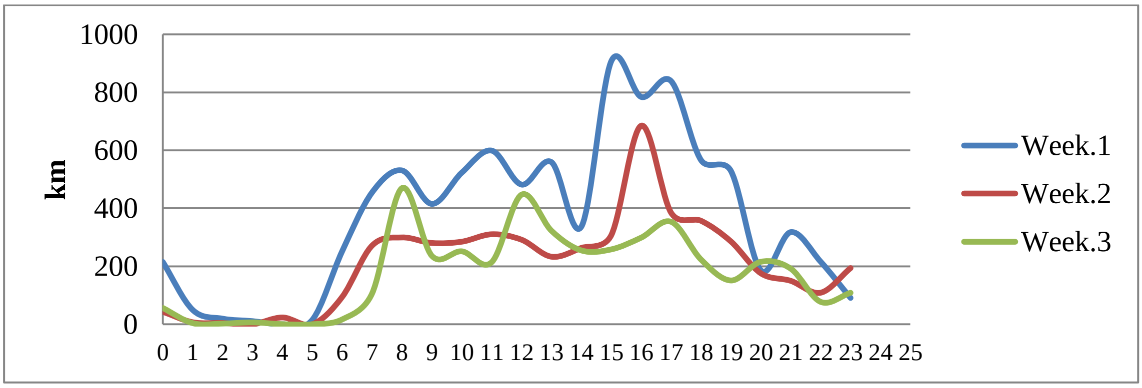

Figure 6 Commute pattern in km during the 24-h

A typical example of the charging pattern can be observed in Figure 7. In the graph, the charging behavior of 10 random users during week 1 is presented. We can see that most of the charging happens early in the morning (3-6 am) or after 2pm. This pattern can be explained by the low retail prices at 6am and 4pm (See Figure 3), which created notable herding phenomena during these specific timeframes. In the next paragraph we will investigate whether these phenomena also exist in the total experimental sample and whether the introduction of a variable-rate pricing mechanism can alleviate the herding problem.

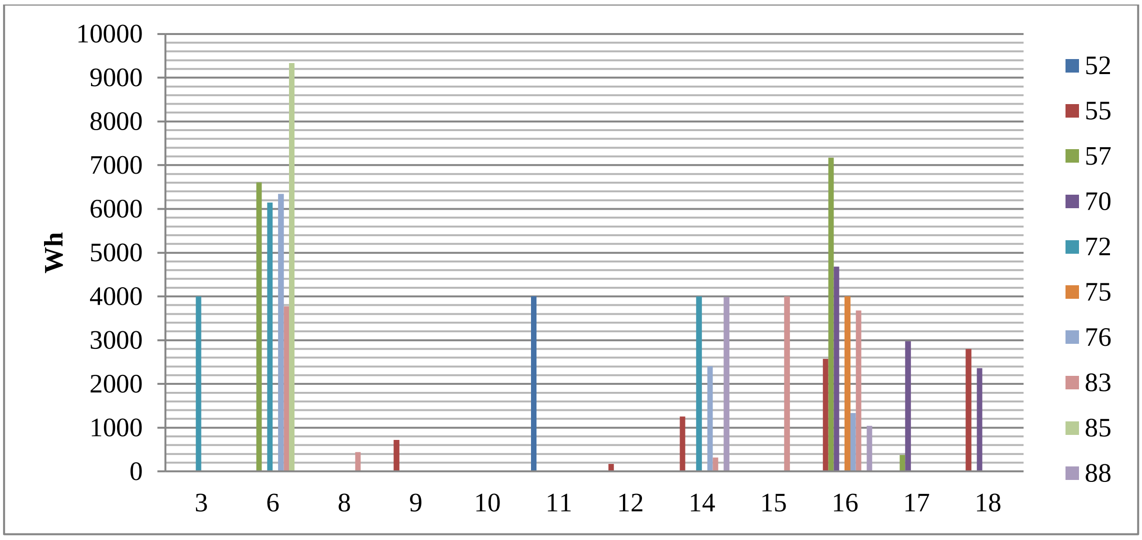

Figure 7 24h charging pattern of 10 random users during week 1 (RTP scheme)

4.3 Experimental Treatment

As described in paragraph 2.3, we want to test whether the amount of capacity charged at each hour of the day is significantly different between the different pricing mechanisms. For that, the total charging amount per hour was divided by the total distance commuted each week (converted in kWh). In Figure 8 and Figure 9, the charging pattern before and after the standardization is presented.

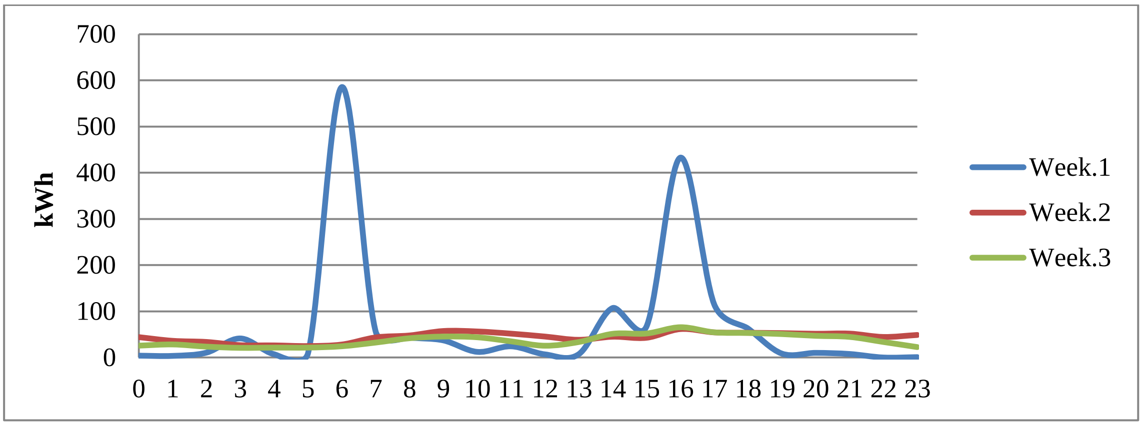

Figure 8 Charging pattern before Standardization (in kWh)

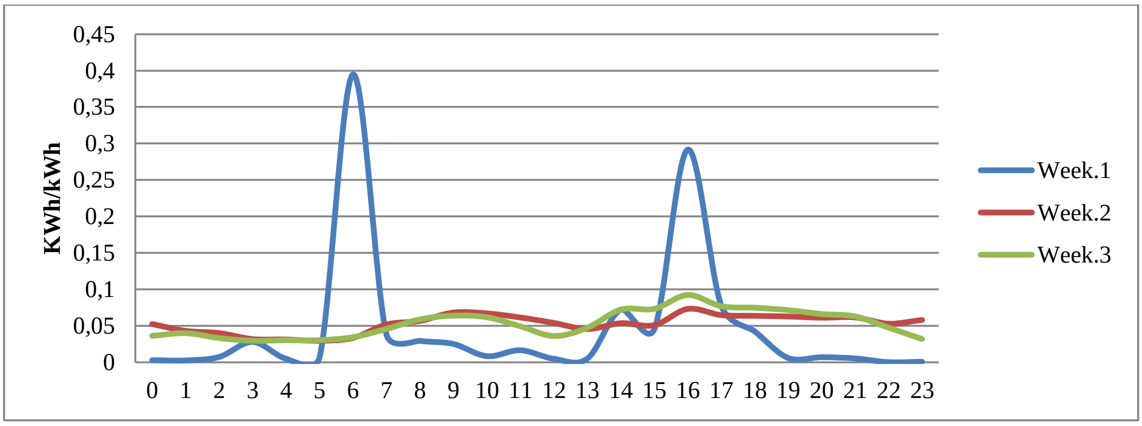

Figure 9 Charging pattern after Standardization (in kWh/kWh)

By taking a first look at the graphs, we can observe that there is a notable improvement in terms of peak reduction between week 1 and weeks 2 and 3, which means that variable-rate pricing contributed to a remarkable smoothing of the demand curve. As described in the previous paragraph and explained by Valogianni et al. (2014), this effect can be attributed to the phenomenon of herding at 6 AM and 4 PM during the first week, which is explained by the retail price curve; as observed in

Figure 3, the retail prices present a minimum value of 0,08€/kWh at 6 AM and a local minimum of 0,11€/kWh at 4PM.

To statistically validate this finding among the individuals' pattern, we want to firstly check whether our data in the three weeks are normally distributed. Kolmogorov-Smirnov (KS) test is highly significant for all variables we test (D(154)= 0,122-0,155, p< 0,05)). Furthermore, the three samples are dependent with each other, since the participants are the same and the measurements are repeated under different experimental conditions. Therefore, we use Friedman tests as an alternative to ANOVA (Statistics, 2015). As expected, for each hour, the capacity distribution charged is significantly different between the three pricing schemes ($\chi^2(2)>50$, $p<0,01$). This can be explained by the different way the charging rate is calculated in the first and second/third week; the charging rate at each hour t will be always significantly lower when variable-rate pricing is implemented, since this method optimizes the charging schedule with r_t often taking values of less than 1kW (when in week 1 r_t is constant at a rate of 3,6 kW).

To compare weeks 2 and 3 separately, pair-sample sign tests with a Bonferroni correction are conducted as an alternative to t-tests, since the data and the differences between pairs (D(154)> 0,08, p<0,05) are not normally distributed (Statistics, 2015). It is found that median charging capacity is significantly different only at 12 AM (Z= -3,064, p= 0,002). During the rest of the day, the median charging capacity is statistically equal. This finding implies that, apart from 12 AM, inserting a variable a_t did not lead to a significant change in the individuals' charging pattern.

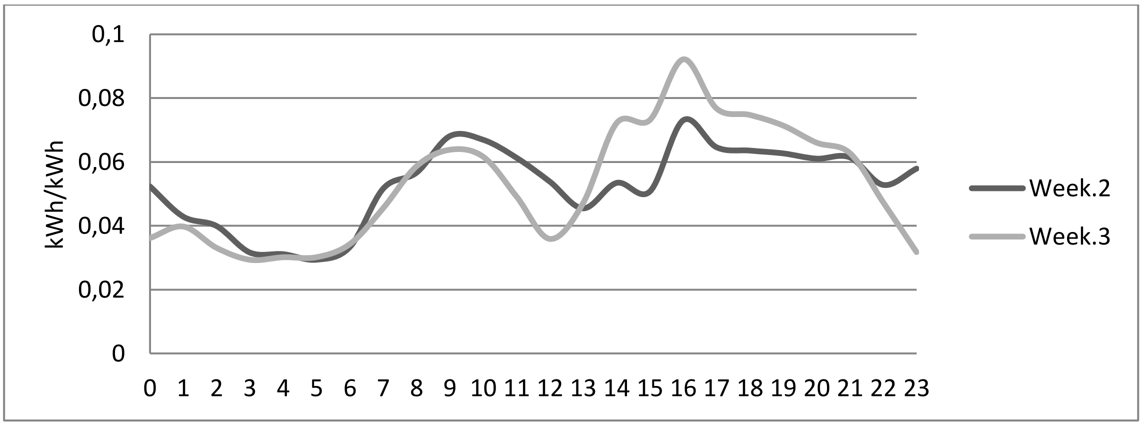

Figure 10 Charging pattern of Week 2 and 3 seperately

In addition, we would like to compare the overall contribution of the pricing schemes to the efficiency of the grid. As discussed in the previous chapters, one way to measure this is the Peak to Average Ratio, where the peak load is squared and divided by the RMS value squared. The results show a notable 80-88% reduction of PARP, when variable-rate pricing is implemented (Table 6). Thus, H1 is supported. This finding is primarily explained by the smoothing of the herding phenomena that occurred during the first week of the experiment (Figure 9). Hence, it can be concluded that inserting a dynamic component in the pricing structure leads to more efficient grid performance. On the other hand, contrary to our initial expectations, the introduction of a variable a_t that is related to the Retail prices does not seem to lead to a further reduction of PARP and thus H2 is not confirmed. To understand the underlying reasons for this result, the level of cognitive load in week 2 and 3 will be separately assessed in the next paragraph.

Peak to Average Ratio			
	PARP	PARP Reduction (%)	Peak Reduction (%)
Week.1- RTP	14,37		
Week.2 -Variable rate with constant α	1,82	87,33	81,50
Week.3 - Variable rate with changing α	2,74	80,92	76,66

Table 6 Peak to Average Ratio

4.4 Cognitive Load

The descriptive statistics of the post-experiment survey are presented below. In total, 110 students out of the 154 participants replied to the survey. From Table 7, it is observed that variable-rate mechanism resulted in higher values of cognitive load. This result is in line with our initial expectations, since this method is more difficult to be understood if detailed information is not provided to the users.

Descriptive Statistics: Cognitive Load					
	N	Minimum	Maximum	Mean	Std. Deviation
Week.1	110	1,0	5,0	2,92	1,08
Week.2	110	1,0	5,0	3,20	,96
Week.3	110	1,0	5,0	3,12	1,22

Table 7 Post-experimental survey results on cognitive load

To examine whether variable-rate pricing led to statistically significant higher values of cognitive load, the responses of week 2 and week 3 will be treated as one. The KS test reveals that neither the samples ($D(110)= 0,155\text{-}0,217$, $p<0,05$) nor the pair differences are normally distributed ($D(110)= 0,106$, $p<0,05$) and thus a pair-sample sign test with a Bonferroni correction is conducted. The results of the test suggest that the introduction of variable-rate mechanism did not lead to significant median differences in the cognitive load of the participants ($Z=-0,804$, $p=0,421$). Thus H3 is not confirmed. This result implies that the participants did not have to make a significant amount of additional mental effort to use variable-rate mechanism, even though the mechanism was perceived as more difficult to understand, as observed in the feedback session of the questionnaire. This phenomenon can be attributed to the fact that the mobile application was suggesting already optimal pricing solutions to the participants and thus they did not have to be cognitive overloaded to perform in an efficient way.

Finally, by comparing the cognitive load of Week 2 and Week 3 separately, it is also observed that no statistical difference is found ($Z= -0,733$, $p=0,464$). This finding is logical since the participants got more acquainted with variable-rate mechanism already from week 2, resulting in non-significant but still lower levels of cognitive load during week 3 (See Table 7).

5. Conclusion

5.1 Introduction

The first chapter of the study formulated the problem statement and research questions. By means of the theoretical and empirical part, the research questions can now be answered. This chapter interprets the results following from the experimental part of the study and analyzes its limitations as well as managerial implications.

5.2 Key Conclusion

The main contribution of this study was to bridge the existing gap between the theoretical approaches and the reality of EV charging by taking into account the behavioral aspect of EV users (See paragraph 1.2). In addition, this study intended to evaluate the best smart charging practices that would lead to a more efficient electric grid. TamagoCar application played a crucial role in this quest, since it enabled the users to interact with their smartphones by letting them intervene when they believed this was appropriate.

The study resulted in the following key conclusions:

1. In line with the results of Valogianni et al. (2014), the introduction of Variable-rate pricing mechanism significantly improved the observed phenomenon of demand peaks when compared to the smart-pricing alternative of Real-Time Pricing and led to an average PARP reduction of 80-87%. This means that variable-rate pricing, which now has been tested both in a simulated and in a reality scenario, tends to result in a significant smoothing of the demand curve. The underlying reason pertains to the fact that EV users are cost-minimizers and thus when they were to select based on a RTP scheme, they were choosing only the cheapest time-frames. This in turn resulted in great demand peaks (herding phenomena) during these hours (Figure 6), which variable-rate pricing mechanism managed to smoothen.
2. Introducing a variable a_t parameter that was depending on the Retail Price did not lead to an even better smoothing of the demand curve. This result was not expected since variable a_t made prices more aggressive and this would have

incentivized users to distribute their charging profile in a more efficient way. The result may be explained by the difficulty that the users were facing to understand the underlying mechanism of variable-rate pricing already from Week 2. As explained in paragraph 4.3 no significant difference was observed in the cognitive load experienced in week 2 and week 3.

3. The cognitive load required by the students did not significantly change when variable-rate pricing was introduced. This result implies that similar mechanisms can be introduced in real-world initiatives without requiring greater amounts of mental effort from the users, while simultaneously helping in improving the efficiency of the electric grid.

5.3 Limitations

Before concluding with the managerial implications of the study, an overview of the limitations of the experiment will be presented. This part aims at establishing the limits of the present study while proposing modifications for future research initiatives.

Firstly, the experiment was conducted in a smart mobile phone environment as part of a university course. The 154 participants (students) were motivated to frequently use the app in order to obtain a bonus grade in the course. This means that the result could have been different if the mechanism was applied in a real-world experiment with real EV drivers. In this case the drivers would have had real motives to use the app in order to save money on their charging costs. Nevertheless, the study presented an interface of real-time pricing mechanisms that could already be applied to real-world experiments and is user friendly (See Figure 4). In addition it confirmed that variable-rate pricing can lead to a more efficient grid.

Related to the first limitation, it should be underlined that our sample was of a really young age (Mean age: 23), which can be considered as a rather tech-savvy sample. This fact was augmented by the academic background of the participants, who were attending the Master in Business Information Management. By changing the profile of our sample, different results could have been observed.

Finally, a major limitation of the study resulted from several GPS/location miscalculations that occurred during the experiment. When using the commute functionality, some participants noticed that the app calculated more kilometers than they actually were doing. To counterbalance this phenomenon, a data clearing based on the commute speed was conducted before the experimental treatment (paragraph 4.2). However, it should be mentioned that this effect did not influence the results of the study, since the charging patterns (research objective) were accurately measured.

5.4 Managerial Implications

In light of the continuous increase of renewable sources of energy in the global energy mix as well as the fast acceleration of electric mobility, innovative ways of increasing demand flexibility are imperative. This study resulted in two main managerial implications on how EV charging can optimally be organized to secure an efficient electric grid, while taking into account the behavioral aspect of the EV driver.

From the side of the grid operator

Real-time pricing without a dynamic proposal creates herding in times when retail prices are low. Herding in turn creates demand peaks and destabilizes the grid. For a successful peak reduction, variable-rate pricing mechanism is proposed. With this method, pricing is not only related to the retail prices, but also to the amount of capacity desired by the EV drivers. The study presented a 77-82% reduction in peak load when moving from Real-Time Pricing to variable-rate pricing.

From the side of the driver

The study revealed that intelligent agents can actually work with and support humans. Through the usage of a smart phone application, people can monitor and in many cases override the decisions of the agents if they think this is appropriate. Additionally, the interaction between human and intelligent agent does not seem to cognitively overload the users and thus such a methodology is proposed for future real-world experiments.

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