Association for Information Systems

AIS Electronic Library (AISeL)

ICIS 2019 Proceedings

Sustainable and Societal Impact of IS

Multiple Vickrey Auctions for Sustainable Electric Vehicle Charging

Konstantina Valogianni
IE University, konstantina.valogianni@ie.edu

Alok Gupta
University of Minnesota, alok@umn.edu

Wolfgang Ketter
University of Cologne, ketter@wiso.uni-koeln.de

Soumya Sen
University of Minnesota, ssen@umn.edu

Eric van Heck
Erasmus University, evanheck@rsm.nl

Multiple Vickrey Auctions for Sustainable Electric Vehicle Charging

Completed Research Paper

Konstantina Valogianni
IE Business School
IE University
konstantina.valogianni@ie.edu

Alok Gupta
Carlson School of Management
University of Minnesota
alok@umn.edu

Wolfgang Ketter
University of Cologne &
Erasmus University Rotterdam
ketter@wiso.uni-koeln.de

Soumya Sen
Carlson School of Management
University of Minnesota
ssen@umn.edu

Eric van Heck
Rotterdam School of Management
Erasmus University Rotterdam
eheck@rsm.nl

Abstract

Electric vehicles (EVs) are important contributors to a sustainable future. However, uncontrolled EV charging in the smart grid is expected to stress its infrastructure, as it needs to accommodate extra electricity demand coming from EV charging. We propose an auction mechanism to optimally schedule EV charging in a sustainable manner so that the grid is not overloaded. Our solution has lower computational complexity, compared to state-of-the-art mechanisms, making it easily applicable to practice. Our mechanism creates electricity peak demand reduction, which is important for improving sustainability in the grid, and provides optimized charging speed design recommendations so that raw materials are not excessively used. We prove the optimal conditions that must hold, so that different stakeholder objectives are satisfied. We validate our mechanism on real-world data and examine how different trade-offs affect social welfare and revenues, providing a holistic view to grid stakeholders that need to satisfy potentially conflicting objectives.

Keywords: Electric mobility, Green IS, sustainability, intelligent agents, smart markets

Introduction

Electricity grids are undergoing fundamental changes moving toward a new digitized era where consumers own *smart* appliances, reside in *smart* homes and can interact with the grid operator via an ICT infrastructure (Abe et al. 2011). This new digitized electricity grid is known as *smart grid* (Amin and Wollenberg 2005). The term smart grid is used to describe a next-generation electrical power system that is typified by the increased use of communications and information technology in the generation, delivery and consumption of electrical energy. What makes the smart grid different from its predecessor - the traditional grid - is the large scale integration of renewable sources, the information availability, and the active role electricity consumers have in it, not only by consuming, but also by producing electricity (photovoltaic panels, wind turbines, combined heat and power (CHP) units, electric vehicle batteries, etc.).

The smart grid, because of its digitized nature, can benefit from Information System (IS) solutions at each stage of the electricity supply chain. For example, on the generation side, advanced solutions have been introduced in order to benefit from the available information (Choi and Kim 2001), such as mechanisms to optimally ramp up reserve capacities and prevent black-outs (Maturana and Riff 2007). In addition, diverse information systems have been proposed in order to facilitate the introduction of renewable sources creating synergies between locally installed generation and consumption units (micro-grids) (Watson et al. 2010, Rieger et al. 2016, Brandt et al. 2017). On the electricity customer side, there is a strong presence of automated solutions such as smart meters, smart appliances that ease human decision making. All these IS solutions set the stage for advanced pricing mechanisms which are able to signal electricity abundance or shortage and shape the customer consumption behavior (Palensky and Dietrich 2011). In Figure 1, we show the connection between the physical and digital layer in smart grids. The communication between these two layers allows for the implementation of advanced management mechanisms at the generation, distribution and consumption side. We focus on the electric vehicle (EV) integration in the smart grid. EVs are important

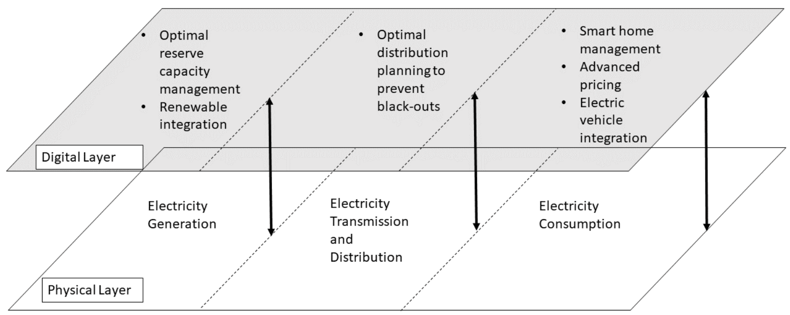


Figure 1. Overview of the connection between physical and digital layer in smart grids

elements of the grid for two main reasons. First, they are significant electricity consumers, suggesting that a massive EV integration needs to be scheduled properly so that the grid is not overloaded and the EV drivers are serviced without problems via the existing infrastructure (Ketter et al. 2018). Second, EVs own batteries which can store electricity. So far, electricity cannot be stored (in large amounts), therefore, the storage features of EVs are expected to introduce more bilateral flows in electricity grids. Now, EV drivers can charge their cars from renewable sources, and feed electricity back to the grid when there is a shortage in supply. Therefore, facilitating a smooth EV introduction in the electricity grid will have significant impact on the social welfare (Fridgen et al. 2014, Valogianni et al. 2018), contributing to societal sustainability.

We examine the scheduling of EV charging from different stakeholders' point of view and present design recommendations. Specifically, we contrast the objectives of grid operators, which are typically non-profit entities with the objectives of profit or revenue-maximizing entities such as electricity providers. Grid operators are responsible for ensuring stability and high quality of service in the grid (Wissner 2011, Kanchev et al. 2011), therefore, their main objective is to maximize social welfare. Electricity providers are responsible for selling electricity to consumers, and make profits through these transactions (Doostizadeh and Ghasemi 2012, Ketter et al. 2016). Therefore, these two objectives might be conflicting and require different design choices. In this context, we take the stand point of grid operators or electricity providers who auction grid capacity to EV drivers. Our contribution responds to the following research question:
How should an EV charging auction be designed, ensuring fast allocation of charging requests, while satisfying social welfare maximization or revenue maximization objectives?

To address this question, we build on Green IS (Dedrick 2010, Watson et al. 2010) and sustainability (Dao et al. 2011, Malhotra et al. 2013) principles and propose an auction-based mechanism, run by either grid operators or electricity providers, which uses information available on the smart grid and schedules EV charging (allocating prices and capacity) in real-time. Auctions, unlike posted-price and capacity allocation mechanisms, are preferred when the demand is not known or easy to estimate (Bapna et al. 2003, 2008). Therefore, in this particular problem, in which the grid operator or electricity provider does not know at each point in time how many EVs will require charging, auctions will contribute to allocating the grid resources efficiently. Our decision variables determine how many EV drivers to accept at each point in time, given the fixed capacity of the grid. Since the grid has fixed capacity, and given the high EV charging demand, some customers might not be serviced. We examine both social welfare maximization and revenue maximization objectives and we explore designs that serve each case, as well as the intersection of the two. Furthermore, our solution requires lower computation time than the state-of-the-art approaches presented in Related Work section making it easily applicable in the smart grid. Finally, we conduct a set of simulations calibrated with real-world data to showcase the practical implications of our mechanism to increase sustainability.

Our paper contributes to the Information Systems - and specifically Green IS - literature (Dedrick 2010, Watson et al. 2010) by supporting the mutli-dimensional decisions of actors, such as grid operators and electricity providers, in the fast-evolving digitized electricity markets. We are interested, specifically, in contrasting the social welfare and the revenue maximization objectives, under the EV charging speed design lens. The EV charging speed design is an important sustainability dimension in the smart grid, as its construction requires consumption of raw materials. Therefore, optimized EV charging designs will increase societal sustainability, without sacrificing user comfort and the grid's reliable operation. We prove new theoretical properties related to optimal charging speed design and EV charging request allocation, and we validate them in simulations calibrated with real-world data. Specifically, we find that the charging designs that achieve maximum social welfare, and the ones that achieve maximum revenues differ. Therefore, this trade-off needs to be examined under the sustainability prism. In addition, our mechanism offers fast computable solutions that can directly be applied to practice, since the computation time is a crucial parameter in the digitized markets. In terms of practical applicability, we test our mechanism with real-world data and provide insights about the societal impact of our auction mechanism on a large scale.

Related Work

Auctions have been used in many different application domains as a means of distributing goods. These domains vary from eBay (Bajari and Hortacsu 2003) and web capacity auctions (Bapna et al. 2003, 2008) to flowers (Kambil and van Heck 1998) and wireless spectrum auctions (Cramton 1997). Auction mechanisms used in EV charging assume different objectives and behavioral characteristics on the customer's side.

Acha et al. (2011) propose a centralized capacity coordination mechanism applicable to EV charging, under the profit maximization objective. Rigas et al. (2013) introduce a centralized mechanism for matching EV charging to various charging stations, accounting for spatial and temporal dimensions. Bhattacharya et al. (2016) extend the concept of second price auctions to be applicable to EV charging. The authors assume a revenue maximization objective and adopt the Vickrey-Clarke-Groves (VCG) mechanism (Vickrey 1961, Clarke 1971, Groves 1973) to clear the auction, which increases the computation time. De Craemer et al. (2014) present a dual implementation for shifting EV charging over time based on a central auctioneer, whereas Robu et al. (2013) introduce an online auction mechanism for EV charging coordination benefiting from some characteristics of the VCG auctions, adapted to reduce computational complexity. Stein et al. (2012) extend the previous mechanism by adding pre-commitment attributes in the auction. Kahlen et al. (2018) propose a centralized fleet management system which is responsible for coordinating the EV charging, while Vandael et al. (2013) describe a three-step top-down charging coordination mechanism. Zou et al. (2013) present a cost-minimizing progressive second price auction for efficiently allocating EV charging requests among multiple bidders. James et al. (2016) describe a profit maximization auction for EV charging allocation, while respecting capacity constraints. All these approaches propose solutions that are computationally quite intensive, making their practical applicability difficult in many occasions[1]. We propose a solution with a very low computation time, which makes it suitable for large scale EV charging scheduling without practical barriers.

Furthermore, most of previous work assumes a profit maximizer or a cost minimizer auctioneer, without contrasting it with the objective of a social planner, such as the grid operator. The smart grid operator (distribution system operator or DSO) is a supervising entity on the smart grid that is responsible for maintaining its quality of service and reliability. Among its duties is the capacity allocation and congestion management,

[1]Typically a VCG mechanism in our setting would have a complexity $\mathcal{O}(n^2)$, while the solution we propose has computational complexity $\mathcal{O}(nlog(n))$. This means that the typical VCG solution would require more time to be calculated, compared to our solution ($n^2 > nlog(n)$), dependent on the participants of the auction n (it is a convention to use n in computational complexity theory).

so that the customers are serviced. Focusing on the EV drivers, the grid operator (DSO) is mainly interested in servicing all EV drivers in the market without creating bottlenecks and without putting the infrastructure under strains (Wissner 2011, Kanchev et al. 2011). Miranda et al. (2015) assume an auction servicing a grid operator (social planner) who aims to fill up a certain grid capacity. They use first price auctions to allocate the charging requests. Zhou et al. (2015) present a social welfare maximization auction, defining it as a social cost minimization objective. However, they do not provide any recommendations about optimal charging speed designs to serve the social planner's objective. Xiang et al. (2016) propose a social welfare maximization auction for allocating fast charging requests, however, they define social welfare as maximizing revenues of the presented auction. Similarly, Hu et al. (2014) and Philipsen et al. (2016) propose online auction mechanisms with low computational complexity, aiming to minimize the cost of the grid operator (auctioneer), while servicing as many charging requests as possible. de Hoog et al. (2016) present a social welfare maximization auction mechanism, aiming to service as many EV drivers as possible connected to the same distribution network.

In Table 1, we present an overview of the EV charging auction literature, on which we are building. We compare the examined work along 5 dimensions that are important for our contribution.

Table 1. EV charging auction literature overview

	Profit/Revenue Maximization	Grid operator's viewpoint	Computational complexity	Delay Reduction	Charging infrastructure design recommendations
Acha et al. (2011)	✓	-	high	-	-
Bhattacharya et al. (2016)	✓	-	high	-	-
De Craemer et al. (2014)	✓	-	medium	-	-
de Hoog et al. (2016)	-	✓	medium	-	-
Hu et al. (2014)	✓	✓	low	-	-
James et al. (2016)	✓	-	low	-	-
Kahlen et al. (2018)	✓	-	medium	-	-
Rigas et al. (2013)	✓	-	high	-	✓
Robu et al. (2013)	✓	✓	medium	-	-
Stein et al. (2012)	✓	✓	medium	✓	-
Vandael et al. (2013)	✓	-	low	-	-
Zhou et al. (2015)	-	✓	low	-	-
Zou et al. (2013)	✓	-	high	-	-
Xiang et al. (2016)	✓	-	low	-	-
Philipsen et al. (2016)	✓	✓	low	-	-
This paper's contribution	✓	✓	low	✓	✓

We take the stand point of a grid operator and an electricity provider and extend the Multiple Vickrey Auction (MVA) mechanism (Bapna et al. 2005) to be applicable to the EV charging domain. In the next section we explain this mechanism. As part of our contribution, we prove new theoretical properties that hold in the social welfare and in the revenue maximization case and provide useful insights to energy policy makers about optimal resource allocation. These properties describe the optimal conditions that must hold in order to maximize social welfare or revenues in the EV charging scheduling problem. Therefore, we present a benchmark that can be used as the "upper-bound" for applied mechanisms in order to evaluate their performance.

To measure social welfare we use the *the delay cost the system (smart grid) suffers in order for all the EV drivers to be serviced*. High social welfare means low overall delay cost. As delay cost, we define the cost that each individual incurs during the time that s/he is not be able to use the EV, because it is plugged-in. For some individuals that they need the EV for driving, every hour that they are unable to use their car is very costly. For other individuals, this charging time might not be of high cost, since they might not need the car for driving. As system's delay cost, we define the overall delay cost of all EV drivers who are using the grid infrastructure for charging. We are following the seminal MVA paper (Bapna et al. 2005), based on which a social-maximizing entity could be interested in optimally servicing the customer portfolio it is facing rather than maximizing revenues. Therefore, this social-maximizing entity is interested in maximizing the number of jobs accepted, instead of the revenues. In our case, a grid operator – being a non-profit entity – is interested in a well-functioning grid, rather than ensuring revenue maximization for other involved parties. This serves as the basis for our social welfare assumption. Similar modeling assumptions regarding social welfare and delay costs have been made in the literature in other contexts (Gupta et a. 2000, Bapna et al. 2005). As a future extension, we are planning to examine richer representations of social welfare by including the surplus of all entities involved in the auction.

Our goal is to assist the auctioneer in making better decisions with respect to scheduling EV charging under the two different objectives presented in the first two columns of Table 1, and with respect to designing the charging speeds so that these objectives are satisfied to different extents. Since these two objectives are very different, they lead to different results. However, stakeholders with these two different objectives exist in the smart grid and have to collaborate. Therefore, the scope of our work is to show that despite the different results of the two objectives, there is grounds for both objectives to be satisfied to a certain extent.

We adopt the main Green IS principles (Dedrick 2010, Dao et al. 2011, Watson et al. 2010) according to which using the abundance of information in our society, we can schedule electricity consumption more efficiently. This optimized use of electricity can lead to higher sustainability levels, since less raw materials will be required for grid capacity expansion to accommodate extra demand. Specifically, in the EV charging domain, using available information for improving decision making is expected to bring significant benefits to the grid (Fridgen et al. 2014). We contribute to the academic literature by proposing a novel mechanism to schedule EV charging, with low computational complexity that can serve as an "upper bound" benchmark for applied mechanisms. We incorporate the delay costs in the EV drivers' decision function and we prove the theoretical properties that guarantee optimal scheduling under the social welfare and revenue maximization objective. In addition, we validate our mechanism on real-world data and we are able to provide useful insights to the policymakers about effective EV charging scheduling and charging level design.

Model Formulation and Structural Analysis

We approach the whole EV charging capacity allocation as a knapsack problem with the grid capacity being the "knapsack" in our case[2]. Currently, there are different EV charging speeds available in the smart grid and these charging speeds have a different effect on the electricity peak demand. These charging levels are offered through charging poles, and it can be that adjacent charging poles offer different charging speeds. We will refer to these levels as charging speeds, since they practically represent different classes of service. Once an EV is plugged in and allocated to a charging speed, this charging speed cannot vary over time and it is constant throughout the whole charging session. A direct analogy can be found in the grid computing and internet literature (Bapna et al. 2008), where different classes represent different internet speeds.

Our goal is to allocate the EV drivers' requests for charging to different charging speeds so that the grid satisfies either social welfare or revenue maximization objectives. We use the overall delay cost the bidders suffer as a proxy for welfare, since the lower the delay cost the more satisfied the bidders are with the service. By delay we define the time that an EV is plugged in for charging, and cannot be used by its owner for driving. The benefits to the grid are measured by the electricity peak demand reduction, since the peak demand is the main determinant for installing new infrastructure (Strbac 2008). Thus, reducing peak demand means reducing the need for extra infrastructure and therefore, higher sustainability on the grid (Watson et al. 2010).

Assumptions

Our set-up assumes $i \in \{1, ..., N\}$ EV drivers (bidders) and an auctioneer (smart grid operator or electricity provider) who receives requests for charging. These requests include a total charging need in kWh, ω_i and an arrival and a departure time, t_a^i and t_d^i, respectively. Each request for an amount ω_i is accompanied with a bid for this amount b_i and a cost δ_i over the delay s/he might suffer. We assume that bids and delay costs are analogous, $b_i \sim \delta_i$, as an EV driver who has a high delay cost (urgency to get her EV charged), would be willing to bid higher for an amount ω_i. The requested electricity ω_i can be charged at one of the charging speeds (in kW) r_j, $j \in \{1, ..., z\}$ depending on the bids. When a request for charging ω_i is allocated to a charging speed r_j then, the binary variable $x_{i,j}$ becomes equal to 1 indicating this allocation. Respectively, after such an allocation, the completion time of this charging request is $\tau_j(\omega_i)$ and holds only if $x_{i,j} = 1$ (otherwise $\tau_j(\omega_i)$ does not exist):

$$\tau_j(\omega_i) = t_{0,i} + \frac{\omega_i}{x_{i,j} \cdot r_j}, \quad x_{i,j} \neq 0 \tag{1}$$

[2] In practice, we are not using the whole grid capacity as the knapsack. Instead, we are using a percentage of it, i.e., $50\% - 80\%$, since the grid should not be operating at the maximum capacity utilization.

We denote as $\tau_j(\omega_i)$ the delay each EV driver i has to suffer until s/he gets the car charged (so that the amount ω_i is loaded) and is measured as the time the EV gets plugged in till the time it is charged and ready to be used by the EV driver. This delay includes the time $t_{0,i}$ that the car i is plugged in but not getting charged (since the grid capacity is used by other EVs) and the time $\frac{\omega_i}{x_{i,j} \cdot r_j}$ that it takes to get charged at a certain charging speed r_j. Each delay has a different cost for each EV driver, therefore we denote this cost by δ_i and increasing delay cost indicates increasing urgency for charging completion. This implies that EV drivers with high delay costs are willing to pay a higher price for EV charging. Therefore, we assume that there is a direct analogy between the bids and the delay costs. In other words, EV drivers that submit high delay costs to the auctioneer have a higher valuation of the requested service and are paying a higher price for this service. If a request ω_i is allocated to a high speed r_j, the duration for its completion decreases. Therefore, urgent requests must be allocated to high charging speeds. The urgency of a request is indicated by the delay cost, δ_i. Each EV driver (bidder) i has a utility function over a request ω_i such that:

$$U(\omega_i, \tau_j(\omega_i), \delta_i, b_i) = \gamma_i \cdot \omega_i - \delta_i \cdot \tau_j(\omega_i) - b_i \qquad (2)$$

By γ_i we denote the weight each EV driver i puts on receiving an electricity amount ω_i and this weight is not dependent on the speed this request gets allocated. The variable b_i is the bid each EV driver submits for an amount ω_i and is directly analogous to the delay cost, i.e, $b_i \sim \delta_i$. We introduce the coefficient δ_i to denote the emphasis (cost) each EV driver puts on this delay. For some EV drivers a potential delay might not be important since they have no urgency in using their EV, whereas for others this delay might be important since they need their EV for driving. The described auction is run every epoch (the duration of the epoch is selected by the auction designer) and we assume that EV drivers who are not serviced in one epoch, appear in the next one waiting to get serviced. We assume no knowledge about the EV driver portfolio each auctioneer is facing, making our mechanism more dynamic and not dependent on specific customer portfolio assumptions.

Multiple Vickrey Auction

The nature of our particular application requires real-time decision-making capabilities, since the smart grid is a fast changing environment with lots of information flows, such as electricity prices, capacity available, EV driver preferences, availability of electricity. Therefore, it is important for the auctioneer to be able to allocate capacity and payments to the EV drivers in real time. Prior research in other application domains has used the Vickrey-Clarke-Groves (VCG) mechanism for payment and capacity allocation (Dash et al. 2007, Dimakis et al. 2006, Krishna 2002). This mechanism ensures incentive compatibility and is, therefore, preferred in set-ups where the EV drivers' true valuations are not known. However, it has a downside which is its high computational complexity (Nisan et al. 2007). Therefore, it might create significant burdens in applying this mechanism in real-world problems with a lot of bidders, where computation of the solution in real time is required.

Typically, in the smart grid large numbers of EV drivers bid for electricity at each point in time. Therefore, despite the incentive compatibility, the VCG mechanism is not suitable for this particular case. It is interesting to mention that a typical VCG solution for 100 bidders would require $\sim 10,000$ time units (in CPU cycles) to be calculated (computational complexity $\mathcal{O}(n^2)$), while our solution would require ~ 200 time units (in CPU cycles) (computational complexity $\mathcal{O}(nlog(n))$). The reason that the VCG mechanism is more computationally intensive than the MVA is that in the VCG mechanism each payment for each bidder needs to be computed differently, and each bidder pays a different price. Specifically, by definition, a VCG payment allocation for N bidders needs to complete N computations wherein each time one of the N bidders is not participating in the action. Therefore, there must be $N \times N$ computations completed. Thus, following the computational complexity theory notation, this leads to a complexity of $\mathcal{O}(n^2)$. In contrast, in an MVA payment allocation with N bidders, a sorting of the bids is sufficient to determine the payments, as all accepted bidders pay as price the first not accepted bid. Considering that a sorting mechanism, typically, has a complexity of $\mathcal{O}(nlog(n))$ explains the greater complexity of VCG (Nisan et al. 2007). Taking into account the aspirations for large EV numbers in the grid by 2030 by the Paris Declaration on Electro-Mobility and Climate Change (100 million by 2030) (UNFCCC 2015), one can understand that VCG mechanism will create burdens in reducing congestion in the grid. Therefore, we build on an alternative, more computationally tractable mechanism the Multiple Vickrey Auction (MVA) approach proposed by Bapna et al. (2005). We modify this auction mechanism to be applicable in our particular set-up and prove new theoretical properties. According to MVA, if there are m units of a good for sale, then the m highest bids win and the $(m+1)^{st}$ bid becomes the price paid for each of the units sold (uniform pricing).

This mechanism while computationally tractable, does not ensure incentive compatibility. However, for large number of bidders, which is the case in our market, incentive compatibility is not an issue due the law of large numbers. Practically, because of the large numbers of bidders involved, the impact of each bidder's misaligned incentives will be negligible. In other words, an untruthful bidder, bidding at a higher price than his/her true valuation, will have no actual gain from this untruthful behavior, because s/he might get a slight priority over the other bidders but this will lead him/her paying a higher price. Therefore, the actual gain will be non-existent or negligible in an auction with a lot of participants (Gupta et al. 2000). Usually, in complex market mechanisms, such as the Federal Communications Commission (FCC) wireless spectrum auctions, the incentive compatibility is not of real concern, because there is no actual gain at an individual level due to the large number of bidders. Furthermore, Bapna et al. (2005) prove that MVA is *posterior regret-free* or (ex-post incentive compatible) in social welfare maximization settings and therefore, there is no actual gain for the bidders if they are untruthful. More importantly, an auctioneer gains more significant advantages by being able to compute the allocation in real-time than by guaranteeing incentive compatibility.

Multiple Vickrey Auction for Social Welfare Maximization

Adapting the MVA logic to our set-up, we formulate the grid operator's problem as a welfare maximization problem. Grid operators are responsible for ensuring stability and high quality of service in the grid, hence, they act as social planners (Wissner 2011, Kanchev et al. 2011). Since we defined the social welfare as reduced delays, the grid operator's problem is practically the aggregate delay cost minimization problem. The delay cost minimizing knapsack formulation with uniform pricing is presented below:

$$\min_{x_{i,j}} \sum_i \sum_j \delta_i \cdot \tau_j(\omega_i) \Leftrightarrow \min_{x_{i,j}} \sum_i \sum_j \delta_i \cdot (t_{0_i} + \frac{\omega_i}{x_{i,j} \cdot r_j}) \tag{3}$$

where $\tau_j(\omega_i)$ is the delay each EV driver i suffers after being allocated to a charging speed r_j, with a respective delay cost δ_i. Here, the objective is to minimize the overall delay cost, therefore, this is the quantity being minimized. However, the delay costs are analogous to the price bids, thus, the bidding behavior is taken into account via the delay costs submitted by the bidders. The constraints of our problem are:

$$x_{i,j} \cdot \frac{\delta_i}{\omega_i} > \frac{\delta_{i+1}}{\omega_{i+1}} \quad \forall i \in \{1, ..., N\} \quad and \quad \forall j \in \{1, ..., z\} \tag{4}$$

$$\sum_j x_{i,j} \leq 1 \quad \forall i \in \{1, ..., N\} \tag{5}$$

$$\sum_i \sum_j x_{i,j} \cdot r_j \leq C \tag{6}$$

$$x_{i,j} = \{0, 1\} \quad \forall i \in \{1, ..., N\} \quad and \quad \forall j \in \{1, ..., z\} \tag{7}$$

$$\frac{\delta_i}{\omega_i} \geq 0 \quad \forall i \in \{1, ..., N\} \tag{8}$$

Constraint (4) ensures that the EV drivers are allocated to charging speeds based on their delay cost over charging amount declarations - and consequently their bid over quantity submissions - in ascending order. The EV driver who values the service the most gets the highest quality of service (charging speed). Constraints (5) and (6) indicate that the variables $x_{i,j}$ are binary and denote whether a service is allocated to an EV driver or not. Constraint (7) ensures that the grid is stabilized by not exceeding the capacity available (in our case we set C lower than the actual maximum capacity available to allow for a buffer on the grid, since it should not be operating at maximum capacity utilization). Equation (8) indicates the assumption that delay costs, processed by the mechanism, have always positive values (negative delay costs are not accepted by the auction).

Multiple Vickrey Auction for Revenue Maximization

If a revenue-maximizing entity, such as an electricity provider, would use our mechanism, then the MVA formulation would be as follows:

$$\max_{x_{i,j}} \sum_i \sum_j x_{i,j} \cdot p_j \tag{9}$$

where p_j is the price of each charging speed level r_j. Subject to constraints:

$$x_{i,j} \cdot p_j \leq \frac{b_{i+1}}{\omega_{i+1}} \quad \forall i \in \{1, ..., N\} \quad and \quad \forall j \in \{1, ..., z\} \tag{10}$$

$$\sum_j x_{i,j} \leq 1 \quad \forall i \in \{1, ..., N\} \tag{11}$$

$$\sum_i \sum_j x_{i,j} \cdot r_j \leq C \tag{12}$$

$$x_{i,j} = \{0, 1\} \quad \forall i \in \{1, ..., N\} \quad and \quad \forall j \in \{1, ..., z\} \tag{13}$$

$$p_j \geq 0 \quad \forall i \in \{1, ..., N\} \tag{14}$$

Constraint (10) ensures that the bids b_i for different service amounts ω_i are selected in ascending order in service classes j, setting as price per class p_j the bid of the last EV driver not accepted in this class $\frac{b_{i+1}}{\omega_{i+1}}$. In this formulation, the bidding behavior of each bidder is taken into account directly via their bids $\frac{b_{i+1}}{\omega_{i+1}}$, as shown in constraint (10). Based on this constraint, the bids over requested charging $\frac{b_{i+1}}{\omega_{i+1}}$ are sorted in an ascending order, and the highest classes accept the highest of them. The first not accepted bid in each class j determines the price for this class p_j. Constraint (14) ensures that the price p_j in each class j has a positive value.

Theoretical Results

First, we present the theoretical properties of the proposed mechanism in the form of propositions. These propositions outline the optimal scheduling that can be achieved in the grid and the optimal charging speed design, and serve as theoretical benchmarks. The proofs of all theoretical results can be provided upon request due to space limitations.

Optimal number of service levels

We examine the optimal number of service levels from a revenue and a social welfare maximization point of view. Proposition 1 shows the optimal number of service levels from a revenue maximization point of view. As we show in Propositions 2 and 3, there is a difference in the preferred service levels depending on the grid operator's objective. In the Simulation section, we examine this trade-off using real-world data for our calibration. In this paper, we do not account for installation costs of the different service levels, as these costs are fixed investment costs that are incurred by the grid only once. Our mechanism needs to be able, given a certain overall capacity, to accommodate EV charging demand, and decide which is the optimal allocation of this available capacity into different service classes. Thus, our mechanism is assumed to be put in place after these fixed costs are being incurred, having as its objective to maximize the variable benefits collected each time the auction is run.

For Proposition 1 to hold, we make the assumptions that at least one of the requested amounts of electricity ω_i is smaller than one of the available capacities C_j. If not, no charging request will be cleared by the auction and the overall revenue collected will be zero.

Proposition 1. *Having multiple charging speeds (classes), is optimal from a revenue maximization point of view.*

Proposition 1 assumes that same number of bidders is accepted both in the auction with one charging speed level and in the auction with multiple charging speed levels implemented In Example 1, we illustrate the rationale of Proposition 1.

Example 1. Assume a system with $N = 4$ bidders in a single-class MVA auction, with bids $b_1 = 4$, $b_2 = 2$, $b_3 = 12$, $b_4 = 7$ monetary units for charging requests $\omega_i = 1, \quad \forall i \in N$. Let us assume that the auction can accept the 3 bidders with the highest bids. Then, the price they all had to pay would be the bid of the fourth bidder which is 2. Therefore, the overall revenue the system would collect, would be $3 \cdot 2 = 6$ monetary units. In a two-class MVA auction, assuming again that in total 3 bidders can be accepted, 2 in the first class and 1 in the second class, the price for the first class would be 7 monetary units and for the second class 4 monetary units. The overall revenue the system would collect would be $2 \cdot 7 + 4 = 18$ monetary units.

Proposition 1 shows that the revenue collected by implementing multiple classes is higher or equal to the scenario of implementing only one charging speed class. Therefore, a revenue maximization entity would benefit from multiple charging speed classes. Next, we show that the lowest delay cost in the system is caused by having only one charging speed level, which corresponds to the highest charging speed. This is noteworthy, given the nature of our problem. It, practically, means that it is optimal for the grid operator to have only the fastest charging speed in place, and schedule the EV drivers in this single class. We prove the optimality of the single charging class, from a social welfare maximization point of view, both in the case that the EV drivers have the same delay costs $\delta_i = \delta \quad \forall i \in \{1, ..., N\}$ and in the case that EV drivers have different delay costs δ_i. The delay costs are the main differentiating factor across EV drivers, therefore, we need to account for both cases that EV drivers have the same (Proposition 2) and different delay costs (Proposition 3).

Proposition 2. *Having one charging speed (class), corresponding to the fastest charging speed, is optimal from a social welfare maximization point of view, when EV drivers have the same delay costs δ.*

Example 2. We assume a single-class MVA system with a charging class $r_1 = 5kW$ and two bidders with the same delay costs $\delta = 5$ and charging requests $\omega_1 = 5kWh$ and $\omega_2 = 6kWh$, respectively. The overall delay cost the system will suffer will be $3.2 \cdot 5 = 16$, since the first bidder needs 1h to charge fully and the second needs to wait for an 1h for the first bidder to complete charging and 1.2h to charge. If the second bidder was scheduled first, the overall delay cost the system will suffer would be: $3.4 \cdot 5 = 17$, since the second bidder needs 1.2h to charge fully and the first one needs to wait for 1.2h and 1h to complete the charging. In the same example, if the system was a two-class MVA with two charging classes $r_1 = 5kW$ and $r_2 = 4kW$, then the overall delay cost the system will suffer will be $3.5 \cdot 5 = 17.5$, if we schedule the first bidder in r_1, whereas, if we schedule the second bidder r_1, it will be $3.65 \cdot 5 = 18.25$. In both cases, the delay cost suffered by the system is greater in the two-class MVA, and, therefore, it is more beneficial for the grid to have a single-class MVA in place.

Proposition 3. *Having one charging speed (class), corresponding to the fastest charging speed, is optimal from a social welfare maximization point of view, when EV drivers have different delay costs δ_i.*

Example 3. Continuing on **Example 2**, but now assuming different delay costs among bidders: $\delta_1 = 5$ and $\delta_2 = 3$, in a single-class MVA, the overall delay cost the system will suffer is $1 \cdot 5 + 2.2 \cdot 3 = 11.6$, if bidder 1 is scheduled first. If bidder 2 is scheduled first, the overall delay cost the system will suffer is $1.2 \cdot 3 + 2.2 \cdot 5 = 14.6$ In the same example, if the system was a two-class MVA with two charging classes $r_1 = 5kW$ and $r_2 = 4kW$, then the overall delay cost the system will suffer will be $1 \cdot 5 + 2.5 \cdot 3 = 12.5$, if we schedule the first bidder in r_1, whereas, if we schedule the second bidder in r_1, it will be $1.2 \cdot 3 + 2.45 \cdot 5 = 15.85$. Similarly to **Example 2**, it is more beneficial for the grid to have a single-class MVA in place. Furthermore, **Examples 1, 2** show that depending on the sequence the bidders are scheduled, the overall delay cost of the system is different.

Bidder scheduling within service classes

Propositions 2 and 3 show that, both in the case that the customers have the same or different delay cost, it is optimal to have only one service class (charging speed) and this service class needs to be the highest charging speed, so that the overall delay in the electricity market is minimized. In this single-class MVA, however, prioritization among bidders is required, since, as shown in **Examples 1,2**, different prioritzation yields different overall delay cost. In Propositions 4, 1 and 2 we show how prioritization among bidders should take place, so that the social welfare to be maximized.

Proposition 4. *When delay costs δ_i and charging requests ω_i differ among bidders, the bidders should be scheduled in a descending order of ratio $\frac{\delta_i}{\omega_i}$, so that social welfare is maximized.*

Example 4. Let us assume two bidders with different delay costs $\delta_1 = 5$ and $\delta_2 = 3$, and different charging requests $\omega_1 = 5kWh$ and $\omega_2 = 6kWh$ in a single-class MVA of $r_1 = 5kWh$. If bidder 1 is scheduled first the overall delay cost the system will suffer is $1 \cdot 5 + 2.2 \cdot 3 = 11.6$. If bidder 2 is scheduled first the overall delay cost the system will suffer is $1.2 \cdot 3 + 2.2 \cdot 5 = 14.6$. So, it is more beneficial for the system to schedule first the bidder with the highest ratio $\frac{\delta_i}{\omega_i}$.

Below, we present two observations following from Proposition 4.

Observation 1. *When delay costs δ_i differ among bidders, and charging requests are the same ω, the bidders should be scheduled in descending delay cost δ_i order, so that social welfare is maximized.*

Example 5. Let us assume two bidders with different delay costs $\delta_1 = 5$ and $\delta_2 = 3$, and the same charging request $\omega = 5kWh$ in a single-class MVA of $r_1 = 5kWh$. If bidder 1 is scheduled first the overall delay cost the system will suffer is $1 \cdot 5 + 2 \cdot 3 = 11$. If bidder 2 is scheduled first the overall delay cost the system will suffer is $1 \cdot 3 + 2 \cdot 5 = 13$. So, it is more beneficial for the system to schedule first the bidder with the highest delay cost.

Observation 2. *When delay costs are the same δ, and charging requests ω_i differ among bidders, the bidders should be scheduled in an ascending charging request ω_i order, so that social welfare is maximized.*

Example 6. Let us assume two bidders with the same delay costs $\delta = 5$, and charging requests $\omega_1 = 5kWh$ and $\omega_2 = 6kWh$ in a single-class MVA of $r_1 = 5kWh$. If bidder 1 is scheduled first the overall delay cost the system will suffer is $1 \cdot 5 + 2.2 \cdot 5 = 16$. If bidder 2 is scheduled first the overall delay cost the system will suffer is $1.2 \cdot 5 + 2.2 \cdot 5 = 17$. So, it is more beneficial for the system to schedule first the bidder with the lowest charging request.

Simulation Environment

To evaluate the proposed auction mechanism in realistic conditions, we build a simulation environment, in which the auctioneer has limited capacity C and the EV drivers bid for amounts of electricity so that they charge their cars. Depending on the modeling assumptions one can set set this limited capacity C lower than the actual available capacity, since it is not beneficial for the grid's reliability to be functioning at the actual maximum capacity (C can be set to the 80% or 50% even of the maximum capacity). The auctioneer uses the model presented by (3)-(8) to schedule EV charging. Below, we present the steps followed by our simulation in each run.

Parameters: Time horizon T, time granularity (epoch duration) Δt, number of EV drivers N, maximum capacity available C

Step 1: The grid auctioneer initiates the auction by auctioning available capacity C for the epoch t with duration Δt.

Step 2: Each $i \in \{1, ..., N\}$ customer participating in the auction is placing her bid b_i for an amount of electricity ω_i for the epoch t, together with her delay cost d_i for this time period.

Step 3: The auctioneer runs the auction presented by (3)-(8) for epoch t.

Step 4: The first m highest bids are accepting in the auction and the bid of the $m + 1^{st}$ bid becomes the price all of the m customers pay for their requested amount of electricity ω_i.

Step 5: The overall amount of electricity of all accepted EV drivers comprises the electricity demand the grid faces during time t and is denoted as $y_t = \sum_{i=1}^{m} \omega_i$.

Step 6: The price during time period t each accepted EV driver pays is $p_t = b_{m+1}$.

Step 7: The auctioneer repeats **Steps 1-6** until the number of epochs t reaches a maximum defined by the time horizon T.

The simulation parameters, such as capacity C, horizon T, number of customers N do not affect the stability of the result, as they are exogenously determined before the auction begins and are not influencing the dynamics of the auction. For example, for customers N and capacity C, the auction mechanism will try to service as many of these N customers as possible, given the capacity C. The horizon T does not influence the result, as the auction takes place during every epoch t, which has smaller duration than T.

To evaluate our mechanism's performance we are interested in two criteria: its ability to reduce peak demand on the grid supporting its stability and reliability and its ability to service as many EV drivers as possible with the minimum delay cost possible. For the first criterion we use the absolute peak in the demand and the peak-to-average ratio (PAR or crest factor) metric and for the second criterion we examine how many customers are delayed. The first criterion is important from a sustainability point of view, as less grid infrastructure would be required, and the second is important from a social planning point of view.

Let $\mathbf{y} = (y_1, ..., y_T)$ denote the temporal vector of the electricity demand curve, the absolute peak in the demand is $y_{peak} = \max_{t \in \mathbf{T}} y_t$ and indicates the maximum demand value during horizon T. A good performance of our mechanism would mean low y_{peak}. Similarly, the peak-to-average ratio (commonly found as crest factor) is calculated as $PAR = \frac{y_{peak}}{y_{rms}} = \frac{\max_{t \in \mathbf{T}} y_t}{\sqrt{\frac{1}{T} \sum_{t=1}^{T} y_t^2}}$. PAR indicates how extreme the peaks in a waveform are. PAR reduction is important because much of the cost of electricity supply is driven by peak demand. In order to have higher stability in the electricity grid, we need a PAR value close to 1.

A social welfare maximizing entity, such as a grid operator, aims for overall low delay cost of all the bidders serviced via the auction mechanism, while servicing as many bidders as possible. Therefore, to assess the impact of our method on the social welfare, we introduce the total delay cost suffered by the bidders divided by the bidders m serviced by the auction: $SW = \frac{\sum_i \sum_j \delta_i \cdot \tau_j(\omega_i)}{m}$. This metric allows, not only to assess the delay cost as an absolute number, but also, the mechanism's ability to service as many bidders as possible and improve social welfare. It is desirable for SW to be as low as possible, since that would be high number of serviced bidders at overall low delay cost.

Data Description

For each simulation run as described by **Steps 1-7**, the requested amount of electricity ω_i per EV driver i is required, as well as their corresponding bids b_i and delay costs δ_i.

To calibrate the charging requests ω_i per customer i we use real-world charging data obtained from the Netherlands during the period January 2013 - December 2013. This data set includes charging observations from 1500 charging poles in the whole country. It has recordings of 10,462 EV drivers and includes in total 231,976 transactions with the grid operator. Our data set includes detailed requests from EV owners to the grid for charging. Each EV driver has a unique ID, and each transaction with the grid is time-stamped and accompanied with the requested amount of electricity. In each simulation run, we draw randomly N number of these requests.

Since currently there is no optimal resource allocation mechanism implemented on the grid operator's side, our data does not include bids for price and delay cost. Therefore, for the EV drivers' price and delay cost bids we assume that they come from a beta distribution parametrized in various ways, $\delta_i \sim Beta_{\alpha,\beta}$, $b_i \sim Beta_{\alpha,\beta}$. The beta distribution is chosen because for various parametrizations of α and β it yields different commonly used distributions such as uniform, Gaussian, etc. The probabilities of each bid, $b_i \in (0, b_{max}]$ or delay cost, $\delta_i \in (0, \delta_{max}]$ drawn from this distribution are:

$$f(b_i; \alpha, \beta) = \frac{1}{B(\alpha, \beta)} \cdot b_i^{\alpha-1} \cdot (1 - b_i)^{\beta-1} \quad or \quad f(\delta_i; \alpha, \beta) = \frac{1}{B(\alpha, \beta)} \cdot \delta_i^{\alpha-1} \cdot (1 - \delta_i)^{\beta-1} \tag{15}$$

where $B(\alpha, \beta)$ is the beta function $B(\alpha, \beta) = \int_0^1 u^{\alpha-1} \cdot (1 - u)^{\beta-1} du$. By b_{max} and δ_{max} we denote the maximum values of bids and delay costs in an auction.

Benchmarks

To validate our method's performance with regard to its ability to reduce peak demand and delays we run simulations, as described by **Steps 1-7**, and compare their outcome with the benchmarks described below.

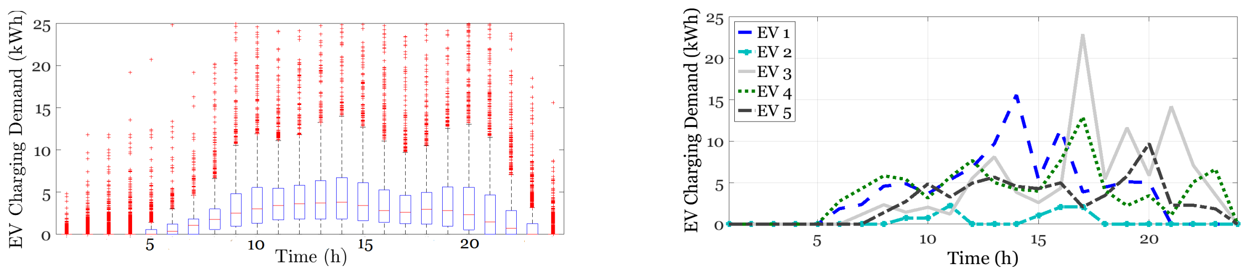
Real-world Charging

First, we compare our mechanism with the way EV charging is currently scheduled by the grid operator. This benchmark depicts the current (real-world) situation where the EV drivers can charge their cars based on their preferences, without any incentives provided by the grid toward reducing peak demand or delays. We refer to this benchmark as *real-world* charging. We calibrate it with real-world charging data obtained from the Netherlands during the period January 2013 - December 2013. This data set includes charging observations from 1500 charging poles in the whole country. It has recordings of 10,462 EV drivers and includes in total 231,976 transactions with the grid operator. In Figure 2(a), we display the box plot of the steady state EV charging demand over a 24h horizon. In Figure 2(b), we display some (anonymized) average daily charging profiles drawn randomly from our data set. We observe that the peak hours overlap for these

EV drivers, which is indicated by the high EV charging demand values during the time 15:00-21:00. This is an indication that the grid will benefit from a mechanism to prevent congestion and alleviate these peaks. This benchmark is not suitable for measuring the overall system delay, as in this mechanism all customers are serviced and there is no built-in possibility to reject customers if they are overloading the grid.

2-class MVA

Secondly, to evaluate our mechanism's ability to reduce delays in the system, we implement the same MVA mechanism (described by equations (3)-(8)) but with two charging levels (service classes) available. In this *2-class MVA* mechanism, for the second service level holds $r_2 = \frac{r_1}{2}$. We show that with the *2-class MVA* the delays are increased and as a result more customers remain unserviced. It would not be possible to use the *real-world* charging for this comparison, since real-world charging is totally uncontrolled without any capacity constraints and therefore, no delays occur. Instead the grid suffers high peak demand.



(a) (b)

Figure 2. (a) EV Charging over a 24 hour horizon (b) Typical average daily charging profiles

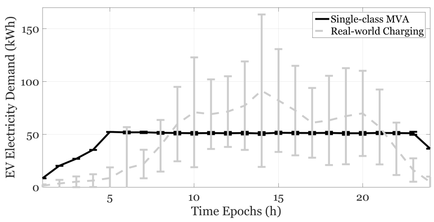
Empirical Evaluation

To empirically test the performance of our mechanism, we implement the simulation environment as described in **Steps 1-7**. Our goal is to measure the impact of our mechanism on grid's peak demand and overall delay, as well to provide design recommendations. The first is of high importance to grid operators since reduced peak demand is coupled with a reliable and properly functioning grid. The second is important for maximizing social welfare and ensuring that as many EV drivers as possible are serviced by the grid. The latter is crucial for auctioneers that have different objectives and require an optimal auction design.

Impact on Peak Demand and Demand Volatilty

To measure our mechanism's ability to reduce peak demand in the grid, we benchmark it against the *real-world* charging. Specifically, we run the auction for 24 epochs (each epoch lasts 1h). We randomly draw M number of bidders per auction, each of whom has different charging requests and different arrival and departure times. We show how the aggregate charging demand is distributed over time using the real-world charging benchmark, and we compare this with applying the MVA mechanism. We run 100 experiments and in each experiment both the single-class MVA mechanism and real-world charging are used. In Figure 3 we show the demand redistribution in the 100 experiments (the error bars show the 95% confidence interval). In this simulation experiment, we assumed a social welfare maximization objective, with one service class. To make a fair comparison of the two results, we assumed the maximum capacity of the service class to be equal to the mean demand of the real-world benchmark, so that there is the same amount of electricity compared in both scenarios. Figure 3 shows that with the single-class MVA the variability of the demand gets reduced significantly. This is attributed to the hard capacity constraint imposed by the grid operator. Furthermore, since the grid operator is maximizing social welfare, s/he will strive to accept as many bidders as possible. To quantify the above comparison, we calculate the peak-to-average ratio (PAR) and the peak demand metrics for both charging mechanisms. We observe that the PAR is reduced in the MVA case compared to the real-world charging, since a direct capacity constraint is imposed together with a social welfare maximization objective. A PAR reduction by 44.12% indicates that the grid operator is able to achieve a less volatile, hence more predictable electricity demand. Demand predictability is crucial in grid balancing, since grid operators that cannot match the expected demand with the existing supply have to resort to expensive solutions, such as buying electricity in the reserve market to prevent black- or brown-outs.

A peak reduction of 42.76% means that the grid operator is able to reduce the instantaneous peaks in the



	Average PAR	Average Peak	Max PAR	Max Peak
Real-world	2.04	91.31	12.87	565.65
single-class MVA	1.14	52.27	1.15	59.99
Reduction (%)	44.12	42.76	91.06	89.39

Figure 3. Electricity demand comparison after adopting MVA and real-world charging

demand by 42.76%. The peak demand is an important metric for the grid operator, since this metric is the determinant of the capacity installed. Specifically, if there is a high peak that lasts for a very short period of time, the grid needs to be able to service this peak and, therefore, needs to have sufficient capacity available. Furthermore, this peak demand is usually covered by expensive peak power plants, which operate using mostly fossil fuels. Thus, reducing peak demand supports the physical infrastructure of the smart grid and increases the sustainability levels.

Social Welfare Increase

Grid operators are, typically, social welfare maximizers, as opposed to other grid stakeholders, such as electricity providers, who are revenue maximizers. Therefore, in the single-class MVA presented before, the grid operator strives to minimize the overall delay cost. Comparing the single-class MVA with the 2-class MVA, we show how our mechanism reduced the delay cost in the system and as a result the social welfare was maximized. We run 100 experiments and in each experiment both single-class and 2-class MVA mechanism are implemented. Each auction lasts 24 epochs of 1 hour duration and in each auction we draw randomly M participants from the data set.

In Figure 4, we present the distribution of the SW metric in single-class MVA and 2-class MVA, over all our simulated results. This figure empirically shows that by implementing a 2-class MVA the ratio of overall delay costs over all serviced bidders is 1.53 ($\mu = 1.53$, $\sigma = 0.0285$), which is higher compared to the single-class MVA ($\mu = 1.36$, $\sigma = 0.0261$). Therefore, from a social welfare point of view, it is beneficial for the grid operator and the EV drivers to have only one class of service (charging speed) implemented. Ideally, this charging speed should be the highest possible allowed by the infrastructure, so that the delays suffered are minimum.

	Average SW	Maximum SW
2-class MVA	1.53	1.59
single-class MVA	1.36	1.43
Reduction (%)	11.02	10.17

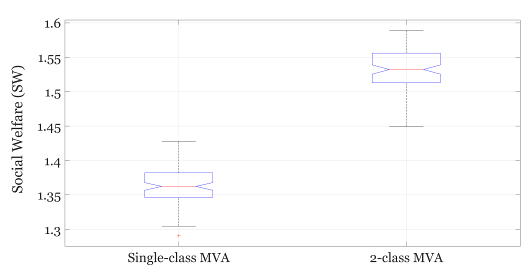


Figure 4. Ratio of overall delay cost over number of serviced bidders (SW): single-class MVA and 2-class MVA

Optimal Number of Service Classes - Revenue Maximization

Proposition 1 shows that it is optimal from a revenue maximization point of view to have multiple service classes, as opposed to the social welfare maximization case. Furthermore, Proposition 1 analytically guarantees the superiority of a multiple class service design, provided that the same number of bidders can be serviced by all designs. However, it is not clear how the revenues will change once bidders start getting rejected from the auction.

We show in Figure 5 how the revenue of the same auction changes as the number of service classes z offered by the grid grow. We make the assumption that there is overall capacity C split in z number of service classes. Furthermore, we assume that each service class $j \in \{1, ..., z\}$ differs from the next higher class by the same capacity increment. Figure 5 is in accordance with past literature on MVA (Bapna et al. 2005) which has showed that the revenue collected from MVA mechanisms is non monotonic. In this auction, there are 79 bids submitted for one epoch t and the overall capacity C of all service classes is 150 kW. The maximum revenue is collected when $z = 9$ service classes are implemented. Figure 5 shows that the overall revenue increases to a maximum and then it starts decreasing. The reason for this decrease is that once the number of service classes z grows, the capacity of those classes decreases, therefore, fewer bidders can be accepted. This rejection of bidders has a positive effect on the overall collected revenue up to a point where the maximum possible revenue is achieved, but after this point the overall trend is decreasing. Therefore, it is beneficial for revenue maximization entities to run such simulations to understand the limits of charging speed designs and the impact of the associated bidder rejection. In this scenario, if an auctioneer had opted for more than $z = 9$ service classes, she would have lost revenues. Furthermore, she would require a higher investment, therefore, this result can inform stakeholders about optimal charging speed designs that cannot be theoretically calculated.

Furthermore, in Figure 5, we display the overall number of bidders accepted in the auction while the number of classes z increases. We observe that the maximum number of bidders accepted in an auction is 44 and this number is only achieved for $z = 1$ and $z = 2$. The revenue in the case of $z = 2$ is higher than the case $z = 1$. This result verifies Proposition 1, according to which even when accepting the same number of bidders, the collected revenue will be higher when the number of service classes z grows. Second, this figure shows that while the number of classes z grows, the overall number of accepted bidders decreases, as there are bidders rejected, because their requests cannot be allocated due to their size ω_i or their bid b_i.

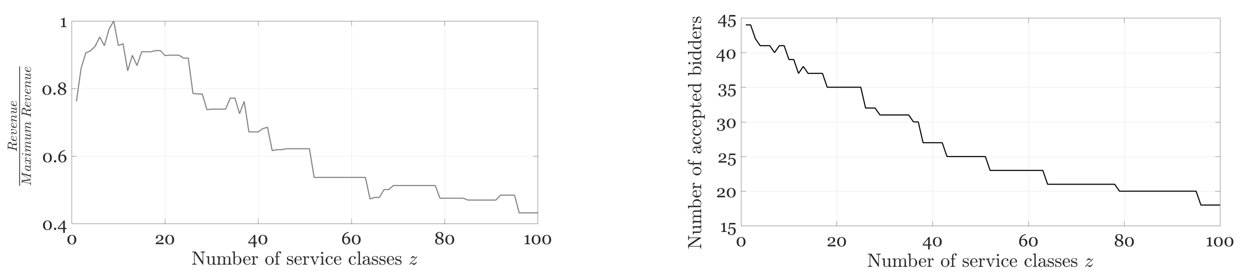


Figure 5. Revenue and number of accepted bidders for different number of classes z

Optimal Number of Service Classes - Revenue and Welfare Maximization

Propositions 1, 2 and 3 show that in a revenue maximization scenario it is optimal to have multiple service classes, whereas in a social welfare maximization scenario one service class yields the highest social welfare. Therefore, it is not possible to satisfy both objectives. However, through simulation experimentation an auction designer can find the optimal number of service classes that satisfy both objectives to some extent. Figure 6 displays the pattern of social welfare and revenue while the number of service classes z grows. To measure social welfare we use the metric $1 - \frac{SW}{Maximum\ SW}$ (right axis in Figure 6), which indicates that a higher value brings lower delay overall delay and higher number of bidders serviced. To measure the revenue, we use the normalized revenue metric $\frac{Revenue}{Maximum\ Revenue}$ (left axis in Figure 6). Similarly to the previous simulation experiment 79 bids are submitted and the overall capacity C of all service classes is

150 kW. Figure 6 shows that there is a declining trend of the social welfare while the number of the classes implemented increases, while for two service classes ($z = 2$) the revenue and social welfare metrics meet. Therefore, our simulation results enrich the theoretical propositions, as they can help grid stakeholders to decide how different objectives can be mutually satisfied without sacrificing significantly social welfare or revenues.

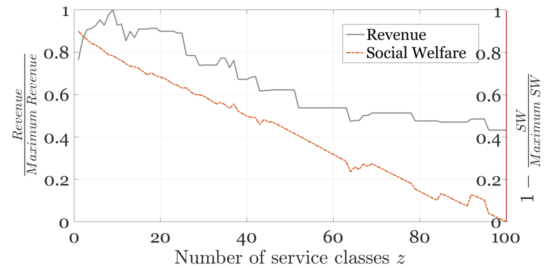


Figure 6. Revenue and social welfare for different number of classes z

The benefits of our approach are diverse. First, it ensures peak demand and volatility reduction, which can be translated to reduced need for installing physical grid capacity, hence, increased societal sustainability. Second, by estimating via simulations the optimal number of charging speeds, grid stakeholders can save costs from installing excessive numbers of charging speeds, as well as conserve raw materials that would be required to be consumed to put this charging infrastructure in place. Finally, by examining the trade-off between revenue maximizing entities and social planners, grid stakeholders can estimate the revenues that might be potentially lost if the social welfare maximization objective is satisfied (e.g. for $z = 1$ in Figure 6), and compensate for these lost revenues via other sources (such as taxation). In this way, grid operators have a more complete view of both conflicting objectives in the grid, and can compensate for potential losses on each side (social planning or revenue maximization).

Conclusions & Future Work

We present an auction mechanism to optimally allocate smart grid resources so that EV charging is coordinated, and grid sustainability is supported. Our mechanism has low computational complexity, making it easily applicable in practice when large numbers of EV charging requests need to be allocated in real-time. Furthermore, our mechanism can be tailored to cater to the needs of different grid stakeholder's providing a more holistic view of the EV charging scheduling. Specifically, we compare the revenue and social welfare maximization objectives and derive theoretical properties regarding the optimal charging speed design. This set of results can provide useful recommendations to grid infrastructure stakeholders that can optimize the charging speed design accordingly, without consuming excessive raw materials. Finally, we validate our theoretical results in simulations calibrated with real-world data and we derive specific charging speed design recommendations that could not be analytically calculated. Analyzing this trade-off between conflicting objectives, we allow for diverse objective satisfaction without sacrificing significant benefits, such as social welfare or collected revenues.

In the future, we plan to integrate bidirectional flows in our mechanism, as right now it only assumes charging and not discharging to the grid (vehicle-to-grid). Furthermore, currently, we plan to elicit the delay costs from real-world interaction with users via a mobile-app, as we are currently drawing them from a set of statistical distributions. Finally, we are planning to enrich our social welfare modeling by including the surplus of all entities involved in the auction.

References

Abe, R., Taoka, H., and McQuilkin, D. 2011. "Digital grid: Communicative electrical grids of the future," *IEEE Transactions on Smart Grid* (2:2), pp. 399–410.

Acha, S., Green, T., and Shah, N. 2011. "Optimal charging strategies of electric vehicles in the UK power market," in *2011 IEEE PES, Innovative Smart Grid Technologies (ISGT)* .

Amin, M. S., and Wollenberg, B. F. 2005. "Toward a smart grid: Power delivery for the 21st century," *IEEE*

Power and Energy Magazine (3:5), pp. 34 – 41.

Bajari, P., and Hortacsu, A. 2003. “The winner’s curse, reserve prices, and endogenous entry: empirical insights from eBay auctions,” *RAND Journal of Economics* pp. 329–355.

Bapna, R., Goes, P., and Gupta, A. 2003. “Analysis and design of business-to-consumer online auctions,” *Management Science* (49:1), pp. 85–101.

Bapna, R., Goes, P., and Gupta, A. 2005. “Pricing and Allocation for Quality-differentiated Online Services,” *Management Science* (51:7), pp. 1141–1150.

Bapna, R., Goes, P., and Gupta, A. 2008. “Auctioning Vertically Integrated Online Services: Computational Approaches for Real-time Allocation,” *Journal of Management Information Systems* (25:3), pp. 65–98.

Bhattacharya, S., Kar, K., Chow, J. H., and Gupta, A. 2016. “Extended second price auctions with elastic supply for pev charging in the smart grid,” *IEEE Transactions on Smart Grid* (7:4), pp. 2082–2093.

Brandt, T., Feuerriegel, S., and Neumann, D. 2017. “Modeling interferences in information systems design for cyberphysical systems: Insights from a smart grid application,” *European Journal of Information Systems* pp. 1–14.

Choi, J.-H., and Kim, J.-C. 2001. “Advanced voltage regulation method of power distribution systems interconnected with dispersed storage and generation systems,” *IEEE Transactions on Power Delivery* (16:2), pp. 329–334.

Clarke, E. H. 1971. “Multipart pricing of public goods,” *Public Choice* (11:1), pp. 17–33.

Cramton, P. 1997. “The FCC spectrum auctions: An early assessment,” *Journal of Economics & Management Strategy* (6:3), pp. 431–495.

Dao, V., Langella, I., and Carbo, J. 2011. “From Green to Sustainability: Information Technology and an Integrated Sustainability Framework,” *The Journal of Strategic Information Systems* (20:1), pp. 63–79.

Dash, R. K., Vytelingum, P., Rogers, A., David, E., and Jennings, N. R. 2007. “Market-based task allocation mechanisms for limited-capacity suppliers,” *IEEE Transactions on Systems, Man and Cybernetics, Part A: Systems and Humans* (37:3), pp. 391–405.

De Craemer, K., Vandael, S., Claessens, B., and Deconinck, G. 2014. “An Event-Driven Dual Coordination Mechanism for Demand Side Management of PHEVs,” *IEEE Transactions on Smart Grid* (5:2), pp. 751–760.

de Hoog, J., Alpcan, T., Brazil, M., Thomas, D. A., and Mareels, I. 2016. “A market mechanism for electric vehicle charging under network constraints,” *IEEE Transactions on Smart Grid* (7:2), pp. 827–836.

Dedrick, J. 2010. “Green IS: Concepts and Issues for Information Systems Research,” *Communications of the Association for Information Systems* (27:1), pp. 11–18.

Dimakis, A., Jain, R., and Walrand, J. 2006. “Mechanisms for efficient allocation in divisible capacity networks,” in *45th IEEE Conference on Decision and Control, 2006*, IEEE.

Doostizadeh, M., and Ghasemi, H. 2012. “A day-ahead electricity pricing model based on smart metering and demand-side management,” *Energy* (46:1), pp. 221–230.

Fridgen, G., Mette, P., and Thimmel, M. 2014. “The Value of Information Exchange in Electric Vehicle Charging,” *Proceedings of the 35th International Conference on Information Systems (ICIS)* .

Groves, T. 1973. “Incentives in Teams,” *Econometrica* (41:4), pp. 617–631.

Gupta, A., Jukic, B., Stahl, D. O., and Whinston, A. B. 2000. “Extracting consumers’ private information for implementing incentive-compatible Internet traffic pricing,” *Journal of Management Information Systems* (17:1), pp. 9–29.

Hu, J., You, S., Lind, M., and Ostergaard, J. 2014. “Coordinated charging of electric vehicles for congestion prevention in the distribution grid,” *IEEE Transactions on Smart Grid* (5:2), pp. 703–711.

James, J., Lin, J., Lam, A. Y., and Li, V. O. 2016. “Maximizing aggregator profit through energy trading by coordinated electric vehicle charging,” in *2016 IEEE International Conference on Smart Grid Communications (SmartGridComm)*, IEEE.

Kahlen, M. T., Ketter, W., and van Dalen, J. 2018. “Electric vehicle virtual power plant dilemma: Grid balancing versus customer mobility,” *Production and Operations Management* (27:11), pp. 2054–2070.

Kambil, A., and van Heck, E. 1998. “Reengineering the Dutch flower auctions: A framework for analyzing exchange organizations,” *Information Systems Research* (9:1), pp. 1–19.

Kanchev, H., Lu, D., Colas, F., Lazarov, V., and Francois, B. 2011. “Energy management and operational planning of a microgrid with a PV-based active generator for smart grid applications,” *IEEE Transactions on Industrial Electronics* (58:10), pp. 4583–4592.

Ketter, W., Collins, J., Saar-Tsechansky, M., and Marom, O. 2018. "Information systems for a smart electricity grid: Emerging challenges and opportunities," *ACM Transactions on Management Information Systems (TMIS)* (9:3), pp. 1–22.

Ketter, W., Peters, M., Collins, J., and Gupta, A. 2016. "Competitive Benchmarking: An IS Research Approach to Address Wicked Problems with Big Data and Analytics," *Management Information Systems Quarterly* (40:4), pp. 1057–1080.

Krishna, V. 2002. *Auction Theory*, Academic Press.

Malhotra, A., Melville, N. P., and Watson, R. T. 2013. "Spurring Impactful Research on Information Systems for Environmental Sustainability," *Management Information Systems Quarterly* (37:4), pp. 1265–1274.

Maturana, J., and Riff, M.-C. 2007. "Solving the short-term electrical generation scheduling problem by an adaptive evolutionary approach," *European Journal of Operational Research* (179:3), pp. 677–691.

Miranda, J., Borges, J., Valério, D., and Mendes, M. J. 2015. "Multi-agent management system for electric vehicle charging," *International Transactions on Electrical Energy Systems* (25:5), pp. 770–788.

Nisan, N., Roughgarden, T., Tardos, E., and Vazirani, V. V. (eds.) 2007. *Algorithmic Game Theory*, Cambridge University Press.

Palensky, P., and Dietrich, D. 2011. "Demand Side Management: Demand Response, Intelligent Energy Systems, and Smart Loads," *IEEE Transactions on Industrial Informatics* (7:3), pp. 381–388.

Philipsen, R., de Weerdt, M., and de Vries, L. 2016. "Auctions for congestion management in distribution grids," in *2016 13th International Conference on the European Energy Market (EEM)*, IEEE.

Rieger, A., Thummert, R., Fridgen, G., Kahlen, M., and Ketter, W. 2016. "Estimating the benefits of cooperation in a residential microgrid: A data-driven approach," *Applied Energy* (180), pp. 130–141.

Rigas, E. S., Ramchurn, S. D., Bassiliades, N., and Koutitas, G. 2013. "Congestion management for urban EV charging systems," in *2013 IEEE International Conference on Smart Grid Communications (SmartGridComm)*, IEEE.

Robu, V., Gerding, E. H., Stein, S., Parkes, D. C., Rogers, A., and Jennings, N. R. 2013. "An Online Mechanism for Multi-unit Demand and its Application to Plug-in Hybrid Electric Vehicle Charging," *Journal of Artificial Intelligence Research* (48), pp. 175–230.

Stein, S., Gerding, E., Robu, V., and Jennings, N. R. 2012. "A model-based online mechanism with precommitment and its application to electric vehicle charging," in *Proceedings of the 11th International Conference on Autonomous Agents and Multiagent Systems-Volume 2*.

Strbac, G. 2008. "Demand side management: Benefits and challenges," *Energy Policy* (36:12), pp. 4419–4426.

UNFCCC 2015. *Adoption of the Paris Agreement*, Paris: United Nations Framework Convention on Climate Change.

Valogianni, K., Ketter, W., Collins, J., and Zhdanov, D. 2018. "Facilitating a Sustainable Electric Vehicle Transition through Consumer Utility Driven Pricing," *Proceedings of the 39th International Conference on Information Systems (ICIS)* .

Vandael, S., Claessens, B., Hommelberg, M., Holvoet, T., and Deconinck, G. 2013. "A Scalable Three-step Approach for Demand Side Management of Plug-in hybrid Vehicles," *IEEE Transactions on Smart Grid* (4:2), pp. 720 – 728.

Vickrey, W. 1961. "Counterspeculation, auctions, and competitive sealed tenders," *Journal of Finance* (16:1), pp. 8–37.

Watson, R. T., Boudreau, M.-C., and Chen, A. J. 2010. "Information systems and environmentally sustainable development: energy informatics and new directions for the IS community," *Management Information Systems Quarterly* (34:1), pp. 23–38.

Wissner, M. 2011. "The Smart Grid–A saucerful of secrets?" *Applied Energy* (88:7), pp. 2509–2518.

Xiang, Q., Kong, L., Liu, X., Xu, J., and Wang, W. 2016. "Auc2Reserve: A differentially private auction for electric vehicle fast charging reservation," in *2016 IEEE 22nd International Conference on Embedded and Real-Time Computing Systems and Applications (RTCSA)*, IEEE.

Zhou, R., Li, Z., and Wu, C. 2015. "An online procurement auction for power demand response in storage-assisted smart grids," in *2015 IEEE Conference on Computer Communications (INFOCOM)*, IEEE.

Zou, S., Ma, Z., and Liu, X. 2013. "Distributed efficient charging coordinations for electric vehicles under progressive second price auction mechanism," in *52nd IEEE Conference on Decision and Control*, IEEE.