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Preference-aware Planning and Operations of Electric Vehicle Charging Clusters: A Data-Driven Prescriptive Framework

*Special Interest Group on Green Information Systems SIGGreen
Pre-ICIS 2021 Workshop*

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Introduction

By 2030 up to 130M fully electric vehicles (EV) are expected to share the roads with the traditional vehicle fleet (IEA 2020). To facilitate this growth and to drive adoption, adequate charging infrastructure needs to be provisioned that accommodates existing user behavior and driving patterns (Avci et al. 2015). Currently, the preeminent charging option – for lack of other viable opportunities – is charging from home (Hoover et al. 2021). As more and more non-homeowners adopt EVs and as commercial fleets are electrified, charging opportunities at the workplace, at popular destinations such as supermarkets and at fleet depots will be needed (Hoover et al. 2021; Jun and Meintz 2018; Lee et al. 2019). We refer to these charging hubs as EV Charging Clusters (EVCCs). With a growing proportion of future charging requests expected to take place in such locally concentrated EVCCs, the challenge of planning, operating and integrating these sites becomes important. We focus here on the decision problem of an EVCC owner/operator who wishes to provide charging facilities and services to a user base with an increasing share of EVs. Our research reveals that by leveraging real-world consumer preference data, by allowing for parallel use of charging equipment and by approaching the EVCC planning challenge from an integrated perspective, much better investment decisions can be achieved. The degree to which the full flexibility of a parked EVs can be exploited during charging depends not only on the preferences of the underlying user populations, but also on the layout and size of the installed on-site charging infrastructure (Ferguson et al. 2018). A complex system with three-way interdependencies between preferences, operational decisions and infrastructure investment emerges. We address these complexities by formulating an integrated decision support system that jointly derives optimal investment and operations decisions over the planning horizon against detailed preference models. Our work makes a number of contributions. First, we use two large empirical parking and charging datasets (>3.8M transactions) to model behavior in unprecedented detail. Second, we use this data as input into a novel integrated decision framework that provides optimal solution to the investment and operations decision. Our optimization model is the first to consider parallel use of charging infrastructure. Third, we explore the impact of different user populations on the sizing and operations decisions of EVCCs. We show that different mixes of parker types may require very different charging infrastructure and provide evidence for the need to incorporate consumer modeling into the EVCC investment decision. In sum, we contribute an IS artifact to support the electric vehicle transition and respond to our community’s call for impactful IS research that addresses grand challenges. The remainder of this paper is structured as follows: We first discuss the literature relevant to this study. We proceed with a description of our research framework. We then present our model followed by an analysis of experimental results. We end with a discussion and outlook.

Related Work

We position our work broadly within the extant research stream of Green IS (Watson et al. 2010). Information systems have been shown to promote sustainable practicing by consumers, to enable smart electricity grids or assist green policy design. Green IS has also been embraced by the design science (DS) community (Rai 2017). DS researchers have brought forward numerous actionable IS artifacts targeted at solving pressing sustainability issues. Examples that are broadly related to our work include decision support systems for real-time electric vehicle charging on parking lots operations (Babic et al. 2018), positioning on-street charging stations in a city based on real-world movement data (Wagner et al. 2014), and balancing shared vehicle fleets (Schroer et al. 2019). Our research contributes to this stream by focusing on EV integration and adoption. We propose a prescriptive IS framework for the problem of preference-based EV infrastructure provisioning at large-scale parking facilities. Our contribution is best classified as belonging to the computational and optimization genre of DS as described in Rai 2017. We utilize both machine learning techniques and mathematical programming, thus drawing from both genres.

Literature on planning and operations of clustered EV charging infrastructure also informs this research. EV charging operations environments range from fully distributed on-street charging and private home charging to charging in large-scale parking lots/depots (i.e., EVCCs). We focus here on research related to the latter application case. In line with the growing acknowledgement of the importance of EVCCs and charging hubs to drive EV adoption (Hoover et al. 2021; Huang and Zhou 2015), academic interest in the topic has intensified. We find that a substantial body of work has developed particularly on topics related to charge management of EVCCs. Early examples include Huang and Zhou 2015 who develop a mixed-integer optimization framework for workplace charging strategies taking into account different eligibility levels and Wu et al. 2017 who propose a two-stage energy management framework for office buildings with workplace EV charging and renewable energy. Nunes et al. 2016 investigate how charging processes can best be coordinated to use parking lots for EV solar-charging. Ferguson et al. 2018 propose an integrated load management approach to optimize EV charging processes for minimum cost taking into account the building base load and PV generation. Finally, Lee et al. 2019 explore several optimization-driven approaches to operational issues in charging hubs. Planning of EVCCs has received somewhat less attention. This may be surprising given the strong relationship between sizing and operations meaning that both aspects should (ideally) be considered jointly. Most extant research resolves the ensuing complexity by using simulation-based approaches. For example, in Kazemi et al. 2016 the authors use a genetic search algorithm on top of an EVCC simulation to derive the optimal size of an EV parking lot. Babic et al. 2018 also use a greedy search over a simulation of a parking lot to derive optimal infrastructure decisions. Li et al. 2020 propose a mathematical programming framework for joint optimization of both size and operations of a small-scale, 100-vehicle EV-capable parking lot. Yet, they utilize highly simplified, deterministic consumer preference assumptions of a single EVCC type and do not consider parallel charging, which adds significant complexity. In a simulation study, Ferguson et al. 2018 show that parallel charging significantly reduces infrastructure requirement while achieving similar service level.

Finally, we review approaches to modelling user behavior. From an EVCC operations perspective three user-level preference inputs are required: time of arrival, required energy and actual time of departure. These parameters define the flexibility with which an EV can be charged (Nakahira et al. 2017). We find that extant research either fully neglects the stochasticity in user preferences by assuming recurring population-level usage patterns (e.g., Li et al. 2020) or makes naive distributional assumptions, e.g., on the size of batteries or the state of charge upon entry from which random draws are taken per each simulation run (Uhrig et al. 2015). Only a handful of studies have access to real-world charging behavior (e.g., Ferguson et al. 2018; Lee et al. 2019). Their charging data, however, only captures served charging demand which is constrained by the on-site charging infrastructure. Consequently, such datasets – on their own – are not suitable for sizing exercises. In sum, our work addresses several important gaps in the charging hub literature. We are the first to use detailed preference modeling on an extensive set of real-world parking and charging data to ensure preference-aware sizing. In doing so we explore the sensitivity of planning decisions to changes in user preferences, a point that has been neglected by existing work. Our model also allows for parallel use of charging infrastructure which significantly boosts performance at the expense of higher operational complexity. Our novel optimization approach addresses this complexity. Our work also

has important societal and sustainability implications.

Model

We define an EVCC as an EV charging-capable parking lot, depot or garage that will typically be attached to an existing building. Both the building and the EVCC receive power from the same grid connection point.

EVCC planning and operations involves two interrelated sets of decisions: the *Investment Decision* and the *Operations Decision*. The first entails the choices of how many units of EV supply equipment (EVSEs) to acquire ($\sum_k x_k$), how many connectors to install per each EVSE ($\sum_i y_{k,i}$) and whether to upgrade the existing grid connection capacity (P^+). The second decision centers on the choice of charging and vehicle routing strategy. The initial assignment ($\omega_{k,j}$) of a vehicle to a specific connector has future implications for the charging rate ($\psi_{k,j,t}$) that is available to that vehicle and other vehicles now and in the future.

Both sets of decisions are influenced by cost data. Naturally, equipment costs ($c^{grid}, c^{EVSE}, c^{Plug}$) constitute an important factor in the investment decision. Additionally, operating cost (cost of energy T_t^e and grid usage T^c) are of relevance in both the planning and operations of the EVCC. Finally, *User Preferences* are a key determinant of the infrastructure and operations of an EVCC. As discussed, three main inputs are important here: (1) time of arrival per vehicle (A_j), (2) duration of stay (δ_j) and (3) requested energy (e_j^d). We assume here that users provide these inputs upon entry into the EVCC (Lee et al. 2019). The parameters determine how flexibly the vehicle can be charged. Taken together EVCC planning and operations decisions result in investment costs (C^Φ) and recurring operating costs (C^Ω) that are required to fulfill the EVCC’s target service level (η^s).

We now lay out our two-stage prescriptive EVCC planning and operations model. Stage I implements a preference learning routine which extracts *User Preferences* from empirical data. In Stage II we derive *Investment Decisions* under the assumption of optimal *Operations Decisions* within a mathematical programming framework. Table 1 provides an overview of notation.

Stage I: Parking and Charging User Preference Learning

User preferences (of an individual j) in an EVCC context are described by the three-dimensional vector $v_j = (A_j, \delta_j, e_j^d)$. We start by building a model of current archetypical parking patterns, thus focusing on A_j and δ_j . To identify parker archetypes we employ clustering, an unsupervised machine learning technique for which we leverage a unique proprietary dataset of parking events. The dataset was provided by a major European real-estate investor and includes parking transactions from seven large-scale parking garages (capacities range from 275 to 2200 parking spots). A mix of workplace, inner-city, and shopping center facilities is available. Per each facility we have transaction-level parking data, meaning each row in our dataset represents one parking event j with corresponding arrival and departure preference information. Individual users cannot be identified due to privacy reasons. We use a full year of data to capture daily, weekly and yearly seasonality. 2019 is chosen as reference year to filter out pandemic-related effects. In total, our data comprises 3.84M parking events.

We cluster parking events j based on A_j and δ_j , the two core parameters of interest at this modeling stage. To account for the circular nature of arrival time A_j , we create two circular features of the following form $A_j^{sin} = \sin(2\pi(A_j/24))$ and $A_j^{cos} = \cos(2\pi(A_j/24))$. This yields the following vector of clustering variables $v_j^{clust} = (A_j^{sin}, A_j^{cos}, \delta_j)$, which we normalize. Given the size of our dataset we limit our algorithm search to clustering algorithms that are sufficiently scalable. We run initial tests with three clustering algorithms: k-means++, a centroid-based algorithm, Gaussian Mixture Models (GMM) and BIRCH, a scalable density-based clustering algorithm. Overall, we find k-means++ to perform best in terms of runtime and stability. While GMM yields relatively similar results, BIRCH performs very poorly, yielding unstable and non-cohesive clusters suggesting that relative density may not be a good identifier of clusters for the given dataset. We thus focus on fine tuning k-means++. To identify good candidate choices for k , we perform extensive quantitative internal validity tests (elbow method, Calinski-Harabasz scores (Calinski and Harabasz 1974), silhouette analyses (Rousseeuw 1987)) and qualitative external validity checks (stakeholder interviews). These (unreported) tests suggest $k = 6$ to be the optimal choice. We assess cluster stability through cross-validation in which

Symbol	Description	Unit
Sets		
\mathcal{I}_k	Set of candidate connectors per EVSE $k \in \mathcal{K}$ and index i	set
\mathcal{J}	Set of unique EVs entering the EVCC during the planning horizon with index j	set
\mathcal{K}	Set of EV supply equipment (EVSE) candidates with index k	set
\mathcal{T}	Set of time periods in planning horizon with index t	set
\mathcal{T}_j	Set of time periods $t \in \mathcal{T}_j$ during which vehicle j remains in EVCC ($\mathcal{T}_j = [A_j, D_j]$)	set
Ξ	Set of decision variables $\Xi = \{x_k, y_{k,i}, P^+, \omega_{k,j}, \psi_{k,j,t}\}$	set
Parameters		
A_j	Arrival time of vehicle j	period
c^{Plug}	Cost per connector	USD
c^{EVSE}	Cost per EV supply equipment (EVSE) (i.e., charging station)	USD
c^{Grid}	Cost per kW of grid connection (i.e., transformer)	USD/kW
D_j	Departure time of vehicle j	period
δ_j	Duration of stay of vehicle j	hours
e_j^d	Total energy requested by vehicle j over duration of stay	kWh
η^s	Service level expressed as ratio of fulfilled vs. actual demand	ratio
H	Duration of a single period t	hours
l_t	Base load of attached facility (e.g., office building excl. EVCC) during period t	kW
l^*	Maximum expected base load of attached facility in month of period t	kW
P^{EVSE}	Maximum power per each EVSE	kW
P^{Grid}	Maximum existing power of grid connection	kW
S	Space limitation in number of parking spots	count
T^c	Cost of induced peak per period	USD/kW
T_t^e	Cost of energy in period t as per TOU tariff	USD/kWh
$U_{j,t}$	Indicator of whether vehicle j is present in the EVCC during period t	boolean
Variables		
C^Φ	Total normalized investment cost for the EVCC per planning horizon	USD
C^Ω	Total cost of operating the EVCC over the planning horizon	USD
$e_{j,t}^s$	Energy supplied to vehicle j during period t	kWh
p^*	Induced max peak attributable to EVCC operations during planning horizon	kW
p^+	Additionally required grid connection capacity that needs to be installed	kW
$\psi_{k,j,t}$	Energy supplied to vehicle j connected to EVSE k during period t	kWh
$w_{k,j}$	Indicator for whether a vehicle j is connected to EVSE $k \in \mathcal{K}$	boolean
x_k	Indicator for whether a charging station is installed at candidate location $k \in \mathcal{K}$	boolean
$y_{k,i}$	Indicator for whether a connector is installed at candidate point i of EVSE $k \in \mathcal{K}$	boolean

Table 1. Nomenclature

we iteratively perform 2-1 splits of the data and re-run k-means++ on the larger dataset, then use the fitted algorithm to predict the labels of the smaller (test) dataset. We find our clustering results to be stable with observations in the test set having the same label 99.14% ($\sigma = 0.51\%$, 100 replications) of the time. We also find that high quality clustering results can be obtained with just three weeks of data (95.28%, ($\sigma = 3.49\%$) accuracy). In Table 2 we summarize our results.

k	Name	Cluster Size		Characteristics (avg, std. in parentheses)	
		N	share	A_j	δ_j
1	<i>Business</i>	671,384	17.47%	7:26am (1.43h)	7.92h (2.73h)
2	<i>Morning Short</i>	1,279,646	33.30%	11:10am (1.33h)	2.12h (1.90h)
3	<i>Afternoon Short</i>	985,710	25.65%	3:03pm (1.00h)	1.73h (1.35h)
4	<i>Evening Short</i>	744,753	19.38%	6:17pm (1.84h)	1.47h (1.30h)
5	<i>Overnight</i>	129,273	3.36%	5:22 pm (4.01h)	15.84h (4.02h)
6	<i>Long-term</i>	32,241	0.84%	2:28pm (4.94h)	37.04h (6.70h)

Table 2. Cluster Results

In sum, we obtain six parker types that are supported both by internal criteria and real-world observation. The largest proportion of our dataset is made up of three short-term parker types (*Morning Short*, *Afternoon Short* and *Evening Short*). These users enter the parking lot in the morning, afternoon or evening respectively and typically stay for periods of 1-2 hours. We also observe a *Business* cluster, which comprises parking events that commence in the early morning (7:26am on average) and last for an average of 8 hours. k-means++ identified two additional segments comprising longer-term parking events. These are *Overnight* parkers, which enter the parking lot in the late afternoon and stay until the next morning (typically 15.8 hours on average) and *Long-term* parkers that stay for periods longer than 24h on average. We also look at the distribution of parker types across the different facilities. Three archetypical facilities can be identified: workplace, destination (supermarkets, malls, etc.) and mixed-use facilities (e.g., inner-city parking facility catering to workers, residents, shoppers and others) (see Figure 1). Understanding and quantifying the sensitivity of the charging infrastructure investment decision to the different compositions of the user base is a core objective of this research.

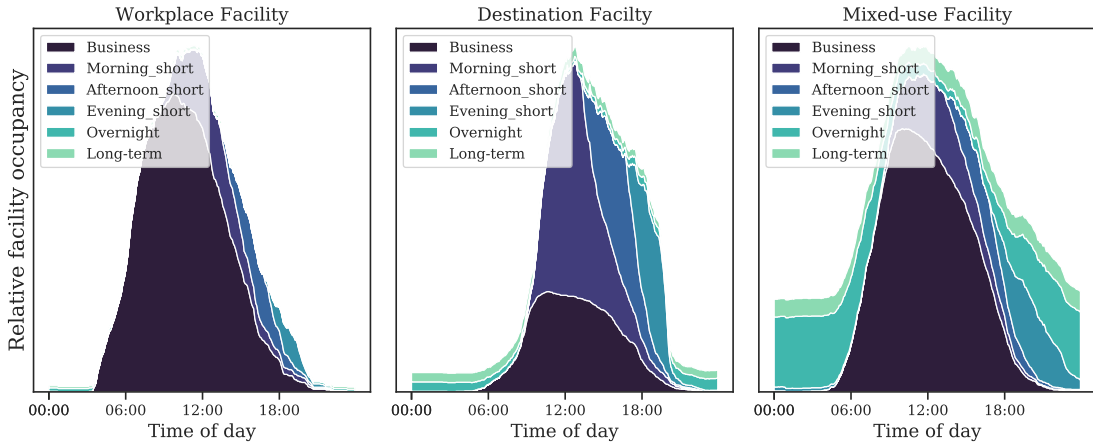


Figure 1. Daily occupation by parker type across three archetypical parking facilities

Finally, we focus on the third required preference input variable: the requested energy per vehicle e_j^d . We employ a novel and real-world dataset by Lee et al. 2019 containing >25,000 charging transactions for the year 2019. Per each charging transaction the full preference vector $v_j = (A_j, \delta_j, e_j^d)$ is available. We blend the charging data (which only contains served sessions that are constrained by the available infrastructure) with our parking dataset (which contains all parking requests per facility) by using techniques from collaborative filtering. We essentially train a prediction model on the labeled Lee et al. 2019 dataset and use the resulting model to predict charging demand in the parking dataset. Specifically, we train a kNN-model on the charging transaction dataset using the set of clustering variables from before as predictors and the requested energy in kWh as target. Cross-validation reveals $k=12$ neighbors to be a good value. We use the trained algorithm to predict charging demand per transaction in our unlabeled parking dataset.

Stage II: EVCC Investment and Operations Decision Algorithm

We formulate the Preference-aware EVCC Planning and Operations decision challenge as a feasibility problem which aims to satisfy all or a specified amount of total charging demand under rate, space, and total capacity constraints. The problem then becomes a cost minimization planning to jointly minimize the investment cost (C^Φ) and the operations cost (C^Ω) of the EVCC while ensuring a certain service level η^s . Formally, the objective can be expressed as follows:

$$\text{Min}_{\Xi} (C^\Phi(x_k, y_{k,i}, p^+) + C^\Omega(\omega_{k,j}, \psi_{k,j,t}, p^*)) \quad (1)$$

Where the investment cost ($C^\Phi(x_k, y_{k,i}, p^+) = c^{Grid}p^+ + \sum_{k \in \mathcal{K}} c^{EVSE}x_k + \sum_{k \in \mathcal{K}, i \in \mathcal{I}_k} c^{Plug}$) is the sum of the grid expansion cost (if any), the cost of EVSEs and the total cost of connectors (plugs). The operations

cost ($C^\Omega(\omega_{k,j}, \psi_{k,j,t}, p^*) = \sum_{j \in \mathcal{J}, t \in \mathcal{T}} T_t^e e_{j,t}^s + T^p p^*$) is defined as the sum of electricity costs plus demand charges arising from the induced peak load attributable to EVCC operations.

$$p^* \geq \frac{\sum_{j \in \mathcal{J}} e_{j,t}^s}{H} + l_t - l^* \quad \forall t \in \mathcal{T} \quad (2)$$

$$\sum_{t \in \mathcal{T}_j} e_{j,t}^s \geq \eta^s e_j^d \quad \forall j \in \mathcal{J} \quad (3)$$

$$\sum_{k \in \mathcal{K}} x_k, \quad \sum_{k \in \mathcal{K}, i \in \mathcal{I}_k} y_{k,i} \leq S \quad (4)$$

$$\frac{\sum_{j \in \mathcal{J}} e_{j,t}^s}{H} + l_t \leq P^{Grid} + p^+ \quad \forall t \in \mathcal{T} \quad (5)$$

$$\omega_{k,j} \leq x_k \quad \forall k \in \mathcal{K}, j \in \mathcal{J} \quad (6)$$

$$\sum_{k \in \mathcal{K}} \omega_{k,j} \leq 1 \quad \forall j \in \mathcal{J} \quad (7)$$

$$\sum_{j \in \mathcal{J}} \omega_{k,j} U_{j,t} \leq \sum_{i \in \mathcal{I}_k} y_{k,i} \quad \forall k \in \mathcal{K}, t \in \mathcal{T} \quad (8)$$

$$0 \leq \frac{\psi_{k,j,t}}{H} \leq \omega_{k,j} U_{j,t} P^{EVSE} \quad \forall k \in \mathcal{K}, j \in \mathcal{J}, t \in \mathcal{T} \quad (9)$$

$$\sum_{j \in \mathcal{J}} \frac{\psi_{k,j,t}}{H} \leq P^{EVSE} \quad \forall k \in \mathcal{K}, t \in \mathcal{T} \quad (10)$$

Demand charges are designed to incentivize efficient utilization of the grid (Gust et al. 2021) and are typically based on the monthly peak load induced by the facility. We therefore define p^* as the excess of the expected facility peak load l^* (excl. EVCC operations) for the month that contains t (Eq (2)). Service level is guaranteed by constraint (3), where, $e_{j,t}^s = \sum_{k \in \mathcal{K}} \psi_{k,j,t} \forall j \in \mathcal{J}, t \in \mathcal{T}_j$. Note that the summation is bounded by set \mathcal{T}_j , meaning that we consider the received energy at the departure time. Both EVSEs and connectors are restricted by the space constraints S of the facility (Eq (4)). At any time, our model ensures that the EVCC's base load and charging loads cannot exceed the total grid capacity (existing and extension), which is enforced by Constraint (5). In terms of vehicle routing and charging, we assign vehicles to chargers upon arrival (one-off decision) and periodically adjust the charging power over the duration of their visit. Constraint (6) allocates vehicle j to spot k only if it is equipped with an EVSE. Equation (7) ensures that each vehicle connects to at most one EVSE. The number of connected vehicles per each EVSE is at most equal to the sum of its connectors (Constraint (8)). Constraint (9) guarantees that vehicle j receives non-negative energy (bounded by the maximum power) from EVSE k only if it is connected to EVSE k . Finally, the total energy outflow for each EVSE must be less or equal to its rated power P^{EVSE} (Constraint (10)).

Numerical Experiments

We test our model through extensive numerical experimentation. For this, we draw directly on the compiled user preference data. To ease comparison, we limit the parking capacity per facility type in scope to 250 vehicles. We use a time-of-use (TOU) electricity tariff from Southern California Edison (SCE) (see Table 3). It also includes a demand charge, which is a monthly grid fee (T^c) of 15.48 USD per each kW of peak capacity demand within that month. Investment costs based on actual quotes made available to us by our industry partner, a major real estate developer. Grid connection cost c^{Grid} is 240 USD/kW, the cost of a 22-kW AC charging station (c^{EVSE}) is set to 4,500 USD per unit¹. By default, we consider parallel charging (up to four) in all simulations, where each additional connection costs $c^{Plug} = 250$ USD. Based on the building base load l_t , we let the peak base load $l^* = \max(l_t) = 450$ kW and the existing size of the grid connection (P^{Grid}) equal to $1.5l^*$.

¹A review of different received offers revealed that the cost driver of AC chargers was not the capacity per charger but the installation and cabling, thus it made sense to only consider the largest AC charger type available

	Summer (Jun - Sep)	Winter (all other months)
Super Off-Peak (8am-4pm)	0.08 USD/kWh	0.06 USD/kWh
On-Peak (4pm to 9pm)	0.23 USD/kWh	0.23 USD/kWh
Off-Peak (9pm-8am)	0.08 USD/kWh	0.08 USD/kWh

Table 3. Time-of-use tariff for large-scale EV charging customers (> 500 kW)

Results

Figure 2 shows the charging decisions (hourly energy consumption) for the three archetypical facility types for summer and winter days. Our model charges vehicles mostly during off-peak hours then, reduces consumption after 4pm during on-peak times.

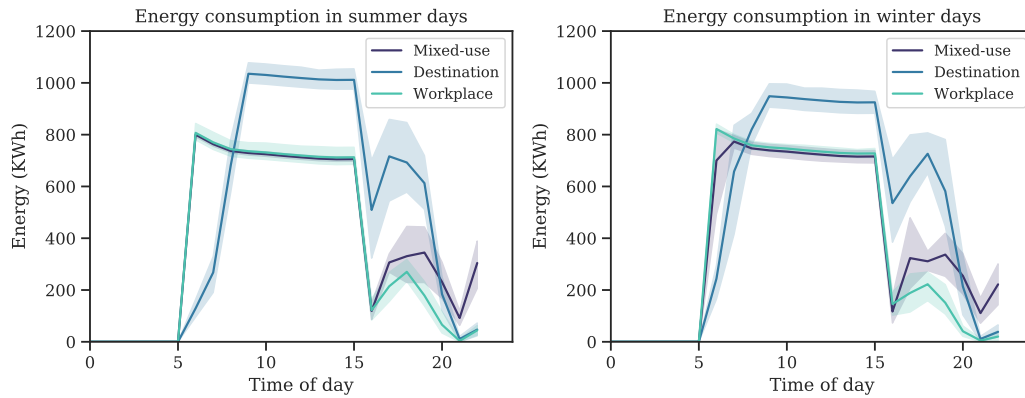


Figure 2. Hourly energy consumption in summer (left) and winter (right)

Workplace and mixed-use facilities have similar patterns, while the destination facility has higher and delayed peak energy consumption. Later arrivals and lower laxity require higher charge rates at later times in the day, but still on-peak hours are largely avoided. Comparing winter and summer days, workplace consumption in winter starts with a higher peak and the peak of destination facility reduces compared to summer. However, the marginal electricity price reduction in super off-peak hours (8am-4pm) does not change the load curve significantly. Investment decisions are depicted in Figure 3. Since our model guarantees a service level for all vehicles, it will install connectors equal to the peak number of parked vehicles. For all three facilities, there are more EVSEs than minimum to take advantage of low price hours. The optimal number of EVSEs (grid expansion) for the destination facility is significantly higher due to a large share of short parkers.

Our analysis of service level (not shown here) reveals that its reduction has a linear effect on the grid expansion, but does not necessarily lead to fewer chargers. There must be a minimum number of connectors (and accordingly chargers) to meet individual demands. Also, even with low service level it might be more cost effective to invest more on charging capacity to take advantage of off-peak energy tariffs. To analyse parallel charging, we test different number of connectors per EVSE. Parallel charging significantly increases asset utilization while requiring similar grid expansion. Also using dedicated chargers has no operational benefit, but requires more investment.

Finally, we benchmark our approach against a status quo investment framework. In a recent property development project we have reviewed, a rule-of-thumb approach was used by which 10% of parking spots were equipped with 22kW chargers to satisfy an anticipated medium-term EV adoption share of 10%. To simulate this naive benchmark we fix the number of EVSEs and connectors in our optimization and let the model determine optimal operational decisions and grid expansion. We then compare it with our optimal approach for a discrete range of adoption rates. The results are shown in Figure 4. Our EVCC approach out-

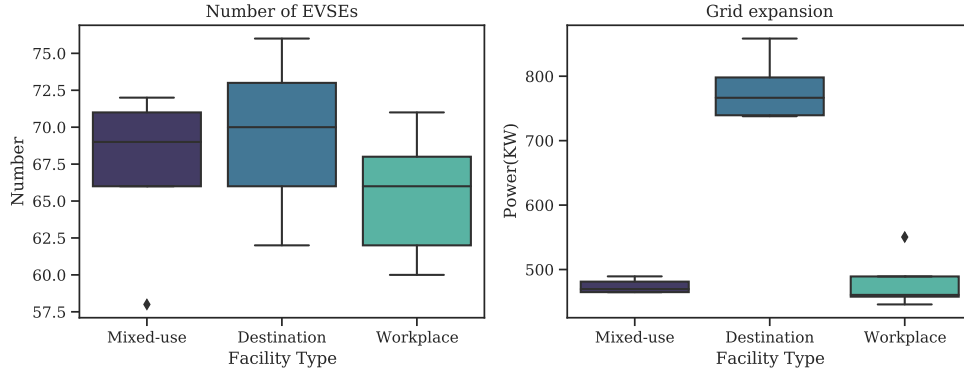


Figure 3. Number of EVSEs and required grid expansion for different facility types

performs in all scenarios in terms of the number of EVSEs (71% less on average) and the investment costs (63% less on average). These numbers might vary from one case to another according to users preferences. To sum up, our model significantly reduces investment costs by using parallel charging and optimal sizing. On the other hand, since we consider optimal operations for both approaches, the operational costs and grid expansion are very similar (i.e., no grid expansion and operational costs reduction using dedicated charges). It also shows that as EV adoption is gradual, the infrastructure expansion should also be gradual as well.

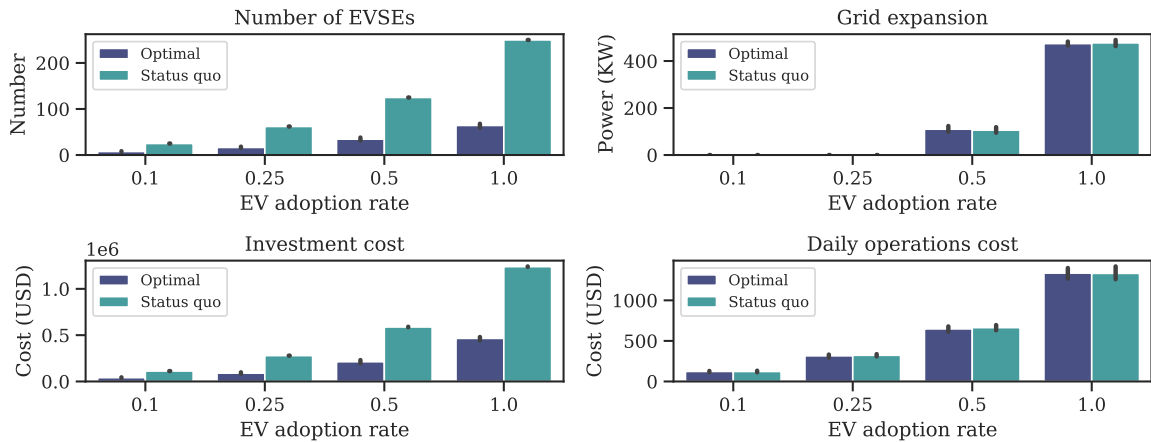


Figure 4. Sensitivity to adoption rate and comparison against status quo planning approach

Discussion

We contribute a Green IS artifact to address the urgent challenge of transport electrification. Beyond that, we make several important academic contributions. First, we develop a novel data-driven taxonomy of parker types along with an estimation of their future charging demand. While previous work had to rely on assumptions of user behavior or used highly-aggregated data from single homogeneous parking facilities, we leverage a unique dataset of parking transactions from diverse facilities, which we blend with another dataset of real-world observed charging demand to achieve empirically-grounded estimates of future charging behavior. Second, we propose a novel integrated modeling approach that simultaneously optimizes investment and operations decision. Previous work either focused on one of the two decision classes or used greedy simulation approaches. We derive globally optimal solutions. Third, we explore the impact of user population heterogeneity on the sizing and operations decisions of EVCCs. Specifically, we explore how differences in the compositions of the parker types impact charging infrastructure requirements. We find that

the EVCC investment decision is highly sensitive to changes in the user mix. Fourth, our work is also the first to consider parallel use of charging infrastructure for sizing charging clusters while ensuring optimal operations. We separately consider the charging station decision and the connection point decision. This assumption adds complexity at the operational level but we demonstrate in several experiments that it can significantly improve asset utilization versus a single-use setup. Our work is not without limitations which provide opportunities for future work. First, given our focus on the planning decision and its sensitivity to user behavior, several simplifying assumptions regarding operations were made. We ignore uncertainty in the arrival, departure and charging behavior of the user population and assume perfect foresight. While this is a common assumption for planning problems, the impact of real-world stochasticity remains to be explored. Such a problem could be cast into a dynamic programming framework which we aim to address in future work. Second, several important sensitivities and trade-off decisions remain unexplored in this research due to scope limitations. For example, it would be interesting to understand how small the grid connection capacity can be given some flexibility in user preferences. Similarly, it would be interesting to explore the trade-off between integrating behind-the-meter decentral storage and generation units (e.g, PV) and the need for grid connection expansion among other analyses. Finally, a dynamic view of the investment decision should be considered taking into account the dynamics of EV adoption, charging behaviour shifts, changes in installation costs and possible shifts in electricity and demand charges.

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