# Optimizing Electricity Procurement for Smart Charging

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## Abstract

This work models a profit-maximizing charge point operator managing a fleet of electric vehicles, facing uncertainty in the flexibility available from smart charging. By leveraging the submodular structure of maximal charging demand, we develop an approach for optimal electricity procurement that accounts for customers' indifference to specific charging schedules within their available charging windows.

## CCS Concepts

• **Mathematics of computing** → *Linear programming*; • **Social and professional topics** → *Economic impact*; • **Information systems** → *Decision support systems.*

## Keywords

Smart charging, Stochastic Optimization

**ACM Reference Format:**
Linda Punt, Yashar Ghiassi-Farrokhfal, and Gar Goei Loke. 2025. Optimizing Electricity Procurement for Smart Charging. In *The 16th ACM International Conference on Future and Sustainable Energy Systems (E-ENERGY '25), June 17–20, 2025, Rotterdam, Netherlands.* ACM, New York, NY, USA, 2 pages. https://doi.org/10.1145/3679240.3734681

## 1 Introduction

In recent years, smart charging of electric vehicles (EVs) has emerged as a crucial technology for enabling the electrification of the transportation sector and supporting the European Union's decarbonization goals [3]. EVs typically remain parked for significantly longer than the time required to charge them, and EV owners often do not require their vehicles to be charged to full capacity at all times. This allows charge point operators (CPOs) to manage charging flexibly, determining both the timing and the total energy delivered within the given constraints. Smart charging leverages this flexibility by distributing charging load optimally over time to minimize costs and enhance the integration of renewable energy sources [4].

To implement smart charging and manage uncertainties in departure times, CPOs often use apps that allow EV owners to specify their departure time and desired maximum charge. This setup delegates charging control to the CPO, which aims to charge the vehicle as much as possible within the provided timeframe. Within the given charging window, users remain indifferent to the charging schedule—offering valuable flexibility to CPOs. This flexibility is especially useful for minimizing electricity procurement costs, as energy is typically bought in day-ahead markets while EV demand remains uncertain in both timing and volume. Although real-time adjustments are possible, they often incur costly imbalance prices. A coordinated strategy—combining optimal forward procurement with smart charging—can help CPOs significantly reduce costs.

While smart charging can help, its effectiveness depends on the flexibility available in individual charging session information that is unknown at the time of bidding in the wholesale market. This makes procurement decisions particularly complex, as CPOs must estimate both total demand and the extent to which charging can be shifted. Each EV's charging needs can be met through numerous possible schedules within its available charging window, leading to an exponential number of potential charging distributions. Given this complexity, it is impractical to consider every possible charging scenario in procurement decisions.

In practice, CPOs rely on historical data or probabilistic forecasting of aggregate load profiles rather than explicitly optimizing for the full range of charging flexibility. In the literature, some studies assess the impact of EV charging on grid investment decisions by considering only uncertainty in the total EV demand per timeslot, thereby overlooking flexibility in both time and volume [1, 2]. Other works that focus on optimizing charging schedules through smart charging often rely on simplifying assumptions, such as known arrival and departure times [5, 7].

To address the above challenges, we model a profit-maximizing CPO for a fleet of EVs, facing uncertainty in the flexibility from smart charging that the fleet can provide. Flexibility in this context refers to a customer's indifference to various charging schedules within the agreed-upon time window. We find that this flexibility gives rise to a *submodular* structure in maximal demand, which enables us to apply a flexible demand model to identify optimal procurement strategies.

## 2 Methodology

### 2.1 EV charging demand

As motivated earlier, our goal is to model demand such that it reflects the flexibility in smart charging as a customer's indifference to various charging schedules within the agreed-upon time window. We can model this by defining the maximal charging demand as a *set function* $\boldsymbol{z} := (z_S)_{S \in \mathcal{P}_N} \in \mathbb{R}^{2^N}$, where it is understood that $z_S$ reflects the maximal combined demand for all timeslots in the set $S$. For instance, consider a scenario with two EV customers, A and B, and two timeslots, where both customers arrive at the start of timeslot 1. Upon arrival, both customers insert their departure time in the app where customer A wants to leave by the end of timeslot 1


*E-ENERGY '25, Rotterdam, Netherlands*

ACM ISBN 979-8-4007-1125-1/25/06
https://doi.org/10.1145/3679240.3734681

and customer B by the end of timeslot 2. For simplicity, we assume that both customers require at most one unit of electricity which can be fulfilled in a single timeslot. Hence, customer B is indifferent between being charged in timeslot 1 or 2, whereas customer A can only be charged in timeslot 1. Then, the maximal demand for timeslot 1, $z_1$, is 2, as both customer A and B would accept it. The maximal demand for timeslot 2, $z_2$, is 1, since only customer B accepts charging in this slot. The combined maximal demand over both timeslots, $z_{1,2}$ sums to 2 units-one for customer A and one for customer B. This set function $\boldsymbol{z} := (z_S)_{S \in \mathcal{P}_N} \in \mathbb{R}^{2^N}$ is *submodular* and *monotone*.

## 2.2 Model formulation

We consider the following profit-maximing model formulation adopted from [6] for $N$ products, where the total charge for timeslot $t \in S$ is restricted by the maximal demand $z_S$ and the charge $y_t$ at each time $t$ is restricted by the procured electricity for that time $x_t$.

$$\max_{\boldsymbol{x} \geq 0} \quad -\boldsymbol{c}^\top \boldsymbol{x} + \mathbb{E}_{\boldsymbol{z} \sim \mathbb{P}} \left[ P(\boldsymbol{x}, \boldsymbol{z}) \right] \tag{Sub-NV}$$

$$P(\boldsymbol{x}, \boldsymbol{z}) := \max_{\boldsymbol{y} \geq 0} \quad \boldsymbol{p}^\top \boldsymbol{y} \tag{Inner-P}$$

$$\text{s.t.} \quad y_t \leq x_t, \qquad \forall t = 1, \ldots, N \tag{1}$$

$$\sum_{t \in S} y_t \leq z_S, \forall S \subseteq \{1, \ldots, N\} \tag{2}$$

The optimal solution of (Inner-P), assuming that timeslots are in order of decreasing price $\boldsymbol{p}$, is

$$y_t^* = \min\{x_t, w_t\} \tag{3}$$

$$w_1 = z_1 \qquad \text{and} \qquad w_t = \min_{Q \in \mathcal{P}_{t-1}} \Big\{ z_{Q \cup \{t\}} - \sum_{\tau \in Q} y_\tau^* \Big\}, \quad t > 1.$$

and the optimal solution $\boldsymbol{x}^*$ obeys the following system of equations:

$$\sum_{\tau = t}^{N} \frac{p_\tau - p_{\tau+1}}{p_t} F_{u_t^\tau}(x_t^*) = r_t, \tag{4}$$

$u_t^\tau := \min_{Q \in \mathcal{P}_\tau : Q \ni t} \left\{ z_Q - \sum_{t' \in Q \setminus t} \min\{x_{t'}, w_{t'}\} \right\}$, and $r_t := \frac{p_t - c_t}{p_t}$.

In general, given some distribution $\mathbb{P}$, it may be difficult to analytically compute the c.d.f.s $G_t(\cdot)$, however, in practice, we are usually availed a data sample that is drawn from $\mathbb{P}$ and is assumed to be representative. Note that solving the sample average approximation (SAA) version of (Sub-NV) would involve a problem that has exponentially many constraints in the number of products $N$, and thus would not be practical for a large-scale problem. However, by exploiting the form and structure of our model, it is possible to solve this efficiently with a data sample. For all $0 < \alpha < \frac{1}{M}$, where $M = \max_t \sup_{x,y} \frac{G_t(x) - G_t(y)}{x - y}$, define the mapping $\boldsymbol{T}_\alpha : \mathbb{R}^N \to \mathbb{R}^N$ such that $(T_\alpha(x_t))_t = x_t - \alpha(G_t(x_t) - r_t)$. The algorithm $\boldsymbol{x}^{(m)}$ defined by $\boldsymbol{x}^{(m+1)} = \boldsymbol{T}_\alpha(\boldsymbol{x}^{(m)})$ converges to $\boldsymbol{x}^*$ that satisfies (4).

## 3 Case Study

We present a case study comparing the procurement strategies of our model (SC) with a heuristic smart charging approach (HSC), which determines its procurement strategy based on total electric vehicle (EV) demand $\boldsymbol{q}$. The HSC aims to reduce peaks and variability by evenly distributing the demand of EV owners who are indifferent between charging during time slots 1 and 2. Then, the optimal procurement level corresponds to the traditional newsvendor solution, given by $x_t^* = F_{q_t}^{-1}(r_t)$.

For this comparison, we set $\boldsymbol{c} = [5, 1]$ and $p_2 = 4$, and examine how the optimal procurement strategy and objective value evolve for varying values of $p_1$ for both SC and HSC. As shown in Figure 1, we find that the objective value of SC consistently outperforms that of HSC, demonstrating the advantages of fully leveraging the flexibility in the system. While $x_2$ remains constant for HSC due to a fixed $r_2$, SC adjusts the procurement strategy dynamically in response to price changes in the first time period. Specifically, when $p_1$ is lower, SC shifts more of the flexible demand to the second period, where the profit margin $p_t - c_t$ is higher. However, as the profit margin in the first period increases, the optimal solution shifts more flexible demand to the first period. Thus, our model demonstrates the value of considering flexibility in procurement decisions.

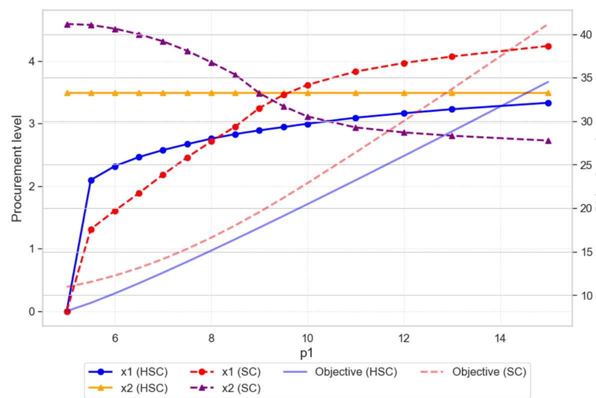


**Figure 1: Optimal procurement decisions $x$ and corresponding objective value across different price levels.**

## Acknowledgments

This work was supported by the European Union under Grant 101036594.

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