Applied Energy 290 (2021) 116779

Contents lists available at ScienceDirect

Applied Energy

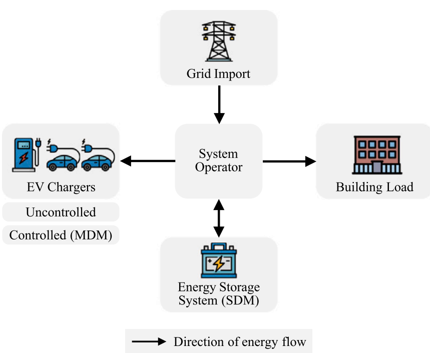
journal homepage: www.elsevier.com/locate/apenergy

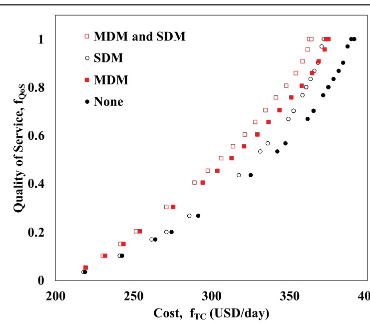
Pareto optimality in cost and service quality for an Electric Vehicle charging facility

Soomin Woo [a,*], Sangjae Bae [a], Scott J. Moura [a,b]

[a] Civil and Environmental Engineering, University of California, Berkeley, 94720, CA, USA
[b] Smart Grid and Renewable Energy Laboratory, Tsinghua-Berkeley Shenzhen Institute, Shenzhen, 518055, China

GRAPHICAL ABSTRACT





- MDM: Mobile Demand Management, i.e., rescheduling of EV charging sessions
- SDM: Stationary Demand management, i.e., using a local energy storage system

ARTICLE INFO

Keywords:
Electric Vehicle charging
Charging infrastructure planning
Robust optimization
Chance constraint
Demand management
Energy Storage System
Flexible charging
Pareto optimality

ABSTRACT

This paper examines the problem of planning an Electric Vehicle (EV) charging facility that provides a high quality of service in charging EVs and incurs a low cost to the facility manager. This problem is challenging because a facility with a larger charging capacity (hence better service quality) can be more expensive to build and operate. This paper contributes to the literature by planning an EV charging facility that overcomes this trade-off and achieves Pareto optimality, i.e. a facility with a higher quality of service but at a lower cost. We propose an optimization model to size an EV charging facility that minimizes the facility cost and guarantees a high quality of service. To reduce the cost further and negate the cost increase from quality service quality, we adopt demand management strategies. Two strategies are explored, namely Stationary Demand Management (a local energy storage system) and Mobile Demand Management (rescheduling charging sessions of EVs). The proposed model produces a facility that guarantees a high quality of service in charging EVs at a minimal cost. A facility with demand management strategies achieves a higher service quality but at a lower cost, compared to a facility without demand management strategies. Stationary Demand Management can reduce the cost similarly to Mobile Demand Management, while the latter can be more challenging in practice due to the compliance issues and demand uncertainty of the drivers.

1. Introduction

Vehicle electrification is a potential solution to reduce greenhouse gas emissions from the transportation sector [1]. To increase the market adoption of Electric Vehicles (EVs), it is crucial to build EV charging infrastructure and supply the growing demand on EV charging energy [2–4]. For instance, California needs to build around 78,000

* Corresponding author.
E-mail addresses: soomin.woo@berkeley.edu (S. Woo), sangjae.bae@berkeley.edu (S. Bae), smoura@berkeley.edu (S.J. Moura).

https://doi.org/10.1016/j.apenergy.2021.116779
Received 19 December 2020; Received in revised form 11 February 2021; Accepted 3 March 2021
Available online 17 March 2021

Nomenclature

ESS	Energy Storage System
EV	Electric Vehicle
MDM	Mobile Demand Management
SDM	Stationary Demand Management
n	Number of EV chargers
b	Scale factors for ESS units [scale]
$P_{\mathrm{EV}}(\tau)$	Charging power to aggregate EVs [kW]
$P_{\mathrm{B,C}}(\tau)$	Power charged to ESS [kW]
$P_{\mathrm{B,D}}(\tau)$	Power discharged from ESS [kW]
$P_{\mathrm{G,I}}(\tau)$	Power imported from the grid [kW]
$P_{\mathrm{G,D}}$	Power used for demand charge calculation [kW]
$E_{\mathrm{EV}}(\tau)$	Time-cumulative energy charged to aggregate EVs [kWh]
$E_{\mathrm{B}}(\tau)$	Energy level of ESS [kWh]
$P^{\star}_{\mathrm{EV,min}}(\tau)$	Power demand in charging EV aggregates, minimum to be satisfied [kW]
$E^{\star}_{\mathrm{EV,min}}(\tau)$	Time-cumulative energy demand in charging EV aggregates, minimum to be satisfied [kWh]
$P^{\star}_{\mathrm{L}}(\tau)$	Power demand from the building use [kW]
$P^{\star}_{\mathrm{EV,\ min,\ MDM}}(\tau)$	Power demand in charging EV aggregates with mobile demand management, minimum to be satisfied [kW]
$E^{\star}_{\mathrm{EV,\ min,\ MDM}}(\tau)$	Time-cumulative energy demand in charging EV aggregates with mobile demand management, minimum to be satisfied [kWh]
$\overline{P_L(\tau)}$	Expected value of $P^{\star}_{\mathrm{L}}(\tau)$
$\sigma^2_{P_L}(\tau)$	Variance of $P^{\star}_{\mathrm{L}}(\tau)$
$\mathcal{F}_{E,\tau}(z)$	Empirical cumulative distribution of $E^{\star}_{\mathrm{EV,\ min,\ MDM}}(\tau)$
$\mathcal{F}_{P,\tau}(z)$	Empirical cumulative distribution of $P^{\star}_{\mathrm{EV,\ min,\ MDM}}(\tau)$
$\mathcal{F}^{-1}_{E,\tau}(\tau)(\alpha_{EV})$	The inverse of $\mathcal{F}_{E,\tau}(z)$ at significance level α_{EV}, i.e., the aggregate EV charging energy demand at α_{EV}th percentile at time τ
$\mathcal{F}^{-1}_{P,\tau}(\tau)(\alpha_{EV})$	The inverse of $\mathcal{F}_{P,\tau}(z)$ at significance level α_{EV}, i.e., the aggregate EV charging power demand at α_{EV}th percentile at time τ
$P_{\mathrm{EV,test,j}}(\tau)$	EV charging power demand for operation simulation date i [kW]
$P_{\mathrm{L,\ test,j}}(\tau)$	Power demand from the building use for operation simulation of date i [kW]
b_{opt}	Optimized scale factors for ESS units [scale]
n_{opt}	Optimized number of EV chargers
$E_{B,\mathrm{max}}$	Nominal ESS energy capacity per unit of ESS [14.0 kWh]
$P_{\mathrm{EV,\ R}}$	Rated power of EV charger [2.33 kW]
$P_{\mathrm{G,I,max}}$	Power capacity for grid import [2000.0 kW]
$P_{B,\mathrm{max}}$	Nominal ESS power capacity per unit of ESS [5.0 kW]
α_{EV}	The percentile value of the EV charging energy, at which the EV charging facility must satisfy [0.95]
$\alpha_{\mathrm{G,\ l}}$	The probability of the grid import power is above minimum, 0 kW [0.95]
$\alpha_{\mathrm{G,u}}$	The probability of the grid import power is below the capacity, $P_{G,I,\mathrm{max}}$ [0.95]
$\beta_{\mathrm{B,i}}$	Initial ESS energy level ratio, [0.5%]
$\eta_{\mathrm{B,C}}$	ESS charging efficiency, [0.98%]
$\eta_{\mathrm{B,D}}$	ESS discharging efficiency, [0.98%]
η_{EV}	EV charging efficiency [0.89%]
b_{max}	ESS scale maximum limit [scale/kWh]
c_{B}	Daily cost per energy storage system unit [0.066 USD /day/kWh]
c_{EV}	Daily cost of an EV charger [0.274 USD/day]
$c_{\mathrm{G,D}}$	Demand charge cost, [19.0/30 USD/kW/day]
$c_{\mathrm{I}}(\tau)$	Time-of-Use electricity cost for time τ [USD/kWh]
dt	Time interval, [1 h]
τ	Time step $\in [1, T]$ [h]
T	Number of time steps in a day [24 h]
N_{cross}	Sample size for cross validation [100 samples]
N_{test}	Number of dates tested for operation simulation [71 dates]
f_{CC}	Daily capital cost ($/day)
f_{OC}	Daily operation cost ($/day)
f_{TC}	Daily total cost ($/day)
f_{QoS}	Performance metric of quality of service in charging EVs (kW)

Level 2 public chargers by 2025 to meet their goal on zero emission vehicles [4]. There are two aspects to consider in building EV charging infrastructure. On the one hand, the facility can be planned to minimize the capital and operation costs. On the other hand, the facility can be planned to achieve high quality of service in charging EVs and help alleviate the range anxiety of drivers [5]. In this study, we define quality of service in terms of satisfying the charging demand. The quality of service can be high when the facility has a sufficient charging capacity to supply the stochastic charging demand in a robust fashion. For instance, the EV charging demand can surge occasionally and a large capacity (with more chargers and/or at higher charging power) to charge will be needed for a high service quality. However, achieving these two goals may be challenging because a facility with a larger charging capacity (hence better service quality) can be more expensive to build and operate [6–8]. In other words, a trade-off exists between cost and service quality.

To the best of authors' knowledge, no study has examined and mitigated this trade-off. Many solve the sizing problem of one or multiple EV charging facilities and analyze the cost reduction from managing the energy demand; however, they do not investigate how to reduce the cost while improving the quality of service [6–15]. To manage the energy demand, some literature study the coordination of the EV charging schedule [8,11,14,15]. A paper [8] shows that the sizing cost is reduced by controlling the EV charging schedule. In [11], the authors also show that the coordination reduces cost, while satisfying the same charging demand. Similar results are shown in [14], where a penalty for incomplete charging demand is included in the sizing problem. The authors in [15] confirm that the control of charging schedule reduces cost in the real operation settings.

Some literature experiment with the plug-in states of EVs to chargers [9,10] to manage the energy demand and reduce cost, though missing analysis on quality of service. A paper [9] analyzed the cost reduction with an 'interchange' algorithm to unplug the EVs that are finished charging and use the available chargers for other demanding EVs. Another paper [10] explores the probability of EVs leaving soon after charging completion and argues that increasing the utilization rate of chargers lowers the facility cost. Some literature reduce the facility cost by not only controlling the charge schedule but also using an energy storage system to control the purchasing times of electricity [12, 13].

Despite the lack of research in enhancing quality of service with cost reduction, there are a few papers that recognize the trade-off problem of cost and service quality [6–8]. These papers measure the quality of service differently. In [6], the researchers showed that unsatisfied charging load can be reduced with increasing planning costs. A paper [7] showed the longer the time drivers spend for charging, the lower the cost, due to longer trips to reach a charging facility and/or lower charging power. The authors in [8] show that the controlled charging schedule can reduce the driver's waiting time for charger availability and the excess charging time over parking time, at lower cost in some cases.

The state-of-art literature does not investigate the problem of increasing cost with higher service quality or suggest how a facility planner may achieve higher quality of service at lower cost. This paper contributes to the literature by (1) analyzing the Pareto frontiers that quantity the trade-off between cost and quality of service and (2) identifying how demand management shifts the frontiers towards lower cost and higher quality of service. We provide an insight to facility planners to select demand management strategies that best meet their needs on cost and quality of service.

In the following, we develop an optimization model to plan an EV charging facility that minimizes the cost and guarantees a high service quality in charging EVs. The results show that the proposed model can plan a facility with a high service quality to charge random demand in a robust fashion. The results also show that increasing quality of service increases the facility cost at optimum. So we analyze the Pareto frontiers in cost and quality of service and test the impact of demand management strategies on these frontiers. We learn that demand management reduces the optimal cost further at a given quality of service, by purchasing grid electricity at cheaper times, reducing the peak power of grid electricity purchase, and building less chargers. With demand management strategies, a facility achieves a higher service quality at a lower cost compared to a facility without the strategies.

The paper is organized as follows. Section 3 develops a robust sizing model to plan an EV charging facility. Section 4 describes the research methodology for the performance analysis of the robust sizing model and for the sensitivity analysis of demand management strategies. Supplementary algorithms are proposed in this section, such as the baseline sizing model to compare the robust model to and the simulation model of the facility operation. Section 5 describes the data used in this paper. Section 6 provides the results on the robust planning model and on the sensitivity analysis with demand management. This paper is concluded with Section 7.

2. Context of EV charging facility

We focus on a single facility that provides charging service through multiple chargers, as well as the building energy load. We explore two strategies of demand management:

- Stationary Demand Management (SDM) leverages the grid import cost with an Energy Storage System (ESS). The ESS is strategically charged (from the grid) and discharges to deliver electricity to minimize the electricity cost [12,13,16]. The discharging is based on time-variant electricity tariffs, i.e., charging when the tariff is low and supplying when the tariff is high, as well as on the demand charge, i.e. discharging when the power demand is at its peak.

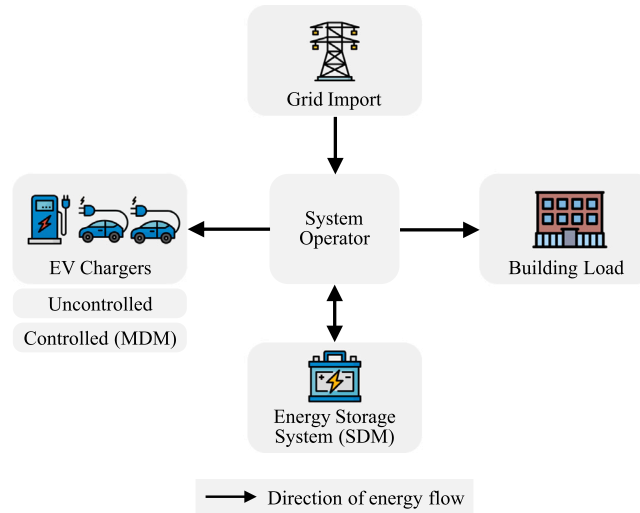


Fig. 1. Illustration of an EV charging facility.

- Mobile Demand Management (MDM) leverages the EV charging load with flexibility in charging schedule. While plugged in, EVs can be charged at any time until it is unplugged, as long as the charging demand is met. Instead of charging immediately upon arrival, an EV charging session may be deferred to alternative times with low electricity tariff and/or at off-peak power demand. This can distribute the charging sessions more evenly across time, which reduces the number of chargers to build as well as the operation cost to charge, but remains at the same quality of service [8,11,14,15]

The aforementioned strategies help reduce both the operation cost with cheaper electricity and the capital cost by installing fewer chargers.

Fig. 1 illustrates the components of an EV charging facility considered in this paper, with arrows indicating the energy flow. The energy flow is balanced by the system operator that connects the facility components. The facility draws energy from the grid and supplies energy for the building load and the EV charging demand. The ESS stores energy and discharges it to supply when needed. The system minimizes the capital cost by finding the most economic sizing of the facility, while monetizing the unsatisfied demand. The capital cost is reduced further when EVs are charged flexibly via MDM and require less chargers to build. The system also minimizes the operation cost by finding the optimal schedule to import energy from the grid. The operation cost is reduced further by leveraging the ESS and charging flexibility, i.e. SDM and MDM.

The grid electricity import is subjected to the Time-of-Use (TOU) tariff and a constant demand charge. EV chargers are installed at a fixed rated power. EV chargers are assumed not to collect profit from charging EVs in this study to isolate the potential over-estimation of profit in the planning process. In other words, the facility is planned conservatively, not over-sizing for a potential charging demand that may lead to a large profit. An onsite ESS is installed and its capacity degradation is not considered. The EVs do not discharge their energy back to the facility. The facility does not export ESS energy to the grid.

3. Robust sizing of an EV charging facility

From the system operator's perspective, the primary goal of an EV charging facility is to secure a high service quality by providing charging EVs as much as needed. However, excessive installation of EV chargers may result in the unnecessary expenditure of capital cost without enhancing the service quality. Therefore, it is important to estimate the level of EV charging demand and decide how much of the demand the charging facility must be designed for. In the following, we define the optimization variables and parameters, state the statistical assumptions, and develop a robust optimization model to find the facility size, including the number of chargers and the battery size of local ESS.

3.1. Optimization variables and parameters

Recall that the system operator targets to minimize the capital and operation costs. Hence, the optimization variables are those that affect the capital investment and the facility operations. The optimization variables include number of EV chargers n, number of ESS units to be installed b, charging power to aggregate EVs $P_{\mathrm{EV}}(\tau)$, ESS charging power $P_{\mathrm{B,C}}(\tau)$, ESS discharging power $P_{\mathrm{B,D}}(\tau)$, grid import power $P_{\mathrm{G,I}}(\tau)$, maximum of grid import power used for demand charge calculation $P_{\mathrm{G,D}}$, time-cumulative charging energy to EV aggregates $E_{\mathrm{EV}}(\tau)$, and energy level of ESS $E_{\mathrm{B}}(\tau)$.

The random parameters (notated with $\star$) are given, including the minimum charging power to EV aggregates $P^{\star}_{EV,\min}(\tau)$, the minimum time-cumulative charging energy to EV aggregates $E^{\star}_{EV,\min}(\tau)$, and the building load $P^{\star}_{L}(\tau)$. The deterministic parameters are given, such as costs (c_{EV}, c_B, $c_I(\tau)$, $c_{G,D}$), power efficiency (η_{EV}, $\eta_{B,C}$, $\eta_{B,D}$), ESS unit capacity ($E_{B,\max}$, $P_{B,\max}$), rated power of EV charger ($P_{EV,R}$, grid power limits ($P_{G,I,\max}$), ESS installment limits ($b_{\max}$), and levels of significance for statistics of random variables (α_{EV}, $\alpha_{G,l}$, $\alpha_{G,u}$).

3.2. Statistical assumptions

We explain the statistical assumptions for the random parameters that will be used in the proposal of a robust sizing model. The random power demand from the building, $P^{\star}_{L}(\tau)$, is assumed to follow a normal distribution, defined independently for each time step, τ.

$$P^{\star}_{L}(\tau) \sim \mathcal{N}(\overline{P_L(\tau)}, \sigma^2_{P_L}(\tau)) \qquad \forall\tau \tag{1a}$$

$$P^{\star}_{L}(\tau_1) \perp P^{\star}_{L}(\tau_2) \qquad \forall\tau_1 \neq \tau_2 \tag{1b}$$

The random demands of EV charging power and energy, $P^{\star}_{EV,\min}(\tau)$ and $E^{\star}_{EV,\min}(\tau)$ respectively, are assumed to follow empirical distributions. Their cumulative distributions are defined respectively as $\mathcal{F}_{P,\tau}$ and $\mathcal{F}_{E,\tau}$, independently for each time step, τ.

$$P^{\star}_{EV,\min}(\tau) \sim \mathcal{F}_{P,\tau}(z) = Pr(P^{\star}_{EV,\min}(\tau) \le z) \qquad \forall\tau \tag{2a}$$

$$E^{\star}_{EV,\min}(\tau) \sim \mathcal{F}_{E,\tau}(z) = Pr(E^{\star}_{EV,\min}(\tau) \le z) \qquad \forall\tau \tag{2b}$$

$$P^{\star}_{EV,\min}(\tau_1) \perp P^{\star}_{EV,\min}(\tau_2) \qquad \forall\tau_1 \neq \tau_2 \tag{2c}$$

$$E^{\star}_{EV,\min}(\tau_1) \perp E^{\star}_{EV,\min}(\tau_2) \qquad \forall\tau_1 \neq \tau_2 \tag{2d}$$

For simplicity, it is also assumed that $P^{\star}_{L}(\tau)$ is independent to the EV charging demand.

$$P^{\star}_{L}(\tau) \perp P^{\star}_{EV,\min}(\tau) \qquad \forall\tau \tag{3}$$

$$P^{\star}_{L}(\tau) \perp E^{\star}_{EV,\min}(\tau) \qquad \forall\tau \tag{4}$$

3.3. Model derivation

We derive our robust planning model for an EV charging facility in the following. We first describe the model with an objective function and constraints with uncertain variables, but this form is unsolvable. Therefore, we use the statistical distribution from the previous section to derive an expected value function for the objective function and second-order cone expressions for the constraints with uncertain variables. The final solvable model is given in Algorithm 1.

3.3.1. Objective function

The objective of our sizing model is to minimize the expected value of the total cost, including the capital cost of EV chargers and ESS and the operation cost, such as electricity cost and demand charge. The cost is calculated in terms of a daily cost. The demand charge is calculated base on the maximum power over 15-minute period. For simplicity, no interest or present value is considered. Formally:

$$J = c_B b + c_{EV} n \tag{5a}$$

$$+ \sum_{\tau=1}^{T} [c_I(\tau) P_{G,I}(\tau)] dt \tag{5b}$$

$$+ c_{G,D} P_{G,D} \tag{5c}$$

where (5a) represents the capital cost for EV charger and ESS installations, (5b) for grid import cost, and (5c) for demand charge cost.

3.3.2. Constraints and reformulations

The objective function J in (5) is linear with respect to the decision variables $(b, n, P_{G,I}(\tau), P_{G,D})$. However, the grid import power $P_{G,I}(\tau)$ is coupled with the building load $P^{\star}_{L}(\tau)$ (which is a random parameter) due to the power balance between supply and demand. The power balance equation can be expressed as:

$$P_{B,D}(\tau) + P_{G,I}(\tau) = P^{\star}_{L}(\tau) + P_{B,C}(\tau) + P_{EV}(\tau), \tag{6}$$

where the left hand side shows the power supply from the ESS discharging and the grid import, and the right hand side shows the power demand from the building load, the ESS charging, and the EV charging. The objective function (5) remains mathematically intractable, due to its coupling to the power balance (6) with stochasticity.

The grid import $P_{G,I}$ is lower and upper bounded by its physical limitation by $[0, P_{G,I,\max}]$:

$$0 \le P_{G,I}(\tau) \le P_{G,I,\max} \tag{7}$$

but this constraint is also intractable due to its coupling to the power balance (6) in the current form.

Therefore, we reformulate the power balance (6) and the coupled Eqs. (5) and (7) to make them tractable. We use the chance-constraint method in [17], given the statistical distributions of random parameters described in Section 3.2. We denote level of confidence on the grid import $P_{G,I}(\tau)$ as $\alpha_{G,l}$ for the lower bound and $\alpha_{G,u}$ for the upper bound. The level of confidence values represent the probability that the grid import power is above 0 kW and below the grid capacity of $P_{G,I,\max}$, respectively. Note that due to the coupling of grid import power $P_{G,I}(\tau)$ to EV charging power $P_{\mathrm{EV}(\tau)}$ shown in (6), the EV charging power $P_{\mathrm{EV}(\tau)}$ can be limited by the grid capacity, $P_{G,I,\max}$.

The normal distribution of $P^{\star}_{L}(\tau)$ is transformed into a cumulative standard normal distribution, Φ. Re-expressing (6) in terms of $P_{G,I}(\tau)$ and taking the upper and lower statistical bounds using the level of significance gives (8) and (9).

$$\begin{aligned}\Phi^{-1}(\alpha_{G,l}) \cdot \sqrt{\sigma^2_{P_L}(\tau)} \le\ & P_{B,C}(\tau) + P_{EV}(\tau) \\ & + P_{G,E}(\tau) - P_{B,D}(\tau) + \overline{P_L}(\tau)\end{aligned} \tag{8}$$

$$\begin{aligned}\Phi^{-1}(\alpha_{G,u}) \cdot \sqrt{\sigma^2_{P_L}(\tau)} \le\ & P_{G,I,\max} - P_{B,C}(\tau) - P_{EV}(\tau) \\ & - P_{G,E}(\tau) + P_{B,D}(\tau) - \overline{P_L}(\tau)\end{aligned} \tag{9}$$

The objective function takes an expected total cost, by taking the expected value of grid import $P_{G,I}(\tau)$ in (6):

$$\begin{aligned}J =\ & c_B \cdot b + c_{EV} \cdot n \\ & + \sum_{\tau=1}^{T} c_I(\tau)[P_{B,C}(\tau) + P_{EV}(\tau) + P_{G,E}(\tau) - P_{B,D}(\tau) + \overline{P_L}(\tau)] dt \\ & + c_{G,D} \cdot P_{G,D}.\end{aligned} \tag{10}$$

In addition to the power balance in (8) and (9), constraints on the power dynamics, capacity limitation, and sizing variables are formulated:

$$E_B(\tau+1) = E_B(\tau) + \left[\eta_{B,C} \cdot P_{B,C}(\tau) - \frac{1}{\eta_{B,D}} P_{B,D}(\tau)\right] dt \tag{11}$$

$$E_B(0) = \beta_{B,i}[bE_{B,\max}] \tag{12}$$

$$E_B(T) = E_B(0) \tag{13}$$

$$0 \le E_B(\tau) \le b \cdot E_{B,\max} \tag{14}$$

$$0 \le P_{B,C}(\tau) \le b \cdot P_{B,\max} \tag{15}$$

$$0 \le P_{B,D}(\tau) \le b \cdot P_{B,\max} \tag{16}$$

where (11) describes the power dynamics of ESS units with efficiency factors for charging and discharging. Eqs. (12) and (13) define the boundary conditions to avoid a myopic use of ESS units in the optimization. Eqs. (14)–(16) describe the energy capacity, charging power capacity, and discharging power capacity of ESS units respectively, in terms of the ESS sizing variable, b. Note we assume a fixed ratio between power capacity and energy capacity of ESS. The optimization variable b scales power and energy capacity relative to nominal values, while keeping the energy-to-power ratio fixed.

For the EV charging dynamics, we consider cumulative energy consumption as a linear function of charging power:

$$E_{EV}(\tau+1) = E_{EV}(\tau) + dt[\eta_{EV} \cdot P_{EV}(\tau)] \tag{17}$$

Other constraints for EV charging are formulated as:

$$E_{EV}(0) = 0 \tag{18}$$

$$P^{\star}_{\mathrm{EV,min}}(\tau) \le \eta_{\mathrm{EV}} P_{\mathrm{EV}}\ (\tau) \tag{19}$$

$$E^{\star}_{\mathrm{EV,min}}(\tau) \le E_{\mathrm{EV}}\ (\tau) \tag{20}$$

$$0 \le P_{\mathrm{EV}}\ (\tau) \le n \cdot P_{\mathrm{EV,R}} \tag{21}$$

where (18) sets the initial cumulative energy zero, (19) and (20) guarantee sufficient charging supply for the demand and (21) constraints the number of EV chargers n to meet the necessary EV charging power capacity. The parameter $P_{\mathrm{EV,R}}$ in (21) can be various charging powers, such as low-level chargers to fast chargers, expanding the range of charger types to be considered in the planning. Note, the random variables $P^{\star}_{EV,\min}(\tau)$ and $E^{\star}_{EV,\min}(\tau)$ make (19) and (20) difficult to solve. Therefore, we reformulate these equations as chance constraints.

With the empirical distributions (2a) and (2b), we can choose a level of significance to represent probable values of charging power and energy demands. At a level of significance $\alpha_{EV,\text{lower}}$, the power and energy demands can be expressed as $\mathcal{F}^{-1}_{P,\tau}(\tau)(\alpha_{EV})$ and $\mathcal{F}^{-1}_{E,\tau}(\tau)(\alpha_{EV})$ respectively. We plan the facility to guarantee such demands, by constraining the lower bounds of power and energy delivery $P_{EV}(\tau)$ and $E_{EV}(\tau)$. Therefore, (19) and (20) can be replaced by (22) and (23), respectively. These constraints, together with (17) and (21), require the number of EV chargers to achieve a robust capacity to the random demand at a percentile of $\alpha_{EV,\text{lower}}$. Note that (22) enforces the model to plan enough EV chargers to satisfy the EV charging demand at α_{EV}th percentile all hours τ.

$$\mathcal{F}^{-1}_{P,\tau}(\tau)(\alpha_{EV}) \le \eta_{EV} \cdot P_{EV}(\tau) \tag{22}$$

$$\mathcal{F}^{-1}_{E,\tau}(\tau)(\alpha_{EV}) \le E_{EV}(\tau) \tag{23}$$

The power value to calculate the demand charge cost is given in (24). As the objective function considers an expected value of demand charge cost, (24) is similarly modified as (25) without the variable $P_{G,I}(\tau)$.

$$P_{G,D} \ge P_{G,I}(\tau) \tag{24}$$

$$P_{G,D} \ge P_{B,C}(\tau) + P_{EV}(\tau) + P_{G,E}(\tau) - P_{B,D}(\tau) + \overline{P_L}(\tau) \tag{25}$$

We consider a maximum limit for the ESS units to be built with a given parameter $b_{\max}$ as (26). The facility planner may use this parameter $b_{\max}$ to reflect the physical constraints for the ESS installment and the facility operator's preference.

$$0 \le b \le b_{\max} \tag{26}$$

3.3.3. Complete formulation

The final model for robust sizing of an EV charging facility is organized in Algorithm 1 for all $\tau = [1,\ldots,T]$. The number of EV chargers is a non-negative integer as (27) and (28). The proposed robust sizing in Algorithm 1 is a convex problem of Integer and Second-Order Cone Programming. The solution guarantees an optimal solution, if feasible.

Algorithm 1: Robust Sizing Model

Minimize (10)

Such that (8), (9), (11), (12), (13), (14), (15), (16), (17), (18), (21), (22), (23), (25), (26),

$$0 \le n, \tag{27}$$

$$n \in \mathbb{Z} \tag{28}$$

4. Methodology

In this section, we describe how we evaluate the proposed sizing model for a robust EV charging facility. Supplementary models for this evaluation are provided, such as a baseline sizing model and the simulation model for the facility's operation. We also describe how we conduct the sensitivity analysis of energy demand management on the facility performance, giving us a clue how to overcome the trade-off between the cost and quality of service. We explain how the Mobile and Stationary Demand Management strategies are implemented and analyzed.

4.1. Performance of the robust sizing model

The proposed robust sizing model is evaluated in comparison to a baseline sizing model that optimizes based on the expected values of random parameters. Since it is impractical to test the performance of sizing models in the field, a simulation model is used to emulate the daily operation of the facility. For brevity, a facility planned by the proposed robust model and the baseline model are termed 'robust facility' and 'baseline facility', respectively. The metrics on cost and quality of service evaluate the performance of robust and baseline facilities. The results are cross-validated with 100 random samples of EV charging demand. In addition, sample trajectories of power and energy in the robust and baseline facilities are presented for detailed discussion.

We describe in the following the baseline sizing model, the operation simulation model, the performance metrics of an optimized facility, and the cross-validation process to compare between the robust and baseline sizing models.

4.1.1. Baseline sizing model

Algorithm 2 describes the baseline sizing model, which uses the expected values of the random parameters. This model is inspired by the work in [18], which considers the operation scenarios to plan a facility, for example the input data for energy use will take 3-day samples each month. This model is applied in the open-source program, called Distributed Energy Resources Customer Adoption Model (DER-CAM) from Lawrence Berkeley Lab. The building power demand $P^{\star}_{L}(\tau)$, minimum EV charging power $E^{\star}_{EV,\min}(\tau)$, and minimum EV charging energy $P^{\star}_{EV,\min}(\tau)$ are represented with their average values with $\overline{P_L}(\tau)$, $\mathcal{F}^{-1}_{P,\tau}(\tau)(\alpha_{EV} = 0.5)$, and $\mathcal{F}^{-1}_{E,\tau}(\tau)(\alpha_{EV} = 0.5)$, respectively. The algorithm is expressed for all $\tau = [1,\ldots,T]$. The proposed baseline sizing in Algorithm 2 is a convex problem of Linear Integer Programming. The solution guarantees an optimal solution, if feasible.

Algorithm 2: Baseline Sizing Model

Minimize (5)

Such that (11), (7), (12), (13), (14), (15), (16), (17), (18), (21), (24), (26), (27), (28)

$$P_{B,D}(\tau) + P_{G,I}(\tau) = \overline{P_L}(\tau) + P_{B,C}(\tau) + P_{EV}(\tau) \quad (29)$$

$$\mathcal{F}^{-1}_{P,\tau}(\tau)(\alpha_{EV} = 0.5) \le \eta_{EV} \cdot P_{EV}(\tau) \quad (30)$$

$$\mathcal{F}^{-1}_{E,\tau}(\tau)(\alpha_{EV} = 0.5) \le E_{EV}(\tau) \quad (31)$$

4.1.2. Operation simulation model

Algorithm 3 describes the simulation model for an EV charging facility's operation. Given the ESS units and the number of EV chargers, b_{opt}, n_{opt}, the total daily cost is minimized by controlling the operation variables for each day in the testing dataset. The facility supplies EV charging demand as much as the charging capacity allows without a cost-minimizing behavior. When the demand exceeds the charging capacity, the EV charging demand is unsatisfied and lost without queuing. The proposed baseline sizing in Algorithm 3 is a convex problem of Linear Integer Programming. The solution guarantees an optimal solution, if feasible.

Algorithm 3: Daily Operation Simulation Model

Minimize

$$c_B \cdot b_{\mathrm{opt}} + c_{EV} \cdot n_{\mathrm{opt}} + \sum_{\tau=1}^{T} dt[c_I(\tau) \cdot P_{G,I}(\tau)] + c_{G,D} \cdot P_{G,D} \quad (32)$$

Such that (7), (11), (13), (17), (18), (24), (33)

$$P_{B,D}(\tau) + P_{G,I}(\tau) = P_{L,\mathrm{test},j}(\tau) + P_{B,C}(\tau) + P_{EV}(\tau) \quad (34)$$

$$E_B(i,0) = \beta_{B,i}[b_{\mathrm{opt}} \cdot E_{B,\max}] \quad (35)$$

$$0 \le E_B(\tau) \le b_{\mathrm{opt}} \cdot E_{B,\max} \quad (36)$$

$$0 \le P_{B,C}(\tau) \le b_{\mathrm{opt}} \cdot P_{B,\max} \quad (37)$$

$$0 \le P_{B,D}(\tau) \le b_{\mathrm{opt}} \cdot P_{B,\max} \quad (38)$$

$$P_{EV}(\tau) = \min(\eta_{EV}^{-1} \cdot P_{EV,test,j}(\tau), n_{\mathrm{opt}} \cdot P_{EV,R}) \quad (39)$$

4.1.3. Cross-validation process

The robust and baseline facilities are compared with cross-validation. The total dates of EV charging demand data are randomly split into a sizing set (training) and a simulation set (testing) in a 7:3 ratio, 100 times. For each training set, empirical distributions of the EV charging demand is calibrated, i.e. (2a) and (2b). The robust and baseline models use these distributions to find the optimal sizing of the facility. The charging demand of multiple dates in the testing sets are used to simulate the robust facility and the baseline facility. Algorithm 4 gives a pseudo-code for the cross-validation of robust and baseline sizing. Note that for cross-validation, the maximum ESS units is set as $b_{\max} = 2$.

Algorithm 4: Cross-Validation of Robust and Baseline Sizing Models

```
Result: Power and Energy Trajectories of Simulated Operation,
        Total Daily Costs, and QoS values
for i = 0; i < N_cross; i = i + 1 do
    Optimize a robust facility with Algorithm 1 as sample i ;
    Optimize an baseline facility with Algorithm 2 as sample i ;
    for j = 0; j < N_test; j = j + 1 do
        Simulate the robust facility for date j with Algorithm 3 ;
        Simulate the baseline facility for date j with Algorithm 3;
    end
    Evaluate the robust facility of sample i with (42) and (43) ;
    Evaluate the baseline facility of sample i with (42) and (43) ;
end
```

4.1.4. Performance metrics

From the operation simulation results, the facility performance is evaluated on the daily operation cost, daily capital cost, total daily cost and the quality of service in charging EVs as f_{OC} (\$/day), f_{CC} (\$/day), f_{TC} (\$/day) and f_{QoS} (kW), given in (40)–(43), respectively.

$$f_{\mathrm{OC}} = \frac{1}{N_{\mathrm{test}}} \sum_{j=1}^{N_{\mathrm{test}}} \left[\sum_{\tau=1}^{T} dt c_I(\tau) P_{G,I,j}(\tau) + c_{G,D} P_{G,D,j} \right] \quad (40)$$

$$f_{\mathrm{CC}} = \frac{1}{N_{\mathrm{test}}} \sum_{j=1}^{N_{\mathrm{test}}} \left[c_B b_{\mathrm{opt}} + c_{EV} n_{\mathrm{opt}} \right] \quad (41)$$

$$f_{\mathrm{TC}} = f_{OC} + f_{CC} \quad (42)$$

Eq. (42) calculates the average daily cost, including the capital cost, electricity cost and demand charge cost, over the simulated dates in the testing set.

$$f_{\mathrm{QoS}} = \frac{1}{N_{\mathrm{test}}} \sum_{j=1}^{N_{\mathrm{test}}} \left[1 - \frac{\max_{\tau \in [1,T]}[P_{EV,\mathrm{test},j}(\tau) - P_{EV,j}(\tau)]}{\max_{\tau \in [1,T]}[P_{EV,\mathrm{test},j}(\tau)]} \right] \quad (43)$$

Eq. (43) for f_{QoS} calculates the quality of service, by measuring how much charging power is not satisfied by the facility's physical capacity. Since the EV charging demand can fluctuate largely throughout the day, it is crucial for the metric to capture the unsatisfied demand at its maximum. Eq. (43) uses time variables, simulation date $j \in [1, N_{\mathrm{test}}]$ and hour $\tau \in [1, T]$ for each date j. The fraction expression has two maximum expressions. The maximum expression in denominator finds the maximum power demand in charging over all τ in j, i.e. the hourly peak power demand of the date j. The maximum expression in the numerator finds the maximum unsatisfied power demand in charging over hours all τ in date j, i.e. the largest difference between the demand and supply of charging power during the day. Therefore, the fraction evaluates the ratio of the maximum unsatisfied power to the maximum charging demand. By subtracting 1 by this fraction, the expression inside the sum measures the satisfaction of charging demand, i.e. the quality of service. The measurements are averaged over all j.

4.2. Sensitivity analysis on demand management

We explore the energy demand management strategies to reduce the facility cost (especially the demand charge cost), while maintaining a level of service quality. Traditionally, the utility companies impose a demand charge cost on the customers to reduce the demand peaks, economize their grid operations, and improve the grid service quality. However, the EV charging demand can surge during the day [19] without consideration to the power peaks in grid import because the demand charge is not internalized to the EV drivers. Therefore, we target to manage the peak in grid import and reduce the cost. In the following, we describe the two strategies for demand management to experiment in this paper.

4.2.1. Stationary Demand Management (SDM)

Stationary Demand Management (SDM) installs ESS units that decouple the facility's energy demand peak and the grid import peak. Regardless of the energy demand, the ESS units can store energy from the grid when it is cheap and flexibly discharge it to supply the demand. The facility can use the stored energy instead of grid import energy during the demand peak and reduce the demand charge cost. The effect of SDM is observed by comparing different maximum limits for the ESS, $b_{\max} = [2, 10]$

4.2.2. Mobile Demand Management (MDM)

Mobile Demand Management (MDM) flattens the peak of total EV charging demand by rescheduling the individual charging sessions. This can achieve a similar effect of the grid network flattening the demand peak with the demand charge, i.e. the facility can reduce the operation cost from power surge and avoid building an excessive charging capacity [20].

We use a heuristic model to reschedule individual EV's charging demand. When a subject EV arrives at the charging facility, its charging session is scheduled based on its known departure time, charging power, energy demand, and the current total demand on charging power at the facility. The charging demand of other EVs in the future is assumed unknown. The subject EV is scheduled to charge when the current total demand so far is the smallest within its parking duration, but it is scheduled to charge its desired energy by its departure. The total demand accumulates with this decision. Once a vehicle starts charging, there is no break in charging within the charging session. The power demand with MDM is the total charging demand after rescheduling for all EVs that arrive at the facility in a day, notated as $P^{\star}_{EV,min,MDM}(\tau)$. This is integrated and cumulatively summed to produce the cumulative energy demand, $E^{\star}_{EV,min,MDM}(\tau)$. Note that only the EV charging demand is rescheduled, not the building energy demand. The effect of MDM is observed by comparing different EV charging demands, i.e. $[P^{\star}_{EV,\min}, E^{\star}_{EV,\min}]$ or $[P^{\star}_{EV,min,MDM}, E^{\star}_{EV,min,MDM}]$.

4.2.3. Sensitivity analysis

To evaluate the effect of SDM and MDM on facility sizing performance, three parameters are explored as a sensitivity analysis. First is the maximum ESS units allowed to build, which helps evaluate the effect of SDM, $b_{\max} = [2, 10]$. Second is the EV charging demands for MDM, $[P^{\star}_{EV,\min}, E^{\star}_{EV,\min}]$ or $[P^{\star}_{EV,min,MDM}, E^{\star}_{EV,min,MDM}]$, which helps evaluate the effect of MDM. Third is the level of significance in EV charging demand, $\alpha_{EV} = [0.05, 0.10, \dots, 0.90, 0.95]$, which results in different qualities of service in charging EVs. The resulting facility sizing is evaluated via the operation simulation in Algorithm 3 with a high level of EV charging demand at 95th percentile.

5. Data

We consider a workplace EV charging facility. We use real-world data on workplace EV charging demand, office building energy demand, and electricity tariff for businesses. We describe the data in the following and other parameters are provided in the Nomenclature.

5.1. EV charging demand

The EV charging demand is represented by the Adaptive Charging Network data from January 1st 2019 to September 9th 2019, collected from the California Institute of Technology (CalTech) campus garage in Pasadena, California [21]. The data describes individual EVs in terms of their time of connection and disconnection to the charger and the total energy delivered. We process the data to aggregate the total power and cumulative energy delivered to the EVs in 15-min increments with an assumption of constant charging power. From this original demand, rescheduled charging demand with MDM is produced.

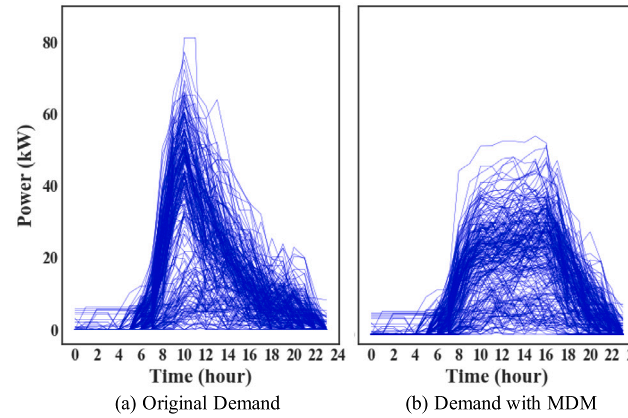


Fig. 2. EV charging demand trajectories for sample dates (California Institute of Technology (CalTech) Campus Garage in Pasadena, California, from 2019/1/1 to 2019/9/9): the left plot shows the original demand and the right plot shows the result from mobile demand management on the original demand.

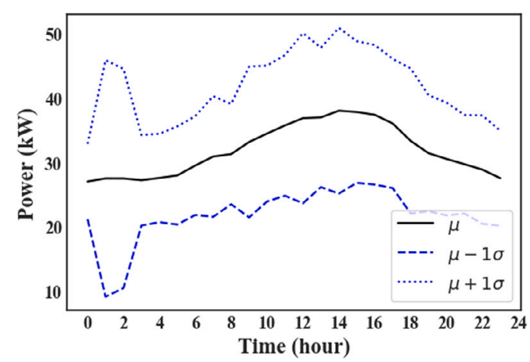


Fig. 3. Building energy demand from sample dates (Lawrence Berkeley Lab Building 74, California, from 2014/1/1 to 2014/9/9): μ denotes the mean value and σ denotes the standard deviation.

Fig. 2 shows the original data and the rescheduled data with MDM in terms of the aggregate power at 15-min intervals. Each line represents each date in the sample. We observe that MDM reduced the peak of power demand with a flatter trend throughout the day. The MDM algorithm does not change the total energy demand.

5.2. Building energy demand

The building energy demand is represented by the data from Lawrence Berkeley Lab Building 74 in California from January 1st to September 9th, 2014 [22]. Fig. 3 shows the mean daily power use plus and minus one standard deviation.

5.3. Electricity cost

We consider a Time-of-Use energy tariff and a demand charge on peak power. The Time-of-Use energy tariff, $c_I(\tau)$ (USD/kWh), is represented by the rates for businesses in summer from PG&E in California as shown in Fig. 4 [23]. The demand charge is assumed as a constant, $c_{G,D} = 19.0$ USD/kW per month.

6. Results

In this section, we evaluate the performance of the robust sizing model compared to the baseline sizing model. The results show that the robust facility produces a higher quality of service than the baseline facility, but incurs in a larger cost due to constructing and operating

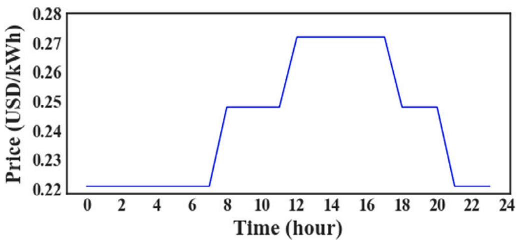


Fig. 4. Time-of-Use electricity price.

Table 1
Cross validation results of optimal sizing and operation simulation.

Model	Average over N_{cross} samples					
	n_{opt}	b_{opt}	f_{OC}	f_{CC}	f_{TC}	f_{QoS}
Robust	31.5	2	257.1	7.0	264.1	0.9963
Baseline	20.5	2	254.0	4.6	258.6	0.9054

f_{OC}, f_{CC}, and f_{CC} are in units of ($/day).

a larger charging capacity. To overcome this trade-off, we analyze how demand management strategies impact the planning and operation of an EV charging facility. The results show that when Stationary and Mobile Demand Managements are applied to a robust facility, it overcomes the trade-off and achieves a higher quality of service at a lower cost, compared to a robust facility without these strategies.

6.1. Performance of the robust sizing model

Table 1 shows the sizing and operation results of the robust and baseline sizing models, averaged over the cross validation sample of size $N_{\text{cross}} = 100$. The robust facility builds more chargers (shown with n_{opt}) than the baseline facility, ensuring a larger capacity to supply the random EV charging demand. For both robust and baseline facilities, the ESS units are planned at the maximum limit, $b_{\text{opt}} = b_{\max} = 2$, because ESS units facilitate flexible grid import and reduce cost. The robust facility has a larger operation cost than the baseline facility because more chargers satisfy more demand, importing more energy for the EVs. With the capital cost of a larger facility, the robust facility has a larger total cost (shown with f_{TC} computed in (42)) than the baseline facility. However, we observe that the daily operation cost (shown with f_{OC}) is much larger than the daily capital cost (shown with f_{CC}). In other words, operation is the major component (above 95%) of the total cost. This validates the need to economize the facility operation, as we will achieve with SDM and MDM in the following section.

The quality of service in charging EVs, f_{QoS}, is larger in the robust facility than the baseline facility. Therefore, f_{QoS} of the robust facility is around 9% higher than that of the baseline facility. To visualize why this occurs, please refer to Fig. 5 with sample trajectories of power and energy during simulated operation. The left column shows the robust facility and the right column shows the baseline facility. The top figures show that the robust facility satisfies most of the EV charging demand, whereas the baseline facility cannot satisfy some EV demand due to its limited charging capacity (around 40 kW).

Note that the operation simulation does not allow charging demand to queue, i.e. when demand cannot be served immediately, then it is considered lost. So the charging demand in the baseline facility becomes unsatisfied; as shown with unsatisfied cumulative energy indicated by the gap between the two curves in the right middle figure of Fig. 5. Therefore, f_{QoS} of the baseline facility is often lower than that of the robust facility, as shown in Fig. 6.

The trade-off between quality of service and increasing cost is illustrated by the bottom row in Fig. 5. If a small capacity ESS is

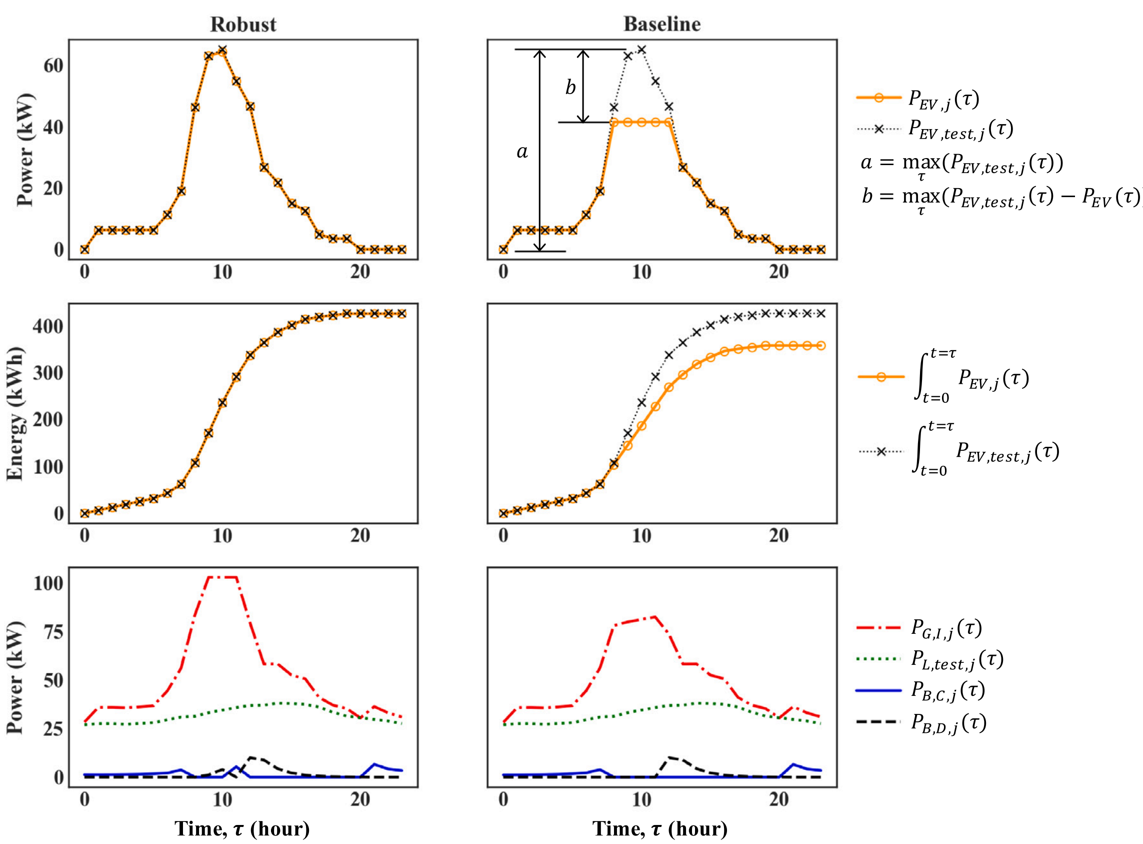


Fig. 5. Sample trajectory of EV charging operation with robust and baseline sizing (Note: $f_{\text{QoS}} = \sum_{j=1}^{N_{\text{test}}}[1 - \frac{b}{a}]$).

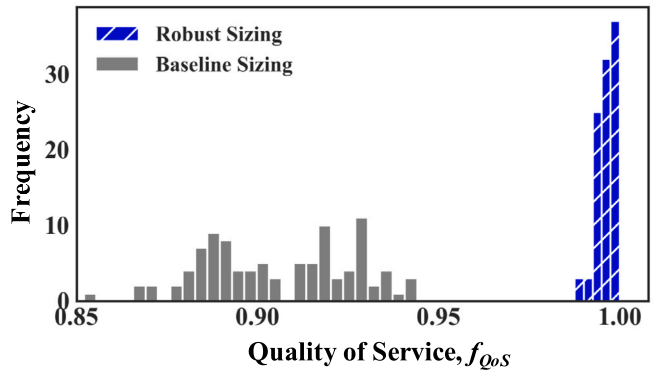


Fig. 6. Quality of service (Cross-Validation of 100 samples with unique demand scenarios).

installed, then both facilities have no choice but to import grid power following the peak of EV charging demand, indicated by $P_{G,I,j}(\tau)$. However the grid import peaks higher for the robust facility than the baseline facility, resulting in a larger demand charge on top of the larger energy cost. Moreover, we realize that the peak charging demand only lasts a short period of time. This means that for the robust facility, much of the charging capacity is not used most of the day. Instead of supplying energy simply as demanded, if the facility can be proactive in managing the demand and make the planning and operation more economical, the trade-off with increasing cost may be reduced. The next section analyzes the impact of demand management strategies on an EV charging facility.

6.2. Sensitivity analysis on demand management

Fig. 7 presents how a robust facility with demand management strategies perform better than a facility without strategies, in terms of both the cost and quality of service. The total cost as f_{TC} is on the x-axis and the quality of service as f_{QoS} on the y-axis. Four scenarios of demand management are evaluated. "None" indicates the scenario with original EV charging demand and the maximum ESS units allowed to be built as $b_{max} = 2$. "MDM" indicates the scenario with rescheduled EV charging sessions (therefore with flattened charging demand as in the right figure of Fig. 2). "SDM" indicates the scenario with a larger maximum ESS units allowed to be built as $b_{max} = 10$. "MDM and SDM" indicates the scenario with both rescheduled EV charging sessions and a larger maximum ESS size allowed to be built. Each data point shows the results of varying levels of significance, α_{EV}. A facility sized with a smaller α_{EV} (from (22) and (23)) yields a smaller f_{QoS}, so the left-most point in each scenario is the result with $\alpha_{EV} = 0.05$ and the right-most point is the result with $\alpha_{EV} = 0.95$. Note the result with $\alpha_{EV} = 0.5$ with scenario "None" is approximates of the baseline sizing model in Table 1, which is based on average values of EV charging demand. The result with $\alpha_{EV} = 0.95$ in scenario "None" corresponds to the robust sizing result in Table 1.

First from the graph we notice that the facility improves the quality of service with a larger cost. Moreover, increasing the cost has an increasing marginal return on the quality of service, i.e. the quality of service improves at an increasing rate as the cost increases. This means that the trade-off between the cost and quality of service is in the favor to build a larger facility. Second, a facility implemented with both MDM and SDM achieves the highest quality of service at a given cost, i.e. the "MDM and SDM" scenario has Pareto optimality to any other scenario in terms of cost and quality of service. Implementing no demand management has the poorest quality of service at a given cost. It is interesting that at a high service quality, the SDM scenario and MDM scenario have similar costs and service qualities. This means that the system operator may choose any of the two strategies to enjoy a similar cost reduction at high service quality. When it is difficult to reschedule EV charging sessions due to issues in driver compliance [24] and uncertain mobility demands, a larger ESS can be installed to result in a similar cost reduction. The capital investment of ESS (SDM) poses a solution to potential issues in operational investment of rescheduling EV charging (MDM). Also, if it is challenging to install ESS units (SDM) for instance due to limited physical space, rescheduling EV charging (MDM) can result in a similar cost reduction.

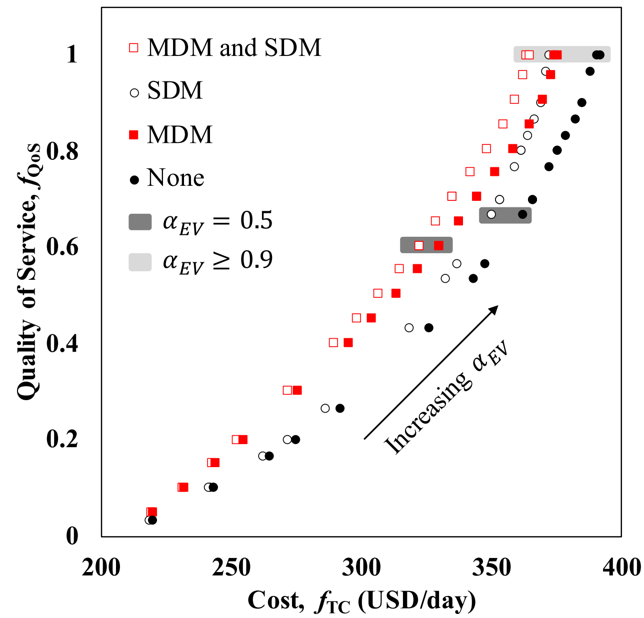


Fig. 7. Pareto curves of cost and quality of service.

In addition to the finding above, Fig. 7 also exemplifies how the proposed algorithm can help the facility planner to finalize the facility size by selecting the level of significance in charging demand α_{EV}. With the figure's visualization of facility performance, the facility operator can choose the level of significance that best suits her business needs. For instance, it is possible that a charging facility is in high competition with neighboring facilities and the operator desires an expensive but a high-quality facility. The facility operator may choose a sizing result with a high level of significance that corresponds to a desired level of service quality and cost.

Also, we see that the finding from Section 6.1 agrees with the results in Fig. 7, i.e., a robust facility builds a larger charging capacity, increasing the quality of service and the cost. Please refer to Table 2, which supplements Fig. 7. For each demand-management scenario, the robust sizing with $\alpha_{EV} = 0.95$ results in more chargers and larger f_{QoS} and f_{TC} than the baseline sizing approximated with $\alpha_{EV} = 0.5$. Therefore, Fig. 7 show the results with $\alpha_{EV} = 0.95$ to be higher in f_{QoS} and f_{TC} than the results with $\alpha_{EV} = 0.5$ in Fig. 7. Note that for all scenarios and sizing models, the optimal solutions produce the ESS units to be built at the maximum limit, $b_{opt} = b_{max}$, where $b_{max} = 2$ for cases without SDM and $b_{max} = 10$ for cases with SDM.

To further explore how SDM and MDM reduce the cost, sample power trajectories over a day are analyzed; refer to Fig. 8. The four columns show the trajectories for the scenarios of "None", "SDM", "MDM", and "SDM and MDM" as explained above, respectively. The top figures show the input data of EV charging demand for planning, indicated by $P_{EV,test,j}(\tau)$. For scenarios with MDM, the charging demand has a reduced peak power but same total energy. Since this figure shows robust facilities planned with $\alpha_{EV} = 0.95$, almost all EV charging demands are met, indicated by coinciding lines of $P_{EV,test,j}(\tau)$ and $P_{EV,j}(\tau)$. The bottom figures show trajectories of operation power.

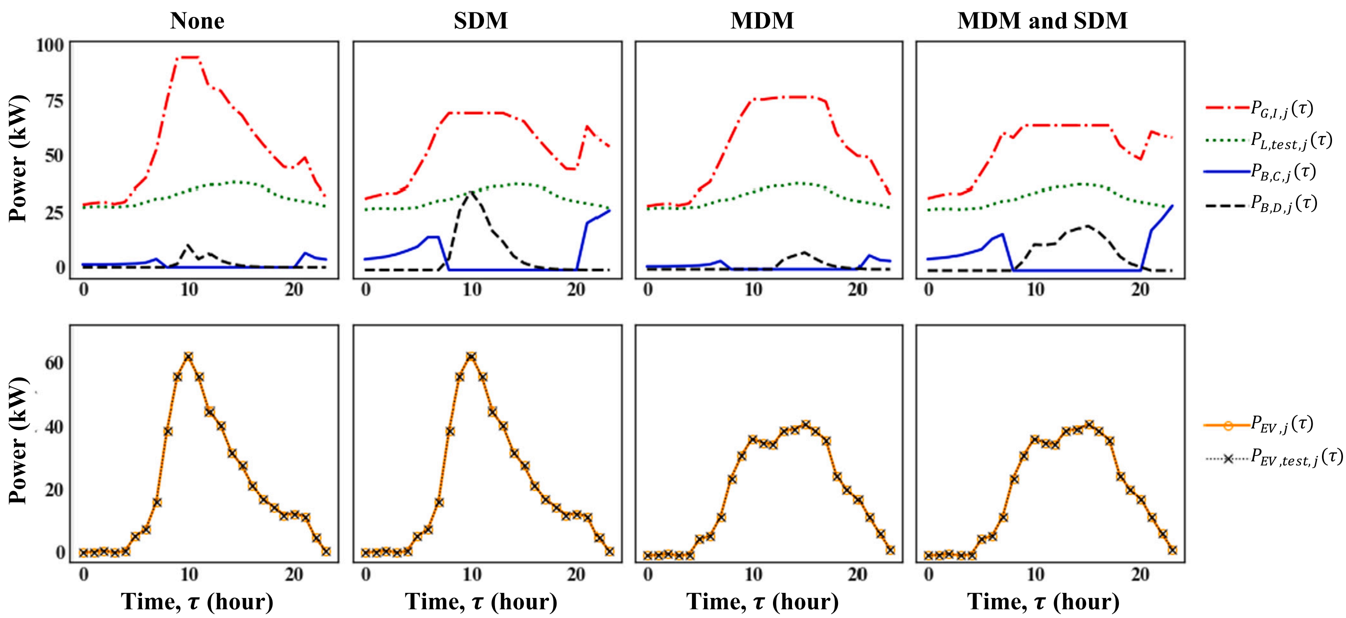


Fig. 8. Sample operation trajectory with mobile and stationary demand management ($\alpha_{EV} = 0.95$).

Table 2
Baseline and robust sizing results with stationary and mobile demand management strategies.

Item	Sizing	Demand management scenario			
		None	MDM	SDM	MDM and SDM
n_{opt}	B	21	12	21	12
	R	32	21	32	21
[a] b_{opt}	B	2	2	10	10
	R	2	2	10	10
f_{QoS}	B	0.7	0.6	0.7	0.6
	R	1.0	1.0	1.0	1.0
f_{TC} ($/day)	B	365.5	329.5	352.8	321.8
	R	390.0	373.9	372.4	362.9

B: Baseline sizing approximated with $\alpha_{EV} = 0.5$.
R: Robust sizing with $\alpha_{EV} = 0.95$.
[a]The optimal solutions produce b_{opt} at the maximum limit, b_{max} for all results ($b_{max} = 2$ without SDM and $b_{max} = 10$ with SDM).

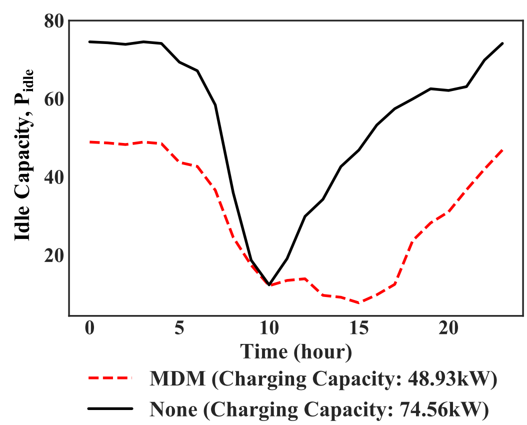


Fig. 9. Efficient use of charger capacity with MDM.

Compared to the scenarios without any demand management ("None"), both SDM and MDM similarly reduce the peak of grid import power (shown with $P_{G,I,j}(\tau)$). The scenario with SDM shows that the grid import peak is reduced by discharging the ESS, shown with $P_{B,D,j}(\tau)$. The scenario with MDM shows that the grid import peak is reduced by flattening the peak of EV charging demand, shown with $P_{EV,test,j}(\tau)$ on the top. Although the total energy of grid import is the same, both SDM and MDM reduce the demand charge by reducing the peak power import from the grid. Moreover, both SDM and MDM avoid high Time-of-Use tariff and reduce the energy cost by discharging the ESS energy or removing the charging sessions, respectively. Although SDM and MDM use inherently different mechanisms, they both reduce demand charge and energy cost and result in similar cost reductions as seen in Fig. 7. Note that the last column in Fig. 8 shows that implementing both SDM and MDM decreases the grid import peak the most, reducing the cost the most.

In addition, we find that a facility with MDM uses the chargers more efficiently than without MDM, which is intuitive as they satisfy the charging demand with less number of chargers. Fig. 9 shows sample trajectories of the charging capacity sitting idle without charging EVs as $P_{idle}(\tau) = n_{opt} P_{EV,R} - P_{EV}(\tau)$. The solid line is the idle capacity without MDM ("None") and the dotted line shows one with MDM. The facility without MDM has a larger charging capacity (74.56 kW = $P_{EV,R} \cdot 32$ chargers) than a facility without MDM (48.93 kW = $P_{EV,R} \cdot 21$ chargers), where we assumed $P_{EV,R}$ = 2.33 kW. However, the facility without MDM uses its capacity only for a short period of time and most capacity is idle for a longer period of time, compared to the facility with MDM.

7. Conclusion

To increase the market adoption of electric vehicles, it is critical to plan an EV charging facility that provides energy to EVs at a low cost with high quality of service. An EV charging facility can be planned with a larger capacity for high quality of service; however, this increases cost. To overcome this trade-off between the cost and quality of service, We propose a solution to plan an EV charging facility that achieves high quality of service at a reduced cost. This paper proposes a robust optimization model to minimize the cost and guarantee high quality of service. To reduce the cost further, two strategies of demand management are explored - namely Stationary Demand Management (installing ESS) and Mobile Demand Management (rescheduling EV charging sessions).

The findings of this paper are highlighted as follows. The proposed robust model for facility sizing guarantees high quality of service in charging EVs at a minimal cost. A facility with demand management strategies achieves high quality of service but at a lower cost, achieving Pareto optimality to a facility without demand management strategies. A facility with either ESS units or rescheduled EV charging demand can reduce the cost similarly at high quality of service. If it is challenging to reschedule the EV charging sessions in practice, the system operator can install a larger ESS to enjoy a similar cost reduction to rescheduling the charging demand. Similarly, if it is technically difficult to install an ESS, the facility operator can reschedule the EV charging sessions instead.

To improve this research further, the planning and operation simulation models can be modified to consider the EV charging demand in individual vehicle level, instead of an aggregate level. For instance, we can model the queuing process of EVs arriving, waiting for an available charger, charging, and leaving. This may optimize the number of chargers more accurately. Also, the analysis on demand management strategies can be more comprehensive. For the impact of SDM on the facility, we explored only two values for the maximum ESS units to be built $b_{\max} = [2, 10]$. However, it is possible that the cost does not decrease further with an ESS sizing above a certain level and this cut-off point for the diminishing return may depend on how the EVs shift their charging (MDM) [12]. Future research can explore the impact of SDM on the facility sizing in more detail by experimenting various values of $b_{\max}$.

For MDM, we assume perfect success of rescheduling EV charging sessions. In reality, MDM can have numerous challenges to reschedule with issues in compliance, awareness, uncertainty, and incentives. In addition, rescheduling of charging sessions may influence the facility performance. Rescheduling EV charging sessions can be modeled as a coupled problem with the facility planning problem for better rescheduling, facility sizing, and operation. Therefore, the effect of SDM and MDM on the facility must be thoroughly investigated for optimal and practical application. Other possible improvements on the planning model include the consideration of ESS degradation, maintenance costs of the facility, and various charger models with different charging power rates.

CRediT authorship contribution statement

Soomin Woo: Conceptualization, Methodology, Software, Validation, Formal analysis, Investigation, Data curation, Writing, Visualization. **Sangjae Bae:** Writing - review and editing, Visualization. **Scott J. Moura:** Supervision, Writing - review and editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgments

This work was funded in part by the National Science Foundation within the Division of Industrial Innovation & Partnerships under Grant 1951197.

References

[1] Fast facts U.S.transportation sector greenhouse gas emissions 1990-2017. Tech. rep., United States Environmental Protection Agency; 2019, URL https://nepis.epa.gov/Exe/ZyPDF.cgi?Dockey=P100WUHR.pdf.

[2] Hall D, Lutsey N. Emerging best practices for electric vehicle charging infrastructure. 2017, URL https://theicct.org/sites/default/files/publications/EV-charging-best-practices_ICCT-white-paper_04102017_vF.pdf.

[3] Dixon J, Andersen PB, Bell K, Træholt C. On the ease of being green: An investigation of the inconvenience of electric vehicle charging. Appl Energy 2020;258:114090. http://dx.doi.org/10.1016/j.apenergy.2019.114090.

[4] Bedir A, Crisostomo N, andEric Wood JA, Rames C. California plug-in electric vehicle infrastructure projections: 2017- 2025 (Report). Tech. rep., California Energy Commission; 2018, URL https://www.nrel.gov/docs/fy18osti/70893.pdf.

[5] Yuan Q, Hao W, Su H, Bing G, Gui X, Safikhani A. Investigation on range anxiety and safety buffer of battery electric vehicle drivers. J Adv Transp 2018;2018:1–11. http://dx.doi.org/10.1155/2018/8301209.

[6] Zhou B, Chen G, Song Q, Dong ZY. Robust chance-constrained programming approach for the planning of fast-charging stations in electrified transportation networks. Appl Energy 2020;262:114480. http://dx.doi.org/10.1016/j.apenergy.2019.114480.

[7] Davidov S, Pantoš M. Planning of electric vehicle infrastructure based on charging reliability and quality of service. Energy 2017;118:1156–67. http://dx.doi.org/10.1016/j.energy.2016.10.142.

[8] Graber G, Calderaro V, Mancarella P, Galdi V. Two-stage stochastic sizing and packetized energy scheduling of BEV charging stations with quality of service constraints. Appl Energy 2020;260:114262. http://dx.doi.org/10.1016/j.apenergy.2019.114262.

[9] Zeng T, Zhang H, Moura S. Solving overstay and stochasticity in PEV charging station planning with real data. IEEE Trans Ind Inform 2020;16(5):3504–14. http://dx.doi.org/10.1109/tii.2019.2955997.

[10] Zhang H, Hu Z, Xu Z, Song Y. An integrated planning framework for different types of PEV charging facilities in urban area. IEEE Trans Smart Grid 2016;7(5):2273–84. http://dx.doi.org/10.1109/tsg.2015.2436069.

[11] Chen H, Hu Z, Luo H, Qin J, Rajagopal R, Zhang H. Design and planning of a multiple-charger multiple-port charging system for PEV charging station. IEEE Trans Smart Grid 2019;10(1):173–83. http://dx.doi.org/10.1109/tsg.2017.2735636.

[12] Haupt L, Schöpf M, Wederhake L, Weibelzahl M. The influence of electric vehicle charging strategies on the sizing of electrical energy storage systems in charging hub microgrids. Appl Energy 2020;273:115231. http://dx.doi.org/10.1016/j.apenergy.2020.115231.

[13] Ding H, Hu Z, Song Y. Value of the energy storage system in an electric bus fast charging station. Appl Energy 2015;157:630–9. http://dx.doi.org/10.1016/j.apenergy.2015.01.058.

[14] Zhang H, Hu Z, Xu Z, Song Y. Optimal planning of PEV charging station with single output multiple cables charging spots. IEEE Trans Smart Grid 2017;8(5):2119–28. http://dx.doi.org/10.1109/tsg.2016.2517026.

[15] Lee ZJ, Lee G, Lee T, Jin C, Lee R, Low Z, et al. Adaptive charging networks: A framework for smart electric vehicle charging. 2020, arXiv:2012.02636. URL https://arxiv.org/pdf/2012.02636.pdf.

[16] Daneshvar M, Mohammadi-ivatloo B, Asadi S, Zare K, Anvari-Moghaddam A. Optimal day-ahead scheduling of the renewable based energy hubs considering demand side energy management. In: 2019 international conference on smart energy systems and technologies (SEST). IEEE; 2019, http://dx.doi.org/10.1109/sest.2019.8849131.

[17] Van Ackooij W, Zorgati R, Henrion R, Möller A. Chance constrained programming and its applications to energy management. In: Stochastic optimization—seeing the optimal for the uncertain. Rijeka: InTech; 2011, p. 291–320.

[18] Milan C, Stadler M, Cardoso G, Mashayekh S. Modeling of non-linear CHP efficiency curves in distributed energy systems. Appl Energy 2015;148:334–47. http://dx.doi.org/10.1016/j.apenergy.2015.03.053.

[19] Apostolaki-Iosifidou E, Woo S, Pruckner M, Lipman T. Electric vehicle charge management for lowering costs and environmental impact. In: 7th IEEE conference on technologies for sustainability (SusTech2020). 2020.

[20] Taylor TN, Schwarz PM. The long-run effects of a time-of-use demand charge. RAND J Econ 1990;21(3):431. http://dx.doi.org/10.2307/2555618.

[21] Lee ZJ, Li T, Low SH. ACN-Data: Analysis and applications of an open EV charging dataset. In: Proceedings of the tenth international conference on future energy systems, e-Energy '19. 2019.

[22] OpenEI. Long-term electricity and gas consumption for LBNL Building 74. URL https://openei.org/datasets/dataset/lbnl-building-74.

[23] PG&E. Time-of-use rates charts. URL https://www.pge.com/en_US/business/rate-plans/rate-plans/time-of-use/time-of-use.page.

[24] Daina N, Sivakumar A, Polak JW. Electric vehicle charging choices: Modelling and implications for smart charging services. Transp Res C 2017;81:36–56. http://dx.doi.org/10.1016/j.trc.2017.05.006.