Facilitating a Sustainable Electric Vehicle Transition through Consumer Utility Driven Pricing

Completed Research Paper

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Abstract

A transition to an electrified transportation system is widely assumed to be an important step along the road to environmental sustainability. However, large penetrations of electric vehicles (EVs) may put electricity grids under critical strain, since peaks in electricity demand are likely to increase radically. Efforts to manage demand peaks through pricing schemes may create new peaks at low-price periods, if large numbers of EV owners try to benefit from low prices. We propose a pricing method, called consumer utility driven pricing*, which learns from EV owners' reactions to sub-optimal prices and adjusts announced prices accordingly. We evaluate our results in simulations, where we find that* consumer utility driven pricing *outperforms current electricity pricing schemes. We test our method in matching both flat and extremely volatile demand profiles and we see that in both cases it performs closely to what it is theoretically possible under perfect information.*

Keywords: Electric mobility, pricing, Green IS, sustainability, smart grid stability

Introduction

Electrification of transportation is expected to contribute significantly to a sustainable society with reduced greenhouse emissions (Williams et al. 2011). Electric vehicle (EV) adoption is heavily incentivized by governments and policymakers as EVs lower local carbon footprint, reduce noise pollution, and have much higher engine efficiency than traditional vehicles (US Department of Energy 2014). Besides the numerous benefits EVs offer, widespread EV adoption threatens the stability of the existing power grid due to the energy needed to charge EV batteries (Knezović et al. 2017).

Grid operators are faced with the important challenge of transitioning to a smart grid with significant presence of EVs without risking its reliability. The local distribution grids are the first ones to be challenged by large EV penetrations, since their capacity cannot accommodate sudden peaks in the demand coming from EVs. This is known as the "last mile problem" and describes the bottleneck that shows up in the local distribution grid infrastructure because of large numbers of EVs charging concurrently (Schmidt 2017). Furthermore, other segments of distribution grids as well as the higher-voltage transmission grids can be destabilized by high EV penetration rates. This could occur if, for example, many residents of a neighborhood own an EV, and they decide to start charging them around the same time in the evening, which is already a time of peak consumption in many areas of the world. The latter can overload several grid segments as well as grid transformers, posing threats to a sustainable EV transition. That effect can be intensified when EV owners start adopting smart charging technologies, designed to satisfy their preferences and optimize EV charging during convenient times for the EV owners.

Grid operators' traditional solution to this challenge would be to build extra electricity grid infrastructure with higher capacity, able to handle such peak loads (Schroeder and Traber 2012). However, this solution would be costly as well as highly unsustainable (Watson et al. 2010), since more raw materials (e.g. copper) will be consumed to expand the grid and more generating capacity will be installed. The EU projections of €150 bn investments for grid infrastructure expansion in 10 years (European Network of Transmission System Operators for Electricity 2018) to cover the extra demand created in the grid show how costly and unsustainable these solutions can be.

A less infrastructure-intensive solution to mitigate peak demand is to design demand response (DR) schemes (Palensky and Dietrich 2011) that provide monetary incentives to EV customers for shifting consumption to low-demand periods of the day. This is primarily achieved by providing variable pricing signals. However, since all customers are receiving the same signals, they tend to react in the same way, creating new peaks during periods that prices are low (Sioshansi 2012). This tendency is expected to increase when smart charging technologies are in place, since they advise EV owners to charge when their individual benefits or cost savings are maximized. This phenomenon is known in the literature as *herding* or avalanche effect (Kim and Shcherbakova 2011). Consequently, a poorly designed DR scheme might not induce the desired consumption pattern in the smart grid but may, instead, create higher peaks in the demand which have a negative impact on grid reliability and require more grid capacity to be covered. Hence, grid managers are interested in price-based DR schemes that are capable of incentivizing consumers to shift their consumption toward a desired profile, without creating new peaks.

In the future, this need for inducing demand profiles that match supply patterns will become more urgent since the penetration of renewable energy sources (RES) is expected to reach up to 75% of the energy supply by 2040 (European Network of Transmission System Operators for Electricity 2018). With such large RES penetrations, demand profiles will be challenged to match the volatile and intermittent generation profiles of RES. Despite being challenging, inducing EV charging demand that matches these profiles will increase the societal sustainability levels, since the EVs will be directly charged from renewable energy.

Inspired by the Green IS framework (Watson et al. 2010, Loock et al. 2013), which suggests that appropriate use of available information can lead to more efficient energy re-distribution and reduced needs for grid capacity investment, we address the following research question:

How can price schemes be designed to induce a desired demand profile without creating herding?

To address this question, we take the stand point of a smart grid operator who wishes to induce a certain EV charging demand. We assume that the grid operator faces an EV population with smart charging in place and, in addition, we assume that the grid operator is broadcasting prices without having prior knowledge about the way EV owners make charging decisions. The latter makes our mechanism flexible and adaptable to any EV population (online flexibility), without requiring assumptions about prior EV charging decisions (no requirement for offline training). That can be helpful for grid managers because prior data about EV charging decisions might not be available or reflective of future charging decisions, given that an EV population might change over time or differ across locations.

Answering this question can be a challenging task, since if all EV owners own smart charging decision support systems (DSS), they can identify the optimal charging slots potentially leading to *herding* in charging. In response to that, we propose *consumer utility driven pricing*, a method to learn EV owner preferences and tailor the pricing schemes to a specific EV population, inducing a profile very close to the theoretically optimal one.

Background and Related Work

Our work contributes to the Green IS (Dedrick 2010, Melville 2010, Watson et al. 2010, vom Brocke et al. 2013, Ketter et al. 2016) and sustainability discussion (Dao et al. 2011, Malhotra et al. 2013), by providing a method to design pricing schemes which can: a) mitigate peak demand, reducing the need for grid capacity expansion and b) induce EV charging demand which can follow volatile generation patterns coming from RES, maximizing renewable consumption and reducing the need for conventional carbon-intensive electricity production. In Table 1 we show how our work contributes to Green IS using the *Integrated Sustainability Framework* proposed by Dao et al. (2011). This framework captures the value of sustainable strategies of firms using the triple bottom line "natural environment, society, and economic performance" (Dao et al. 2011), but there are direct analogies with our approach to facilitate a smooth EV transition in a sustainable grid. We outline these analogies in Table 1. In the row with header "Today" we show what our approach can currently contribute to a sustainable grid, whereas in the row with header "Tomorrow" we show that our approach can support a sustainable EV transition coupled with high RES penetration. In the Evaluation section we present relevant scenarios to reflect the contribution of our method to "Today" and "Tomorrow".

	Internal (EV owner)	**External** (grid)
Today	**-Strategy** -Optimize EV charging so that individual utility is maximized **-Pay-off** -Lower charging costs -Preference satisfaction	**-Strategy** -Induce EV charging desired by the grid **-Pay-off** - Stability and reliability - Peak and volatility reduction
Tomorrow	**-Strategy** -Optimized EV charging becomes broadly available **-Pay-off** -Public more open to EV adoption -Sustainable e-mobility -Charging cost savings	**-Strategy** -Induce EV charging matching RES generation profiles **-Pay-off** - Stability and reliability - Sustainable EV charging - Smooth EV transition coupled with high RES penetration

Table 1. Integrated Sustainability Framework adapted from Dao et al. (2011)

We, first, present work related to smart grids and the transition to electric mobility. Second, we review literature on price-based DR, from which our method draws its basic principles and objectives and highlight our contribution. Furthermore, we put our contribution into a general IS perspective, since the problem we are addressing has a lot of parallels with optimizing system utilization, for example, in cloud computing.

Smart Grid and the Transition to Electric Mobility

The smart electricity grid is the evolution of the traditional electricity delivery infrastructure, with technological advancements playing increasingly crucial roles in generation, transmission, distribution, and consumption. It is becoming a smart market (Bichler et al. 2010) for electricity; decisions can be facilitated by intelligent DSS that can act on behalf of people or organizations. In this smart electricity market, RES (Koolen et al. 2017) and electric mobility (Knezović et al. 2017) will play a crucial role in establishing environmental sustainability. Pricing mechanisms can be powerful tools toward shaping EV charging demand to follow a desired profile, such as generation patterns of RES and facilitate a sustainable EV integration.

Common methods proposed in the literature to shape charging demand include aggregation of EV customer profiles (Vandael et al. 2013, Hu et al. 2016, Tang et al. 2016, Kahlen et al. 2018). EV aggregators tend to make collective decisions about strategically placing EV charging in time and place so that they maximize benefits for their fleet. Furthermore, mechanisms that reject charging requests depending on grid capacity installed (distribution transformer's side) have been proven effective in reducing peak demand (Muñoz et al. 2016). However, both categories tend to not always satisfy customer preferences, since they have to reject individual requests to meet a global objective.

In addition, auction mechanisms have been proposed as ways to coordinate EV charging. Gerding et al. (2013) propose a two-sided market approach to allocate charging timeslots among EV customers and to avoid charging congestion. Robu et al. (2013) present an online auction mechanism where EV owners state their timeslots available for charging and also bid for power. From an infrastructure standpoint, Avci et al. (2015) and Mak et al. (2013), describe optimal placement plans for battery charging stations so that the EV charging is facilitated properly to serve EV owners. However, pricing mechanisms are easier to be implemented given that they do not require any specific implementation on the EV charging station and have higher customer acceptance, since customers are used to receiving price signals in exchange for a service. Nevertheless, current pricing schemes tend to create *herding*, as we also confirm in our Evaluation section, especially when smart charging DSS become broadly available. *Consumer utility driven pricing* mitigates herding without requiring prior knowledge about the customer portfolio it is facing, being easily adjustable to customer needs.

Demand Response for EV Charging

Demand response (DR) refers to "changes made in electricity consumer behavior after receiving a certain signal" (Siano 2014, Palensky and Dietrich 2011). These signals can be either price incentives (Siano 2014) or alleviations for not consuming during peak hours, or have other forms (e.g., emergency signals for reducing consumption) (Palensky and Dietrich 2011). The DR categories that focus on designing prices able to incentivize certain electricity consumption are known as price-based DR (Palensky and Dietrich 2011, Valogianni and Ketter 2016). Our proposed *consumer utility driven pricing* has as its goal to induce a desired EV charging demand, therefore, it draws from the price-based DR literature, focused on EV charging. Next, we review the most relevant to our approach DR literature.

Marzooghi et al. (2016) present an aggregated DR method for integrating RES in the energy supply mix. They present a general market framework in which RES can be easily integrated, while they assume cost-minimizing end users equipped with photovoltaic panels (PV) and EVs. Along similar lines, Mahmoudi et al. (2014) propose a wind offering strategy to be integrated in a three-floor electricity market, in which the wind energy suppliers are employing DR. Tan et al. (2014) present a pricing DR model for EV charging to match a certain profile, while adding a price parameter which implicitly reduces *herding*. Shao et al. (2012) introduce a DR method which accounts for customer choices in term of appliance prioritization. Specifically, they account for all loads available on the customer side, asking customers to set priorities on loads (appliances) and based on these priorities peak load reduction is achieved. Soares et al. (2013) present a model for scheduling EV charging using "trip reduction" or "trip shifting" DR techniques, which is solved with Particle Swarm Optimization (PSO). Some of the previous works address the problem from a macroscopic point of view, in which all markets (from wholesale to retail) are considered. Furthermore, in all aforementioned work the end users are modeled as cost minimizers and their decisions are not in focus, due to the macroscopic character of the models. Our proposed pricing scheme focuses on the retail market and examines the way EV owners are making charging decisions, accounting for their individual utility function among other parameters. This addition creates new insights for grid operators about the actual behavior of EV owners when it comes to accepting or reacting to broadcasted prices. In addition, we benchmark our approach with extremely volatile demand profiles to examine the boundaries of its performance.

Parallels to Optimizing System Utilization

The problem of shaping EV charging to match a desired profile is analogous to the problem of optimizing system utilization. For example, in grid computing, server capacity must be allocated to specific consumer requests depending on the size and the duration of a request. Bapna et al. (2005) and Bapna et al. (2008) present an online auction mechanism to optimally price and allocate "one-time digital products in the form of streams". Similarly, Tang and Chanson (2000) present an algorithm to optimally allocate jobs on a grid of heterogeneous computers, given certain capacity. Furthermore, allocating and pricing spare cloud capacity has triggered interest in the academic community. Agmon Ben-Yehuda et al. (2013) deconstruct the "instance pricing scheme" used by Amazon to incentivize optimal utilization of its capacity. The authors show that Amazon is using a hidden price component (AR(1)) on top of the market-driven price. Building on these findings, Singh and Dutta (2015) propose an algorithm to forecast the Amazon spot prices and provide some guidance to customers anticipating these prices.

The cloud/server capacity allocation problem shows a lot of similarities with the electricity markets. First, a lot of terminology such as “spot prices” has been borrowed from the electricity market domain (Singh and Dutta 2015). Furthermore, to determine these spot prices, all previous works are based on an auction taking place before allocating the available capacity, similarly to the electricity market auctions. However, there are differences that necessitate separate handling of these two similar problems. First, aggregating capacity across different locations is easier in the cloud computing setting, compared to electricity grids (Singh and Dutta 2015), compromising the feasibility of a global auction. Consequently, there is a need to solve any congestion problems locally, therefore, our proposed pricing mechanism is easier to be implemented, without requiring additional ICT infrastructure to facilitate local auctions. Furthermore, EVs have different arrival and departure patterns that need to be communicated to an auctioneer for setting up a capacity allocation auction. Finally, the valuation that an EV driver has for some amount of electricity that will allow her to drive to a certain location is derived from a different logic compared to the valuation a business might have for a certain capacity on a server or in the cloud. Therefore, there is vast literature (Gerding et al. 2013, Robu et al. 2013, Muñoz et al. 2016, Kahlen et al. 2018) dealing with electricity markets separately from optimizing system utilization in general.

Model Description

Our analysis takes the standpoint of a grid operator or an electricity provider. We use the grid operator as an example for the rest of this analysis. The presented results can be applied to electricity providers, as well. The grid operator is facing the problem of shaping electricity demand toward a desired profile, such as a less volatile demand profile. It is important for the grid operator to be in control of shaping the electricity demand, since this allows for a more stable and reliable grid. For instance, achieving a demand profile with lower volatility reduces the unpredictability of electricity demand as well as demand peaks. In order to achieve a desired demand profile, the grid operator must “communicate” with EV customers to induce a certain charging behavior. One effective way of establishing communication between grid operators and EV customers is price-based DR. Grid operators typically lack a priori information about how EV owners evaluate prices and make charging decisions. They are only able to observe aggregate EV charging demand in response to prices.

EV owner’s Problem

EV owners receive prices from the grid operator over a future time horizon T and decide about when and how much to charge. In order to make well-informed decisions with respect to charging their vehicles, EV owners should be assisted by smart systems that learn from their behavior and propose beneficial charging plans. Being supported by a decision support system (DSS), EV owners can overcome potential cognitive overload and process all available information (volatile prices, driving preferences, renewable availability, etc.) more effectively in order to arrive at better decisions. We demonstrate how such a DSS might function, and we use it in our simulations to create insights about the effect of such a system in the smart grid. We assume that EV owners have as their main objective to maximize expected utility $U(\cdot)$ from EV charging c_t, $\forall t \in \mathbf{T}$. The DSS representing each EV owner solves the utility maximization problem described below (Eq. (1)) and derives an optimal EV charging demand vector $\mathbf{c}^* = [c_1^*, ...c_T^*]$ over the planning horizon T.

$$max_{[c_1,...c_T]}\mathbb{E}\{\sum_{t=1}^{T} U(c_t) \cdot \lambda_t\} \tag{1}$$

subject to constraints (2), (3), (4), (5). The parameter λ_t is a binary variable denoting the charging availability of the EV during time $t \in \mathbf{T}$. Therefore, $\lambda_t = 1$ indicates availability for charging.

Constraint (2) binds EV charging within the power range allowed by the grid and the charger ($p_{max,t}$). EV charging, c_t, $\forall t \in \mathbf{T}$, is measured in electricity units (kWh), while the charging power constraint, $p_{max,t}$, is indicated in power units (kW). Therefore these boundaries need to be multiplied by the time granularity Δt to comply with the units of the EV charging demand $\mathbf{c}^*$. This constraint applies to each charging pole (depending on infrastructure capabilities) and can vary depending on location. For example, fast charging stations have different maximum allowable charging rates, $p_{max,t}$, compared to household charging installations.

$$0 \leq c_t \leq p_{max,t} \cdot \Delta t \cdot \lambda_t \qquad \forall t \in \mathbf{T} \tag{2}$$

The right side of Eq. (2) restricts the charging during time periods that the EV is available for charging (when $\lambda_t = 1$).

Each EV owner has her own driving deadlines $t_d \in \mathbf{d}$. By each deadline t_d the EV needs to have enough energy E_d in the battery to last until the next t_{d+1} opportunity the EV owner expects to be able to charge (assuming $t_d < t_{d+1}$, $\forall t_d \in \mathbf{d}$). Therefore, the energy added to the battery c_t when the EV is not driving together with the amount stored in the battery for $t = 0$ reduced by the electricity spent for driving D_t till the deadline t_d is at least equal to the amount required E_d till the next deadline t_{d+1} (Constraint (3)). The number $|\mathbf{d}|$ and the timing of deadlines t_d as well as the charging requirements E_d and the electricity spent for driving D_t by each deadline vary across EV owners and are not known to the grid operator. SoC_0 is the state of charge at time $t = 0$. Constraint (4) models the initial charge level of the battery at the beginning of planning horizon T.

$$SoC_0 + \sum_{t=1}^{t_d} c_t - \sum_{t=1}^{t_d} D_t \cdot (1 - \lambda_t) \geq E_d \qquad \forall t_d \in \mathbf{d} \tag{3}$$

$$SoC_0 = SoC_{initial} \tag{4}$$

At the end of a time horizon T the DSS needs to have charged a total of:

$$SoC_0 + \sum_{t=1}^{T} c_t = \sum_{d=1}^{|\mathbf{d}|} E_d + \sum_{t=1}^{T} D_t \cdot (1 - \lambda_t) \tag{5}$$

The amount $\sum_{d=1}^{|\mathbf{d}|} E_d$ can be 0, which means that the EV has charged just enough to cover driving: $\sum_{t=1}^{T} D_t \cdot (1 - \lambda_t)$, or $\sum_{d=1}^{|\mathbf{d}|} E_d > 0$ depending on how risky an EV owner is toward charging enough to drive or having a sufficient surplus of electricity in her battery.

Individual Utility

Each EV owner's objective function (Eq. (1)) maximizes individual utility $U(c_t)$ of EV charging. We follow the mathematical modeling definition of *utility function*, (Russell and Norvig 1995): "The agent's preferences are captured by a utility function, $U(\cdot)$, which assigns a single number to express the desirability of a state." In our formulation, the DSS assigns a value to each state (state is an EV charge level) depending on the consumer's desire for this state. This utility function $U(c_t)$, consists of the value that this amount of electricity has for an EV owner, $V(c_t)$, reduced by the cost of this amount, $c_t \cdot P_t, \forall t \in \mathbf{T}$ (Robu et al. 2013, Bhattacharya et al. 2014). The valuation function $V(c_t)$ varies across EV owners and is a result of individual preferences. The DSS estimates this valuation function from previous actions (training period). We describe this process in the next section. By P_t we denote the price per electricity unit (€/kWh), which is broadcasted by the grid operator in advance of the planning horizon T. For each EV owner's utility function we assume the formulation in Eq. (6).

$$U(c_t) = V(c_t) - c_t \cdot P_t \tag{6}$$

Therefore, substituting Eq. (6), objective function (1) becomes:

$$max_{[c_1,...c_T]} \mathbb{E}\{\sum_{t=1}^{T} (V(c_t) - c_t \cdot P_t) \cdot \lambda_t\} \tag{7}$$

subject to (2)- (5). Since the prices $P_t, \forall t \in \mathbf{T}$ are known to the DSS representing the EV owner in advance of the planning horizon, as well as the charging availability λ_t, $\forall t \in \mathbf{T}$, the expectation applies only to the valuation faction $V(c_t)$ which is different across EV owners and results from their individual preferences. Therefore, Equation (7) becomes:

$$max_{[c_1,...c_T]} \sum_{t=1}^{T} (\mathbb{E}\{V(c_t)\} - c_t \cdot P_t) \cdot \lambda_t \tag{8}$$

Estimating Valuation Functions

The valuation function $V(c_t)$ expresses the value that an EV owner puts on a certain EV charge c_t. Therefore, it results from EV owner preferences and varies across individuals. It encompasses all idiosyncratic attributes that lead to a person's preference for an EV charge c_t over an EV charge c'_t ($c_t \succ c'_t$) for a price P_t.

Since we cannot measure all the psychological attributes which lead to a preference $c_t \succ c'_t$, we presented the customers with different charging amount options $c_t, c'_t, ...$ tied to a certain monetary value. For example, assume a scenario where an EV owner has to charge a certain amount of electricity within a day, so that she has enough electricity to drive the next day. In this scenario the EV owner can choose between charging 3kWh at a total cost €3 (denoted as $B_1 = (3kWh, €3)$) or wait till prices drop and charge 4kWh at the total cost of €3, $B_2 = (4kWh, €3)$. This is feasible in our set up because the grid operator announces the prices well in advance for the whole time horizon T, therefore, EV owners can plan their charging based on their preferences. EV owners can choose from a continuous space of consumption values, starting from 0 to the maximum capacity of their EV batteries. Choosing B_2 ($B_2 \succ B_1$) would mean that an EV owner is willing to pay less per kWh and consequently has lower valuation of each electricity unit than a person who would choose $B_1 = (3kWh, €3)$, ($B_1 \succ B_2$). Repeating this process, we asked the EV owners to attach a monetary value to certain electricity amounts (depending on their needs) and from the data points matching electricity amounts to monetary values we could approximate their function $V(c_t)$ over EV charging c_t.

Assuming a customer has the following preferences $B_1 = (1kWh, €1)$, $B_2 = (2kWh, €3.2)$, $B_3 = (3kWh, €4)$, $B_4 = (5kWh, €5.3)$ and $B_5 = (6kWh, €6)$ [1], they belong to an implicit trajectory of continuous preferences representing her valuation function of EV charging (Chen and Pu 2004, Russell and Norvig 1995). Plotting these preferences on a graph (Figure 1) we can get the best fit function which connects these preferences and derive an expectation for function $V(c_t)$ of this particular customer, $\mathbb{E}\{V(c_t)\}$. This function provides an estimation of how this EV owner values the amounts of electricity charged in her battery. Literature has assumed that this valuation function yields non-increasing marginal valuation for each extra electricity unit (Robu et al. 2013, Bhattacharya et al. 2014, Zheng and Shroff 2014). However, this is a modeling assumption without empirical validation. Therefore, we make no assumption about the structural form of this valuation function $V(c_t)$ until we derive its form from real-world data (Preference Collection Process).

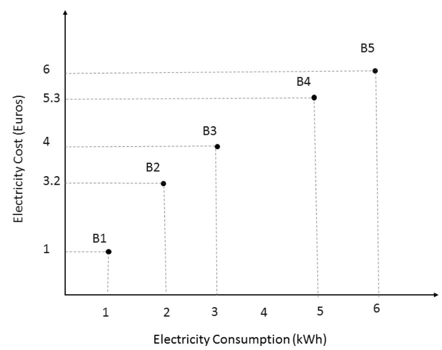


Figure 1. Preference trajectory of an exemplary customer

To collect EV owner preferences we asked an EV owner population to put a certain value onto varying amounts of electricity consumed. To interact with the population in question and track their preferences we extended the mobile-app presented by Koroleva et al. (2014). This mobile-app extension demonstrates how the EV owner DSS elicits individual preferences.

Mobile-app for Preference Collection

The mobile-app *TamagoCar* (Koroleva et al. 2014) provides users with the experience of driving and charging an EV. Specifically, the app has a virtual EV battery that gets depleted while the user commutes. It identifies automatically when a user commutes using the phone's accelerometer and tracks the difference between GPS coordinates. In our setting, we crosschecked the speed of all the commutes to ensure that there was no gaming of the system. During each commute the app gets activated automatically and depletes the virtual EV battery, based on the distance commuted. In order for the user to be able to commute, the EV battery on the mobile-app needs to be charged. Charging can happen in two ways: a) the user selects to *charge* immediately based on the current prices or b) the user selects to *schedule* the charging on time intervals when the prices appear to be more beneficial (in case of price variation during the day). In order

[1] These numbers serve as an illustrative example and they do not represent real data.

to ensure a fair comparison among users we used an efficiency score ($e = \frac{Total\ Cost}{Total\ Electricity\ Consumption}$). This score represents the main logic behind an EV owner who strives to minimize cost: charge most of electricity when prices are low and refrain from charging when prices increase. Therefore, a consumer with a high efficiency score is a consumer who tried to benefit the most from the price variation. If a user commutes without having the battery charged enough (or runs out of battery while commuting) she receives a penalty in her efficiency score. The main screens of the mobile-app are presented in Figure 2.

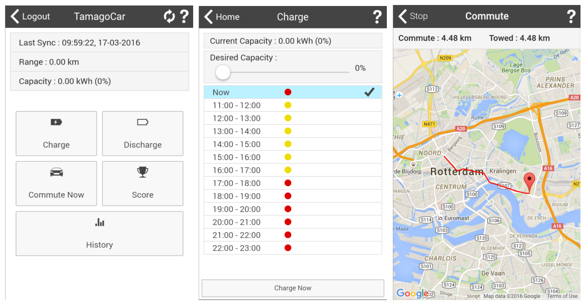


Figure 2. TamagoCar main screen, charge screen and commute screen

Preference Collection Process

In order to elicit user preferences with respect to electricity consumption, we conducted a one-week data collection with the TamagoCar mobile-app. The sample of the data collection was a group of business school graduate students in the Netherlands. This population choice is suitable for this context since the subjects of the data collection are young, tech-savvy, and keen on adopting new technologies such as EVs. This population segment is aware of the benefits of electric mobility (such as sustainability) and uses mobile-apps for many daily activities. Therefore, it is natural for them to have a mobile-app for EV charging scheduling. In addition, they live and work/study in the Netherlands, therefore, they match the commuting patterns and habits of the Dutch data sets we are using in our Evaluation section[2]. University students have been used as subjects in numerous data collection processes and experiments in the field of information systems (Bhattacherjee and Premkumar 2004, Kim and Benbasat 2009). Furthermore, past research has shown that experimental subjects are not different, no matter if they are students or belong to the general public (Exadaktylos et al. 2013), especially, since the task they have to perform is commute and charge their EV, as they would normally do, without being influenced by their student identity. Despite the latter and acknowledging the fact that collecting data from university students might pose a limitation, we only utilized the user preferences and not the commuting patterns to calibrate our simulation. The commuting patterns of the students were not used for calibration, since they might not reflect the actual driving behavior of an average consumer. User preferences when it comes to valuing EV charging are less likely to be biased in a student population, since the charging decisions based on prices are not influenced by their student identity (unlike their commuting behavior). Future work could address this limitation by launching the same data collection in a general population sample.

The preference data collection took place between September 28^{th}, 2015 and October 4^{th}, 2015. The participants were asked to commute at least once per day or on average at least 5 times per week. Furthermore, they were asked to charge during each day enough so that they have electricity to drive the next day. We excluded from our sample persons that did not commute once per day or on average at least 5 times per week. In this way, we ensured that at least their daily commute was captured. For this daily commute, they had to plan their EV charging accordingly.

The prices provided for this week were variable prices comprised of Dutch electricity wholesale prices adjusted to account for taxation and network fees. These prices were announced before each day, so that the participants could plan their charging accordingly. Since they had the requirement to charge enough electricity within 24h, to cover for their commute in the next day, they had no intermediate deadlines within the day to influence their decision. Therefore, their decision about how much to charge was solely based on

[2]Their motivation was tied to their course grades: they were given a sign-up bonus grade for participating in the process and an extra bonus for being in the top 30 list of the leaderboard. In this way, they were incentivized both to participate and to strive for cost savings.

the valuation they put on certain amounts of electricity. Deciding to charge when prices are high, indicates a high valuation of this particular amount of electricity (e.g. for charging from a state of charge of 10% to a state of charge of 50%). On the other hand, once a person decides to postpone charging for a lower price period, it means that this person does not have a high valuation for this particular amount of electricity, probably because the state of charge is high enough to allow for her daily commute.

Data Collection Sample and Valuation Results

The total number of participants in the data collection were 154 (56 female, 92 male and 6 with gender not reported) in the age range of $[20, 27]$ with a mean of 23 years old. In order to elicit their preferences we asked them to decide when to charge their EV based on the prices and their own driving needs. Therefore, persons who were willing to pay a higher price for a certain amount of electricity, had a higher valuation for this particular amount. For example, in Figure 3(a) we show the different charges for the customer with ID 23 during the duration of the data collection. Over a week time period, customer 23 charged her battery 6 times (some of the charges coincide on the same line), which means that on average she had to plan the charging for the next day. Each charge has a different cost depending on the electricity prices at this time of the day. We normalized all charging events so that they are in the same system of coordinates (start from 0) and are directly comparable.

We observe that customer 23 tries to charge small amounts of electricity when the costs are high and larger amounts when the prices are lower. From these charging choices, we derive an approximation of the $V(c_t)$ function, as illustrated in Figure 1. In this case, the points are represented by lines starting from 0 state of charge to a certain state of charge. The vertical axis indicates the total electricity costs paid by this customer in order to obtain the amount of electricity indicated on the horizontal axis. Specifically, in our context the customers had to choose between charging a specific amount at a certain electricity price, or wait till another point in time during the day that the prices will be different. They had the option choose through all possible choices since they know the prices in advance. For example, a person might have to choose between charging 3kWh at a total cost €3 (choice $B_1 = (3kWh,€3)$) and some other events like waiting till prices drop and charge 4kWh at the total cost of €3, $B_2 = (4kWh,€3)$. All these choices indicate each person's preferences and will help the DSS maximize the utility function $U(c_t)$, given the derived approximation of the $V(c_t)$ function for this particular subject.

Deriving the best fit polynomial function of the charging events in Figure 1, we get a quadratic valuation function of EV charging. To derive the best fit polynomial we calculated the curve with the highest adjusted R^2 which was for the quadratic curve with $R^2 = 97.17\%$. In this quadratic form we consider only the upward part of the parabola (growing until the maximum point at a decreasing rate). In this example for customer 23 we observe how the valuation of electricity differs depending on the battery's state of charge. From 0kWh to 3kWh we see a steeper increase in the valuation than from 3kWh to 4kWh, which indicates the change in the preferences once the EV owner has some electricity stored in the battery (3kWh) compared to the situation when the battery is empty (0kWh). This means that when an EV owner has an empty battery, she is more prone to charge at higher prices, hence, she puts higher valuation to EV charging at this point.

We repeat the same process followed for customer 23 for all 154 subjects in our sample and calculate the valuation function over the whole population (best fit polynomial function). In Figure 3(b), we show the individual charging events of all subjects as data points starting from 0 state of charge and the average valuation function of this population. In this population the best-fit valuation function approximation is the quadratic curve $V(c_t) = -0.13 \cdot c_t^2 + 1.56 \cdot c_t$ with the highest adjusted $R^2 = 93.18\%$. This result verifies the modeling assumptions made in the literature (Robu et al. 2013, Bhattacharya et al. 2014, Zheng and Shroff 2014) that the EV charging valuation functions have non-increasing marginal valuation for each extra electricity unit charged in the battery. The expectation of $V(c_t)$ for each EV owner is estimated by the DSS representing her in the market and it is private information. In the rest of the paper, in accordance with the literature (Robu et al. 2013, Bhattacharya et al. 2014, Zheng and Shroff 2014) and our findings, we assume a valuation function with non-increasing marginal valuation for each extra electricity unit charged.

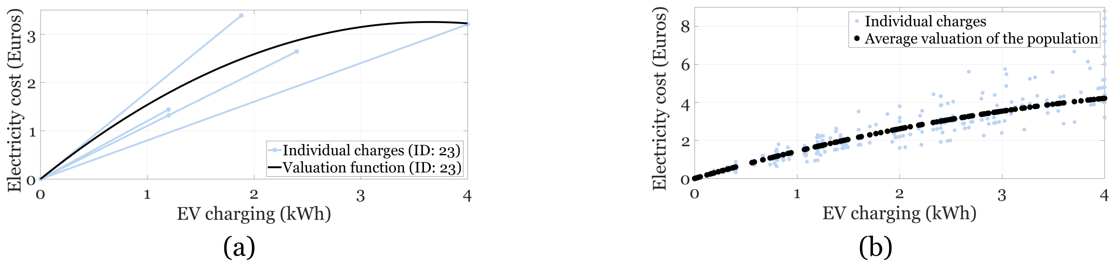


Figure 3. Individual charging preferences and associated costs: (a) customer with ID 23 (b) whole population

Smart Grid Operator's Problem - Consumer Utility Driven Pricing

To induce a desired electricity demand profile, grid operators (or electricity providers) broadcast prices to the EV population. These prices shape the overall EV charging demand a grid operator observes. In order to set electricity prices in a way that will induce a desired EV charging demand, grid operators need to know the individual valuation functions of the EV owners in the population, their charging availability vectors and their specific deadlines. However, these parameters are private and not communicated to the grid operators. Thus, it is not possible for them to analytically calculate the optimal prices for inducing a desired charging profile, given the EV customer information they have at their disposal. To address this challenge, we propose a price setting method, called *consumer utility driven pricing*, which is based on learning the average valuation function of an EV population from its reaction to sub-optimal prices. First, we show how the optimal prices can be set by the grid operator in a scenario where the valuation function $V(c_t)$ of the EV population is known (perfect information scenario).

Optimal prices when $V(c_t)$ is known to the grid operator (perfect information scenario)

Ideally, the grid operator would like to know the exact decision function $U(c_t) = V(c_t) - c_t \cdot P_t$ of each EV owner, or of the whole population on average. If the grid operator had this information, she would be able to assume an average EV owner representing the population and solve her utility maximization problem. Through this process she would be able to define optimal prices which can induce a certain demand profile.

In each EV owner's utility function $U(c_t)$, the valuation function $V(c_t)$ is the only unknown parameter, since the prices P_t are determined by the grid operator and broadcasted to all EV owners. First, we show how given a certain valuation function of an EV population, $V(c_t) = \alpha \cdot c_t^2 + \beta \cdot c_t$, with parameters α and β known to the grid operator, she can set optimal prices so that she achieves a desired demand profile in a time horizon T. And later, we relax this assumption of knowing the valuation function of the population, and introduce *consumer utility driven pricing* to learn an estimation of these valuation function parameters.

The optimal prices under perfect information are presented in Proposition 1 and this result serves as an intermediate step for calculating the *consumer utility driven prices* (Proposition 2). The proofs of Proposition 1 and 2 are omitted due to space limitations but are available upon request.

Proposition 1. *When the grid operator knows the valuation function of the EV population it is facing,* $V(c_t) = \alpha \cdot c_t^2 + \beta \cdot c_t$, *the optimal prices to induce an average desired profile,* $\mathbf{c}^* = [c_1^*, ...c_T^*]$, *are:*

$$P_1 - 2 \cdot \alpha \cdot c_1^* = ... = P_T - 2 \cdot \alpha \cdot c_T^* \tag{9}$$

Proposition 1 shows that all prices over time horizon T are related through $P_1 - 2 \cdot \alpha \cdot c_1^* = ... = P_T - 2 \cdot \alpha \cdot c_T^*$. Furthermore, it shows that there is a set of optimal price vectors, all of which need to satisfy the relationship in Proposition 1. To select one of these optimal price vectors, the grid operators need to select one of the prices, e.g. P_1 and express the rest $P_t, \forall t \in \{2, ..., T\}$ as: $P_t = P_1 + 2 \cdot \alpha \cdot (c_t^* - c_1^*) \qquad \forall t \in \{2, ..., T\}$

Consumer utility driven pricing when $V(c_t)$ is not known to the grid operator

In reality, the valuation function $V(c_t)$ is not known to the grid operator, since it encompasses all idiosyncratic characteristics of each EV population the grid is facing. One assumption that the grid operator can make is that this valuation function $V(c_t)$ yields non-increasing marginal valuation for each extra electricity unit ($V(c_t) = \alpha \cdot c_t^2 + \beta \cdot c_t$), which is a common assumption made by EV charging literature (Robu et al. 2013, Bhattacharya et al. 2014, Zheng and Shroff 2014) and validated by our real-world data in Estimating Valuation Function section. Based on this assumption, grid operators know that the optimal prices should be satisfying $P_1 - 2 \cdot \alpha \cdot c_1^* = ... = P_T - 2 \cdot \alpha \cdot c_T^*$ (Proposition 1), but the parameters α and β of this population are unknown. The parameter β is not influencing the optimal prices, hence, it is not required to be learned by the grid operators. The parameter α is the one influencing the optimal prices and needs to be learned from the EV customers' reaction to prices. To learn this parameter, grid operators interact with the EV population and estimate it from the EV charging responses they receive. We call this price setting method *consumer utility driven pricing*, due to its ability to adapt to customers' responses and market conditions.

Consumer utility driven pricing is flexible as well, since potential additions of customers with different valuation functions or drop-outs of existing customers, can be observed on-line and the grid operator can adapt the broadcasted prices. Since the electricity grid is a fast-changing environment, the grid operators need to act in real time to adjust the prices and, therefore, it is crucial to react quickly and adapt on time to changes in the consumer portfolio. We show below how *consumer utility driven pricing* works and in section Evaluation: Simulation Scenarios we evaluate its performance in simulations, comparing it with commonly used benchmarks.

Assume the grid operator broadcasts sub-optimal prices $P'_t, \forall t \in \mathbf{T}$ since she has no information about the the parameters α and β in the valuation function $V(c_t) = \alpha \cdot c_t^2 + \beta \cdot c_t$. After broadcasting prices $P'_t, \forall t \in \mathbf{T}$, the grid operator observes an average charging profile $\mathbf{c}' = [c'_1, ..., c'_T]$ in the EV customer population, which is not the desired profile $\mathbf{c}^* \neq \mathbf{c}'$.

Proposition 2. *When the grid operator has no information about the parameters α and β of the valuation function of the EV population it is facing, $V(c_t) = \alpha \cdot c_t^2 + \beta \cdot c_t$, and only observes the average charging demand $\mathbf{c}' = [c'_1, ..., c'_T]$ to sub-optimal prices $P'_t, \forall t \in \mathbf{T}$, the* consumer utility driven *prices to induce an average desired profile $\mathbf{c}^*$ are:*

$$P_1 - 2 \cdot \hat{\alpha} \cdot c_1^* = ... = P_T - 2 \cdot \hat{\alpha} \cdot c_T^*, \tag{10}$$

where $\hat{\alpha} = \frac{\sum_{t=2}^{N} \frac{P'_1 - P'_t}{2 \cdot (c'_1 - c'_t)}}{N-1}$ and $\mathbf{N}$ is the subset of $\mathbf{T}$ ($\mathbf{N} \subseteq \mathbf{T}$) that includes only the time intervals t for which $c'_t \neq 0$: $\mathbf{N} = \{t|_{c'_t \neq 0}\}$.

Consumer utility driven prices are not optimal, however, the provide a good approximation for setting the prices so that a desired profile is achieved. We compare the performance of *consumer utility driven prices* against benchmarks and against the optimal prices assuming perfect information on the grid operator's side in section Evaluation: Scenario Analysis. We find that *consumer utility driven pricing* outperforms the benchmarks and yields a result close to the optimal one under perfect information. Next, we present the data sources used to calibrate our simulation used for the evaluation of our mechanism.

Data Calibration

In order to assess the impact of our method in the grid, we calibrate it with real-word data. We use the Netherlands as a setting for our tests; all calibration data sets originate from this country. Below we describe the data used for its calibration.

Driving Profiles and EV types

Each EV owner's driving profile includes the number of deadlines $|\mathbf{d}|$ throughout the day, the timing of each deadline $t_d \in \mathbf{d}$, $\boldsymbol{\lambda} = [\lambda_1, ..., \lambda_T]$ over time horizon T, the driving needs vector $\mathbf{D} = [D_1, ..D_T]$, as well as the expected electricity E_d required to be charged by each deadline t_d. To calibrate these individual parameters we use real-world commuting data from the Dutch Bureau of Statistics (CBS).

Different EVs have different battery sizes and require different times to charge fully. In our simulations, we assume different EV types (Tesla S 40kWh, 60kWh 85 kWh and Nissan Leaf). Since the shares of population that own each car are unknown, we draw from a distribution where Nissan Leaf has a 40% probability of appearance and each Tesla model has a 20% probability of appearance. These probabilities are chosen due to the fact that Nissan Leaf is a more affordable car for the general public.

Pricing Schemes - Benchmarks

Since the aim of this paper is design pricing schemes capable of assisting grid managers to induce a certain EV charging demand, we model the different types of electricity pricing schemes currently in the market.They serve as benchmarks for our proposed *consumer utility driven pricing*. We use these pricing schemes to calibrate the parameter $P_t, \forall t \in \mathbf{T}$ and examine their effect on the aggregate charging demand of an EV population. First, we present EV charging results under the current pricing schemes (flat pricing) without the use of a smart charging DSS on the EV owner's side. Second, we use two more advanced pricing schemes, namely, time-of-use (TOU) and variable pricing.

Flat pricing - NL data This benchmark consists of data from the Netherlands during 2013. This data set includes EV charging transactions starting from January 11^{th}, 2013 to December 31^{st}, 2013 (source: charging infrastructure company). In total it represents 1500 EV owners and 231,995 charging transactions with the grid. All these charging transactions took place under flat pricing schemes, providing no incentives for the EV owners to optimize or shift EV charging based on cost savings. The mean and standard deviation of the daily charging demand is shown in the boxplot diagram of Figure 4. This benchmark serves as our baseline, reflecting the current EV charging situation. It does not assume any smart charging DSS on the EV owners' side. Instead, it reflects EV charging purely driven by EV owners' behavior and convenience.

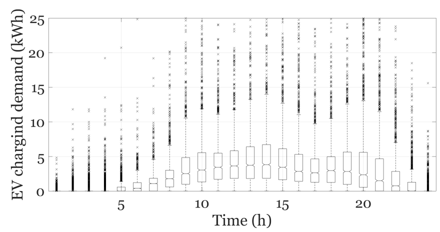
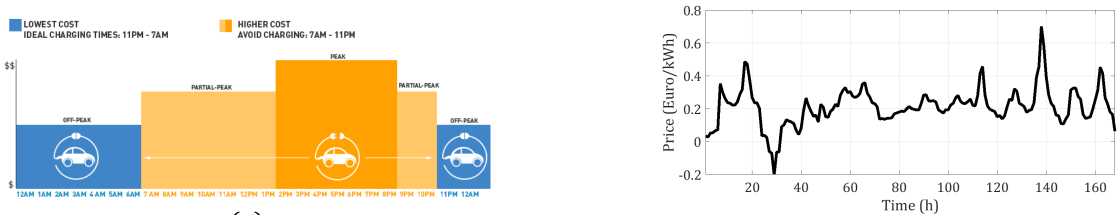


Figure 4. Mean EV charging demand and variability under flat pricing (steady state curve)

Time-of-use pricing Time-of-use (TOU) pricing is a form of tiered electricity pricing used by electricity providers to counter-incentivize consumption during part-peak or peak hours (Palensky and Dietrich 2011). This form of pricing is quite common for household consumption subscriptions but not as common for EV charging pricing. At the moment Pacific Gas and Electric Company has implemented a time-of-use (TOU) pricing scheme for EVs in the form of a three-part tariff (Figure 5(a)). We use this pricing scheme to run simulation results where EV owners are equipped with the presented smart charging DSS. We have converted the currency to reflect European prices since all our data originate from the Netherlands. The converted prices are: €0.38 for Peak [14:00-21:00], €0.20 for Part Peak [7:00-14:00] and [21:00-23:00], and €0.10 for Off peak [23:00-7:00]. TOU schemes can bring customer benefits via smart charging, since the EV owner's DSS can optimize charging based on prices.

Variable pricing One of the most advanced electricity pricing schemes are the variable pricing schemes, also known as real-time pricing schemes (Palensky and Dietrich 2011), which are effective in incentivizing electricity consumption when demand is low and providing counter-incentives when demand is high. These pricing schemes are reflecting the actual matching between demand and supply to determine the electricity prices and can have price rates which change every 1 hour or even 15 minutes, which is typically the smallest billing time interval (Palensky and Dietrich 2011). Since there is no variable pricing scheme for EV charging in the current electricity market, we construct a variable pricing scheme which reflects matching the demand and supply in the wholesale market. Through this pricing scheme we aim to capture the availability of supply in the electricity market. For this purpose, we use the European Power Exchange (EPEX) SPOT clearing prices (Figure 5(b)), in which the price variation indicates the energy availability. Figure 5(b) depicts a typical weekly price curve. In order to compare the outcome of these schemes, they must bring the same revenue to the electricity provider over a time period T (revenue equivalent), therefore we normalized the variable pricing scheme to give the same daily average price per kWh as the TOU scheme. These prices serve as an example of variable schemes, without loss of generality any other variable scheme could be used. Using all aforementioned data sources, we create a simulation in which we evaluate the performance of our



(a) (b)

Figure 5. (a) Time-of-Use pricing scheme (source: Pacific Gas and Electric Company). (b) Variable weekly price curve (constructed using EPEX SPOT clearing prices).

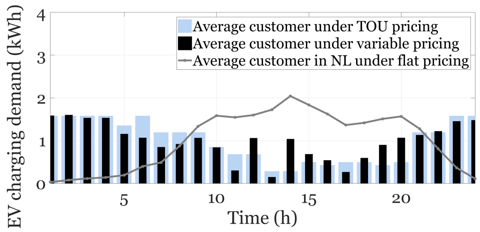
mechanism in various scenarios. The details of this evaluation are presented below.

Evaluation: Scenario Analysis

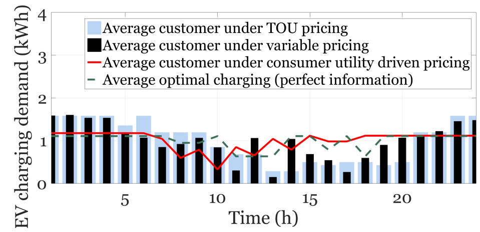
We build a simulation environment that approximates the conditions of an energy market where EV owners have to purchase electricity to charge their EVs. We create our simulation based on Power Trading Agent Competition (Power TAC) (Ketter et al. 2016) software platform which allows to implement large-scale smart grid simulations. In this simulation, we assume that there exists one grid operator broadcasting electricity prices. Furthermore, we model a population of EV owners, each of whom is represented by a DSS, responsible for deciding on the optimal EV charging profile based on the utility maximization objective.

First, we apply both TOU and variable prices in our simulation. We compare this result with the charging under flat pricing from NL without a smart charging DSS in place. In Figure 6(a) we show how the overall EV population (average valuation function $V(c_t) = -0.13 \cdot c_t^2 + 1.56 \cdot c_t$) reacts to the TOU and variable prices. Neither of the two pricing schemes redistributed the demand to reduce volatility. Instead, most of the customers tend to follow the low prices and shift part of their EV charging during the low price periods. Therefore during the night time [23:00-06:00] there are peaks in the demand, coming from the concentration of all EV charging on these time periods (*herding*). To mitigate this effect, we apply our proposed *consumer utility driven pricing* on the same population. Typically, grid operators are interested in a flat demand profile, assuming that the supply profile is also flat. In this way, there is high match between demand and supply and low risk of black or brown-outs in the grid. Therefore, we show, first, a scenario where the desired charging profile is entirely flat $c_t^* = 1kWh \quad \forall t \in \mathbf{T}$ (Figure 6(b)). This scenario represents the current situation, "Today", in Table 1.

To quantify the effect of *consumer utility driven pricing*, compared to the currently used variable and time-of-use prices, we use the peak-to-average ratio (PAR) metric ($PAR = \frac{max_{t \in \mathbf{T}} c_t}{c_{rms}} = \frac{max_{t \in \mathbf{T}} c_t}{\sqrt{\frac{1}{T}\sum_{t=1}^{T} c_t^2}}$). PAR is also known as "crest factor" and indicates how extreme the peaks in a waveform are. PAR reduction is important because much of the cost of energy supply is driven by peak demand. A PAR value closer to 1 indicates lower volatility. Also, we use the absolute peak, $max_{t \in \mathbf{T}} c_t$, as an indicator, since higher absolute peak means higher need for extra infrastructure to accommodate peak demand. These two metrics are calculated for our sample population and are compared with the pricing benchmarks described before. In Table 2 we see that *consumer utility driven pricing* induces a charging demand very close to the desired profile and has the lowest PAR and and absolute peak among the benchmarks. Furthermore, we see that *consumer utility driven pricing* can reduce the absolute peak by almost 43% compared to the current situation in NL (flat pricing) and by 27% when TOU or variable prices are introduced. This can be translated to a $[27\% - 43\%]$ grid capacity reduction and an analogous sustainability increase, especially considering the future investments for grid expansion.



(a)



(b)

Figure 6. (a) Average customer's charging under TOU and variable prices. Comparison with the average customer in NL under flat pricing. (b) Average customer's convergence to the desired charging profile $c_t^* = 1kWh \ \ \forall t \in \mathbf{T}$. Benchmarking with variable, TOU pricing and optimal charging (perfect information).

	PAR	Absolute peak (kWh)
Flat pricing - NL data	1.51	2.04
Time-of-use pricing	1.40	1.58
Variable pricing	1.51	1.60
Consumer utility driven pricing (desired profile $c_t^* = 1kWh \ \ \forall t \in \mathbf{T}$)	1.15	1.17
Average optimal charging (perfect information)	1.09	1.11

Table 2. PAR and absolute peak comparison

Figure 6(b) shows that *consumer utility driven pricing* can induce a profile close to flat. Both PAR and absolute peak are good indicators for scenarios where flat profiles are the desired ones. However, when RES become broadly adopted as electricity supply sources, a volatile demand profile would be required. The reason is that many RES (such as wind turbines, photovoltaic panels, etc.) have volatile production patterns, and therefore, they require a similarly volatile demand pattern to ensure high grid reliability.

Using *consumer utility driven pricing*, energy stakeholders can induce EV charging demand profiles of any shape, catering to the needs of a grid with large RES penetration. Specifically, energy providers being under the emissions regulation pressure are striving for having renewable generation as part of their energy portfolio. This renewable generation is typically highly volatile and intermittent since it depends to a large extent to the weather conditions (wind turbines, PV panels, etc.). Therefore, it is essential for energy stakeholders to be able to induce demand profiles that match the highly volatile generation patterns of the future ("Tomorrow" in Table 1). To test *consumer utility driven pricing*'s ability to induce any type of volatile demand profiles, we run simulation scenarios in which the average desired charging profile was drawn from a uniform distribution $c_t^* \sim U(0.1, 6)$, $\forall t \in \mathbf{T}$. Due to the stochastic nature of the desired profile ($c_t^* \sim U(0.1, 6)$, $\forall t \in \mathbf{T}$) and to establish the clear performance of our method, we run 100 simulation scenarios where $c_t^* \sim U(0.1, 6)$, $\forall t \in \mathbf{T}$. These simulation scenarios represent rather volatile demand profiles and can serve as extreme evaluation cases, which typically are difficult to be matched with traditional TOU or variable pricing schemes. The daily average of one of the 100 profiles is depicted in Figure 7(a).

To evaluate the ability of our method to match this profile, using PAR and absolute peak would not be appropriate, since high volatility is desirable. Instead we use the mean absolute percentage error (MAPE) as metric to evaluate how close the induced profile is to the desired one. This metric is also known as mean absolute percentage deviation and is used to measure forecasting accuracy. It is calculated as MAPE $= \frac{100}{T} \sum_{t=1}^{T} |\frac{c_t^* - c_t'}{c_t^*}|$, where c_t' is the observed charging $\forall t \in \mathbf{T}$. In Figure 7(a) we see that the charging under *consumer utility driven pricing* compared to the desired one has a MAPE of 18.61%, whereas the charging under optimal prices assuming the grid operator has perfect information about the populations valuation function has a MAPE of 17.13%. This result shows that *consumer utility driven pricing* can achieve results very close to the ones that a grid operator would achieve if she had perfect information about the way EV owners evaluate prices. For the 100 simulation scenarios we compute the average MAPE across all of them. Comparing the average charging under *consumer utility driven pricing* with the desired profile $\mathbf{c}^*$, gives a

MAPE in the spectrum $[9.50\%, 32.33\%]$ with an average value of 19.54%, across 100 simulation runs. Comparing the desired charging with the optimal charging under perfect information gives a MAPE in the spectrum $[7.86\%, 22.71\%]$ with an average value of 15.32% across 100 simulation runs (Figure 7(b)). Figure 7(b) shows

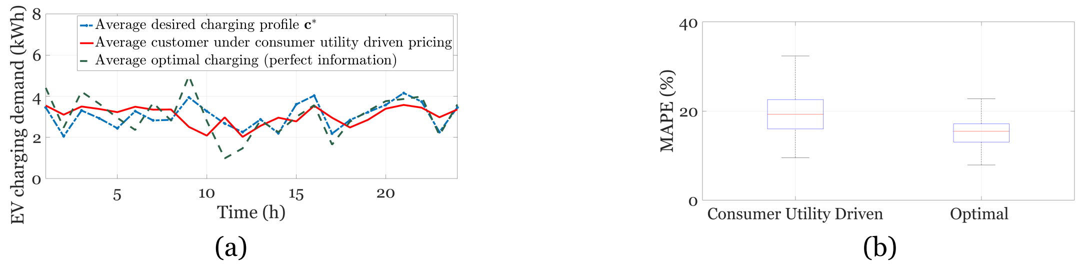


Figure 7. (a) Average customer's convergence to a desired charging profile $c_t^* \sim \boldsymbol{U}(0.1, 6)$, $\forall t \in$ T. (b) MAPE of the average charging under *consumer utility driven pricing* and MAPE of the optimal charging.

that *consumer utility driven pricing* is deviating on average by 19.54% from the desired profile, compared to 15.32% that the charging would deviate from the desired if the grid operator had perfect information about the population's decision function. This 15.32% is attributed to all private deadlines t_d, charging requirements E_d, charging availability vectors $\boldsymbol{\lambda}$ and all other private constraints which vary across individuals and cannot be captured by the grid operator. This outcome indicates that *consumer utility driven pricing* is performing very well in inducing a profile not that far from the charging a grid operator would induce, if she had perfect information about the exact valuation function of the EV population.

Conclusions and Future Work

Electricity markets are complex and volatile environments, in which decisions need to be made fast in order for the grid to be stabilized. The addition of EVs in these fast-paced environments creates new challenges, since significant amounts of electricity need to be managed to ensure grid stability. Energy policymakers are trying to find ways to design pricing schemes that will re-distribute part of the peak demand in order to alleviate the grid infrastructure and ensure its reliability. To address this challenge, we presented *consumer utility driven pricing*, a method to learn from EV owners' reactions to sub-optimal prices and adjusts the broadcasted prices accordingly. We evaluated our results in simulations, where we found that *consumer utility driven pricing* outperforms the currently used benchmarks, yielding results close to the theoretically optimal ones. We tested our method in inducing both flat and extremely volatile demand profiles and we saw that in both cases it manages to induce profiles close to what it is theoretically possible under perfect information. Our method requires no prior knowledge of the EV charging population, since it can learn its decision function through interactions with the EV owners. That makes it flexible and applicable to any EV population. Furthermore, it supports grid stability and sustainability by inducing demand profiles which are flat or can follow RES generation patterns. Therefore, grid operators and electricity providers can benefit significantly from our insights in their effort to facilitate a sustainable EV transition.

Our results create new streams for future research. Integrating vehicle-to-grid capabilities in our mechanism will create interesting insights for future scenarios when vehicle-to-grid (V2G) becomes available at a large scale. Furthermore, it would be valuable to examine the effect of *consumer utility driven pricing* within energy cooperatives which act as groups of consumers with common objectives. In such cooperatives, matching EV charging with RES generation can create significant energy and cost savings.

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