Transport Policy 149 (2024) 122–138

Contents lists available at ScienceDirect

Transport Policy

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

Managed residential electric vehicle charging minimizes electricity bills while meeting driver and community preferences☆

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ARTICLE INFO

Keywords:
Electric vehicle
Charging management
Electricity bills
Residential load

ABSTRACT

Transitions to electric vehicles (EV) are expected to increase electricity use in residences, where most tend to recharge. We develop a mathematical programming framework for shifting residential EV charging during low electricity pricing hours to minimize the additional electricity costs that a household incurs from charging their vehicle. The model also aims to meet additional household and their community preferences by adopting four secondary objectives: charging as soon as possible when the user arrives at home, charging as late as possible before the user leaves home, charging for valley filling and peak shaving of the residential load, and charging in a shared community hub by using a fast charging station. We analyze granular residential energy data from a sample of Austin households in 2018. We conduct an empirical analysis to compare households' electricity bills under four electricity pricing schemes, including flat rates and time-of-use rates, both with and without a separate meter for EV charging. Our findings indicate that if charging behaviors remain unchanged, installing a separate meter for EVs is more expensive than treating EVs as another residential plug load. However, under time-of-use EV charging tariffs, households should adjust their charging behaviors, as validated by our optimization model. Implementing all four secondary charging objectives successfully avoids the on-peak periods of the EV charging rate and reduces households' overall daily electricity costs by 38.87 % during the summer and by 44.3 % during the winter. Charging as soon as possible, charging as late as possible, and charging at a shared station provide drivers with increased flexibility. Charging as soon as possible and charging as late as possible lead to the lowest charger utilization, with the former having the longest charging stop time before home departure and the latter allowing for the longest charging start time upon home arrival. Charging at a shared station gives rise to the lowest share of charging time over dwell time. Charging for valley filling and peak shaving of the residential load offers less flexibility but has the advantage of flattening the load curve and mitigating high peak loads. This proves crucial in safeguarding the community's energy distribution infrastructure.

1. Introduction

Since the introduction of electric vehicles (EVs) in the U.S. automobile market, more than 2.4 million electric automobiles have been sold (California Energy Commission, 2022). Zero tailpipe emissions, improved energy efficiency, and low operating costs are some of the light-duty vehicle electrification benefits. The transition to EVs is expected to increase electricity use in residences, where most users tend to charge (Tal et al., 2020). As shown by Muratori (2018), even though the introduction of EVs barely increased the overall energy consumption at the household level, the shape of aggregate household electricity demand was affected due to uncoordinated EV charging. As a result, the peak load of the distribution transformers would increase, which could reduce their lifespan. Empirical insights show that the adoption of EV home-charging increases the grid load by 7%–14% during peak hours (Qiu et al., 2022). The absence of managed charging could be detrimental to such residential distribution infrastructure and result in cost increases for charging and maintenance (Szinai et al., 2020). In comparison, a controlled EV charging scheme could lower the grid's operating cost while achieving significant reductions in renewable resources curtailment (Dean and Kockelman, 2022). By integrating solar generation and avoiding charging at peak times, a managed

☆ This research was partially supported by the National Science Foundation, United States CAREER grant [CBET-2237881]. We also acknowledge the support provided by a Research Support Grant by the Office of Undergraduate Research at the University of Illinois Urbana-Champaign, United States.

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https://doi.org/10.1016/j.tranpol.2024.01.022
Received 11 May 2022; Received in revised form 24 June 2023; Accepted 25 January 2024
Available online 29 January 2024

charging scheme provides flexibility and minimized electricity costs for households.

To tackle household energy cost increases and efficiency concerns, while addressing potential grid load challenges, we propose managed EV charging schemes at the residential and community levels. Such schemes aim to minimize the cost incurred by an EV driver reflected in their residential electricity bill and associated with home EV charging while examining the impacts of coordination of charging at a community level to avoid severe grid impacts. This paper focuses on developing such managed charging frameworks to facilitate more efficient personal and community charging management and cheaper electricity bills at the household level for EV charging. The proposed charging schedule management shall benefit EV drivers by reducing charging-related electricity costs and the utilities by coordinating charging schedules at the community level.

While recently there have been a handful of pilot managed charging programs conducted in the U.S. that are primarily run by electric utilities, there is currently no unified policy or initiative in place to encourage or mandate managed charging at the community level. This is primarily due to the lack of common managed charging open protocols (Smart Electric Power Alliance, 2019). Nonetheless, the increasing interest from electric utilities in managed charging and the growing number of compatible charging and electricity infrastructure facilities ensure a promising future of managed charging schemes at a larger scale (Smart Electric Power Alliance, 2019).

The remainder of the paper is organized as follows. In Section 2, we summarize work related to clustering and travel pattern inference and literature on residential unmanaged and managed EV charging practices. Then, we give an overview of the contribution of our work. In Section 3, we use and analyze Pecan Street Inc.'s granular residential electricity load data of a sample of Austin, TX households in 2018 (Pecan Street Inc., 2020). In Section 4, based on the residential energy consumption and EV charging patterns of these households, as well as the rates provided by the local utility's tariff (Austin Energy, 2020), we compute their actual monthly and annual electricity costs for several billing scenarios. Section 5 presents a EV charging optimization framework that minimize energy consumption costs while adhering to traveling needs, power limits, battery capacity constraints, and charging flexibility preferences (i.e., AFAP, ALAP, peak-shaving and valley-filling, and shared DCFC station use). In Section 6, we obtain residential travel patterns through applying k-means clustering to real-world household energy consumption data from Pecan Street Inc. We then integrate these into the optimization models, enabling direct comparisons between unmanaged and managed EV charging profiles. Such data-driven analytics and comparisons offer insights into the benefits of EV charging flexibility and control.

2. Literature review

To characterize residential electricity usage and find the distinctive profiles between different seasons, a range of studies applied clustering techniques, particularly k-means, on energy load data (Rhodes et al., 2014; McLoughlin et al., 2015; Choksi et al., 2020; Nuchprayoon, 2014; Jessen et al., 2022; Amri et al., 2016; Okereke et al., 2023). The profiles of residential electricity usage can provide valuable information regarding the daily routines of households (Abreu et al., 2012; Costa and Matos, 2016). These may imply the travel patterns of a household that owns a vehicle, including departure and arrival times at residence and average energy demands associated with travel. Notably, studies (Movahedi et al., 2023; Zhang and Qian, 2018) have shed light on the role of electricity/energy consumption as a strong predictor for travel demand and pattern, while others (Sørensen et al., 2021) demonstrate that the charging behavior of EV owners is highly correlated with local traffic volumes, indicative of household travel patterns.

Several studies have explicitly focused on employing k-means clustering to investigate EV charging behaviors. Comprehensive survey of machine learning techniques applied to EV charging, highlight the popularity of k-means clustering for identifying distinct charging patterns (Shahriar et al., 2020). Other studies utilized k-means clustering to identify and analyze EV charging behaviors (Xydas et al., 2016; Zhang and Qian, 2018). Xydas et al. (2016) employ a similar k-means clustering approach to our paper but uses the Davies–Bouldin index for evaluation, while we utilize the Silhouette Score to determine the optimal cluster number. Furthermore, Zhang and Qian (2018) apply k-means clustering to a similar dataset sourced from Pecan Street Inc., affirming the applicability and relevance of this method for interpreting EV charging patterns. In our paper, the analysis of the travel patterns of households with EVs is integrated into the EV charging optimization modeling to gain insights and uncover real-world implications.

Building upon this body of literature, it is crucial to understand the underlying charging practices that shape EV users' behaviors. There have been a growing number of studies that have examined EV charging behaviors under unmanaged and managed charging practices. Unmanaged charging practices include charging "as fast as possible" (AFAP) (Flath et al., 2014; Yoon and Kang, 2017) and "as late as possible" (ALAP) (Flath et al., 2014). AFAP is an unsophisticated strategy to charge whenever possible. Once the vehicle is plugged in, it will be charged at the maximum power level till reaching the battery capacity. ALAP delays the driving availability of EVs by recommending charging as late as possible. Under ALAP, EVs will start charging at the latest time slot available and finish charging right before departure. Results show that AFAP charging typically takes place during times when grid loads are higher than average. Thus, AFAP results in higher peak loads and average costs. ALAP charging, corresponding to delayed charging, occurs during the late night or early morning hours, which leads to lower costs and peak loads relative to AFAP. It should be noted that these two charging practices are generally not considered in the context of managed charging. Rather, they simply serve as unmanaged charging strategies and are evaluated as heuristics to compare their effectiveness against managed charging practices.

On the other hand, managed charging practices are determined by setting the EV charging problem as a convex optimization one. A number of studies, including Flath et al. (2014), Yoon and Kang (2017), Kontou et al. (2017), Sioshansi (2012) and Wu et al. (2020), propose a charging strategy that minimizes the total charging cost. This strategy is typically formulated as a linear or mixed-integer program. These studies show that the minimum cost scheme has been effective in reducing the average charging cost under a time-of-use electricity tariff. Moreover, numerous studies (e.g., Yoon and Kang (2017), Wu et al. (2020), Ioakimidis et al. (2018) and Zhang et al. (2014)) have advocated for the practice of valley-filling and peak-shaving the electric grid load. This practice aims to enhance the stability of the electric grid load when EVs are integrated into the power system. A common method to formulate this practice is to construct a nonlinear programming model that minimizes the variance of the grid load. Results show that under such a charging practice, the optimal charging profile would become a flatter curve by shifting peak-hour charging to late nights or early mornings.

In addition, the concept of shared charging stations within charging hubs has emerged as an alternative approach to residential EV charging. These shared charging stations can not only provide incentives for prospective vehicle owners to purchase EVs but also help alleviate common challenges associated with EVs, such as range anxiety (Wood et al., 2018; Ouyang and Xu, 2022). Several studies (e.g., Huang and Zhou (2015) and Li et al. (2020)) develop optimization frameworks that aim to minimize the lifetime cost of shared charging stations and maximize the driving range of EVs in the setting of workplace charging. Results support that managed charging of shared charging stations can effectively decrease the cost of operations under time-of-use rates. Other researchers (e.g., Ucer et al. (2019) and Buckreus et al. (2021)), adopt simulation models to look specifically into direct current fast charging (DCFC), an increasingly popular choice for a shared charging station (Xie et al., 2018). While the high charging power of a DCFC station allows EV drivers to finish charging in a short period of time, a DCFC charging station is usually characterized by high peak load and low utilization, which could result in high capital and electricity costs compared to other power rates of shared charging stations (Muratori et al., 2019; Owens and Dwyer, 2015).

The existing literature on managing EV charging schedules has predominantly focused on minimum cost optimization without extensively exploring the impact of different charging preferences. This research gap motivated our study, which aims to address this limitation and shed light on the broader implications of managed charging schedules. Our work highlights the flexibility of managed charging schedules when they are designed to be responsive to real-world time-of-use electricity rates, considering not only cost optimization but also various secondary objectives.

To fill this important research gap, we examine the effects of different charging preferences on EV charging profiles and evaluate their performance against a set of comprehensive measures. By going beyond the traditional objective of cost minimization (Cheng and Kontou, 2023), our study explores how alternative charging strategies, such as charging AFAP, ALAP, peak-shaving and valley-filling, and shared DCFC station use, impact the charging patterns of EVs. We investigate how these preferences influence the temporal distribution of charging events, the peak charging power, the overall grid load, and the degree of flexibility available to EV drivers.

3. Data description

We use the Pecan Street dataset, which hosts one-minute residential energy use data for households that own and operate EVs in the year 2018 in Austin TX. The summation of the electricity use of all 9 households is shown in Fig. 1. For the dataset, the following hold:

- The solar power profile corresponds to power generation via photovoltaic arrays.
- The grid load profile with a positive y-value suggests drawing power from the electricity grid, while a negative value means feeding power generated by their solar panels to the grid. In Fig. 1, the grid load is negative when solar power reaches its peak value. It can be inferred that the negative value of grid load is due to solar power's net metering.
- The original charging profile with a positive value suggests that the EV is charging.

We focus on households' expenditure as reflected in their electricity bills in this research. The monthly electricity bills of households heavily depend on the electricity tariff offered by the utility service territory of the residence. We leverage the flat rate and the time-of-use electricity rate schedule from the City of Austin Fiscal Year 2021 Electric Tariff (see Table A.6 in Appendix). The flat rate schedule is currently implemented while the value-of-solar rate, time-of-use rate, and EV 360 charging rate schedules are pilot programs. Specifically, the time-of-use power supply charges (under the time-of-use rate schedule) can be used to substitute the power supply adjustment rates (under the flat rate schedule) "for a term of no less than 12 consecutive billing cycles" (Austin Energy, 2020). The time-of-use power supply charges for residential energy are different in summer and non-summer seasons, weekdays and weekends, and on-peak and off-peak hours. Similar variations hold for the EV 360 charging rates. Fig. 2 presents these cost functions. It should be noted that the off-peak rate for charging is \$0 because the pilot program intends to offer unlimited off-peak EV charging at home. Given that both the time-of-use power supply charges and PEV charging station charges lie entirely in off-peak hours during weekends and, thus, there is no price variation on weekends, this paper only focuses on the power supply charges on

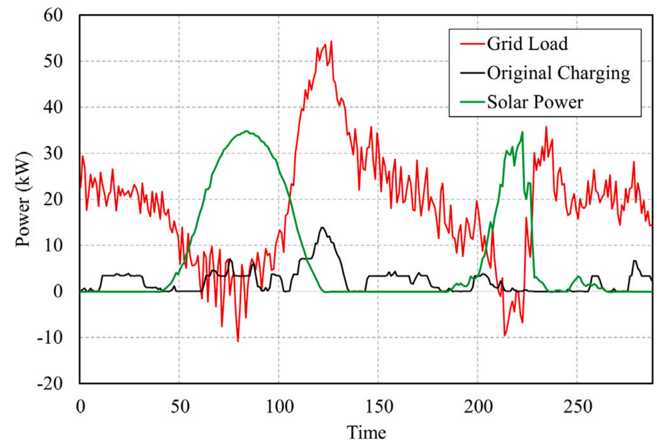

Fig. 1. Indicative grid load, solar power, and EV charging power profiles on two summer days for the households' sample.
Source: Pecan Street Inc. Dataport (Pecan Street Inc., 2020).

weekdays when formulating cost-minimizing optimization models for EV charging management that can make a difference. The metered kilowatt-hour output of the household's photovoltaic system multiplied by the value-of-solar rate can serve as credit applicable to offset the household's monthly electricity bill. Since the value-of-solar rate is constant and will not have an impact on the optimal charging profiles, solar credits are not considered in the optimization models.

A set of exogenous parameters related to EVs and charging power constraints are expected to impact charging and its electricity bill. Specifically, battery capacity is assumed 40 kWh, similar to a 2019 Nissan Leaf's. Note that the EV type discussed in this paper is limited to Battery Electric Vehicles (BEVs). The charging efficiency is set at 77% (U.S. Department of Energy, 2020). We also assume that the households install Level 2 charging equipment since EV owners commonly install such chargers at home (Lee et al., 2020). Level 2 charging with units operating at 30 Amps is able to deliver 7.2 kW of power (U.S. Department of Energy, 2021). While 7.2 kW charging power is the input parameter to our base scenario, we also consider scenarios under different charging powers. Therefore, optimal profiles with Level 2 charging operating at 16 Amps (3.3 kW) are compared with the base scenario in the sensitivity analysis section (Webasto, 2021). In addition, we consider DCFC for the shared charging scenario with one 50 kW port (Ucer et al., 2019). Endogenous parameters, such as the households' travel patterns, are estimated using Pecan Street power profile data. Both exogenous and endogenous parameters will serve as inputs to our optimization framework.

4. Empirical analysis results

Before formulating a managed charging model for minimizing household electricity costs, we are interested in calculating electricity bills for existing residential energy consumption with electric vehicles, under the new electricity rate plans. This analysis emphasizes the need to employ managed charging schemes since without controlled charging or charging behavior changes, household electricity bills will most likely increase. An example of a household electricity bill calculation based on the applicable utility rates in the Austin Electric Tariff is given in Table 1. The calculation is performed on an indicative summer month (June 2018) of a randomly selected household. During this month, the household's total energy consumption is 1604 kWh, and 199 kWh out of 1604 kWh is used for EV charging. 9.98% of EV charging takes place during on-peak hours and 10.87% of residential energy is consumed during on-peak hours. The 15-minute interval of maximum EV charging demand of the month is 3.42 kW.

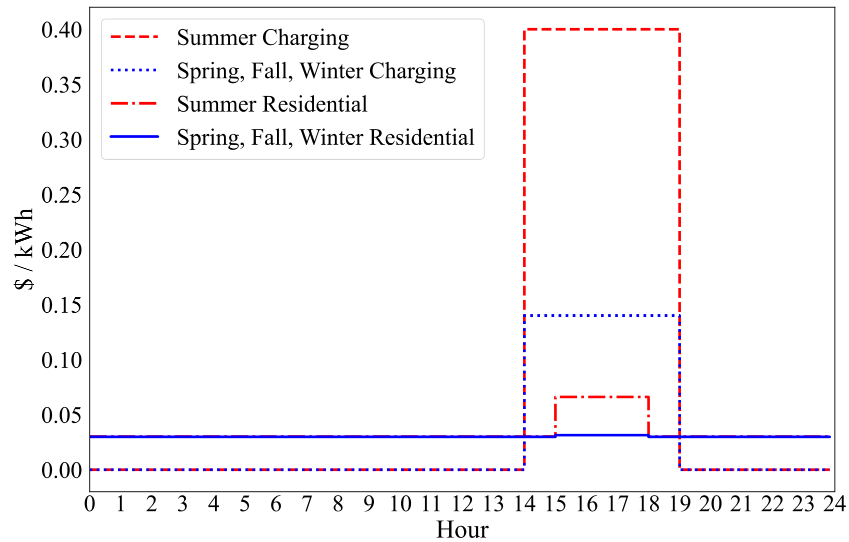

Fig. 2. Time-of-use cost functions (Austin Energy, 2020).

There are four pricing scenarios we take into consideration. The first is the default flat rate schedule when EV charging is considered as part of the residential loads. Only the total residential energy consumption matters in this scenario. The resulting total bill is only $175.67, the least among the four scenarios. The second scenario is the flat rate schedule when there is a separate meter installed for EV charging. The resulting total bill is $187.36, the second-largest among the four. The residential energy consumption (excluding EV charging) and the distribution of EV charging over the hours of the day are the determining factors of the total bill. The third scenario is the time-of-use rate schedule when EV charging is considered a part of the residential services. The resulting total bill is $180.75, around 3% higher than the default flat rate schedule. The time of residential electricity consumption directly affects the total bill. The last scenario is a time-of-use rate schedule when there is a separate meter for the EV charging station. The resulting total bill is $191.81, the most expensive of the four scenarios. Both the time-of-day variation of the residential energy consumption (excluding EV charging) and the EV charging time matter since billing is calculated based on two different time-of-use electricity cost functions.

The fact that the total bill is higher in the case of a separate EV charging meter can partly be ascribed to the $30 monthly basic charges. Nonetheless, even without this $30 basic charge, the total bills with a separate EV charging meter are still higher than those without a separate one. Would installing a separate EV charging meter lead to a higher bill? We argue that it will probably not. Without any behavioral changes or charging management strategies, 10% of the EV charging takes place during on-peak hours in this indicative example. In fact, the average percentage of on-peak hour EV charging for all households reaches 17.72% (Pecan Street Inc., 2020). Households can potentially shift their behavior and recharge during off-peak hours, thus cutting a major portion of their total bills.

We proceed with using Pecan Street household residential energy data under the four electricity tariff scenarios. Fig. 3 shows the simulated electricity billing results under these pricing scenarios in the year 2018 for the households with EVs. Installing a separate meter for EV is on average more expensive than including EV as part of the residential energy consumption. This result is expected since in 2018 households were charged based on a flat electricity rate schedule, and the bill was affected by the total energy consumed. In accordance with existing literature, residents are expected to adjust their EV charging behavior under a time-of-use EV charging rate (Qiu et al., 2022). We formulate a managed EV charging model in the following section anticipating a response to the hourly changes in electricity rates. The objective is to minimize the cost of electricity bills when a separate meter is installed for the EV charging station at home. Households would realize minimum cost and electricity when shifting their charging behavior under the time-of-use rate through our optimization framework.

5. Methodology

5.1. Problem description

Our analysis results shown in Section 4 suggest that despite that the households have the lowest electricity bill under the flat rate schedule, we set out to measure how much we can further reduce the households' EV charging electricity costs by shifting the EV electricity consumption to off-peak hours. This reduction would only be possible under a time-of-use rate schedule, which is a common rate scheme for EV charging today (Chakraborty et al., 2019). We intend to specifically investigate the case when a separate meter for EV charging is installed. The ultimate goal of our proposed computational process is to demonstrate charging savings that can be accrued through a managed charging protocol for EVs and the flexibility offered to meet additional management preferences. We set as our main goal the minimization of electricity cost. We make assumptions that are essential for determining modeling parameters associated with EV driving and charging operations, which are presented below.

- Once the EV driver arrives at home, the vehicle is available to be plugged in and charge.
- The energy needed for the next trip of each household is a parameter calculated based on the driver's next trip driving needs.
- Every household has only one EV.
- During each time of day, the charging power of an EV is a constant parameter (based on the assumed power level of the EV charger).
- Every household makes only one trip a day (e.g., commuting round trip) and only charges once at home.

The process is initiated by identifying the set of inputs, estimating parameters from Pecan Street data (Pecan Street Inc., 2020), and formulating the optimization framework that meets the electricity bill minimization objective. Fig. 4 is a graphic representation of the computational workflow.

The computational process is initiated by identifying classes of EV arrival and departure times to and from residences based on the residential power profile data. Then, under the assumed EV battery size

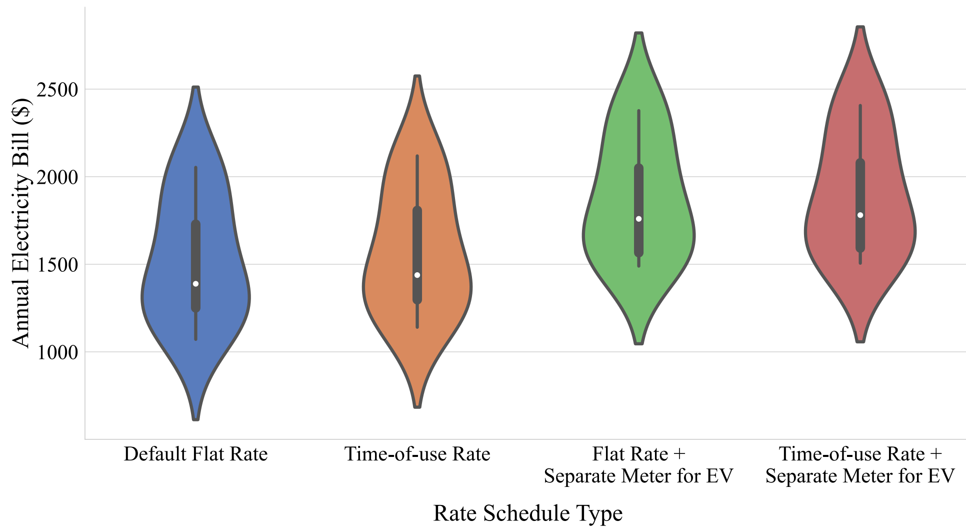

Fig. 3. Comparison of variation of annual household electricity bills, including EV charging, under four different electricity rate schemes.

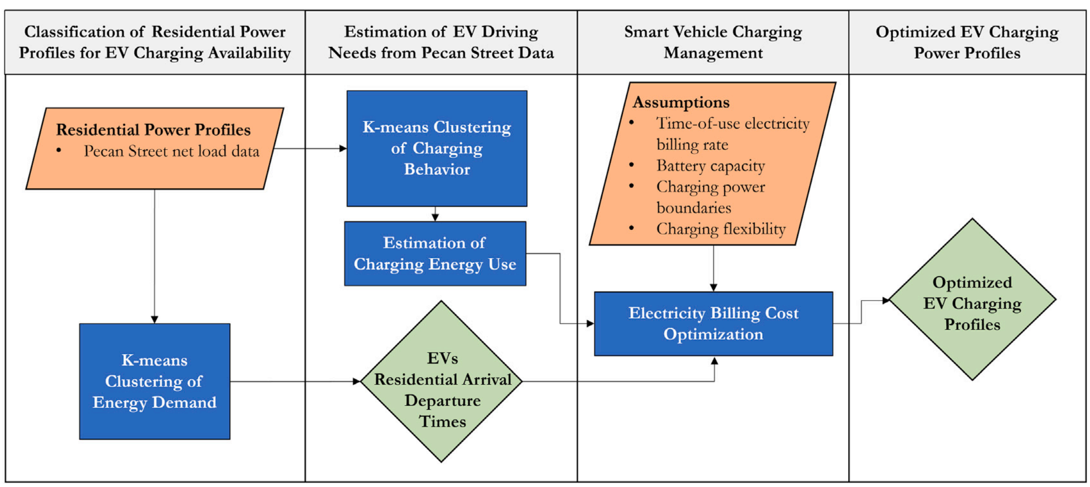

Fig. 4. Computational workflow of the presented analysis.

and charging efficiency parameters from the existing literature, Pecan Street power profile data are used to estimate the travel patterns of each household's EV through k-means clustering. The results from the aforementioned processes, along with the assumed power bounds, serve as parameters in the convex mathematical program that is formulated to minimize each household's electricity bill. The results show the centrally optimized EV charging profiles.

5.2. Clustering and travel pattern inference

To characterize the energy use of households, we first find the most representative daily total electricity demand profiles and daily EV charging profiles for each of the households with EVs through k-means clustering. Note that the days with no power consumption are dropped, and the raw 1-minute power data (both electricity demand and EV charging) are aggregated to 10-minute power data, which will later serve as an input to our optimization model. Then, the results of the two clustering are used to infer the households' arrival and departure times, and daily travel energy demand, respectively.

5.2.1. K-means clustering

The k-means clustering algorithm is implemented using the KMeans function in the scikit-learn Python library (Pedregosa et al., 2011) and follows the description in Hartigan and Wong (1979). We apply the algorithm on the daily profiles of both the total electricity demand and the EV charging demand for each household.

In the initial step, this algorithm selects k daily profiles (either the total electricity demand or the EV charging demand) as the initial cluster centroids. Specifically, we adopt the "greedy k-means++" initialization method to speed up convergence by making the initial cluster centroids more distant from each other (Arthur and Vassilvitskii, 2007)

Once the distances between each daily profile and the cluster centroids have been computed, we proceed to allocate each daily profile to a cluster based on its distance from the nearest centroid. Subsequently, the updated cluster centroids are determined by calculating the average of the daily profiles within each cluster. We continue this process iteratively until the distances between the daily profiles and their respective cluster centroids are minimized (Arthur and Vassilvitskii, 2007). The objective of k-means clustering can be written as:

$$\sum_{i=1}^{D} \min_{\mu_j \in C} (\|x_i - \mu_j\|^2)$$

where x_i is the ith daily profile, μ_j is the centroid (or mean) of the daily profiles in the jth cluster, and C is the set of disjoint clusters with size k.

Table 1
Example of an electricity billing scenario of an Austin household in June 2018.

	kWh per Tier	Charges
*Default flat rate**		
Customer's charge		$10.00
Tier 1	500	$14.01
Tier 2	500	$29.16
Tier 3	500	$39.07
Tier 4	104	$9.68
Tier 5	0	$0.00
Community benefit charges		$8.27
Regulatory charge		$16.18
Power supply adjustment charge		$49.35
TOTAL BILL		$175.67
*Flat rate with separate meters for EV charging**		
Customer's charge		$10.00
Tier 1	500	$14.01
Tier 2	500	$29.16
Tier 3	405	$31.60
Tier 4	0	$0.00
Tier 5	0	$0.00
Community benefit charges		$7.25
Regulatory charge		$14.17
Power supply adjustment charge		$43.23
EV charging basic charges		$30.00
EV charging power supply charges		$7.95
TOTAL BILL		$187.36
*Time-of-use rate**		
Customer's charge		$10.00
Tier 1	500	$14.01
Tier 2	500	$29.16
Tier 3	500	$39.07
Tier 4	104	$9.68
Tier 5	0	$0.00
Community benefit charges		$8.27
Regulatory charge		$16.18
Time-of-use power supply charges		$54.43
TOTAL BILL		$180.75
*Time-of-use rate with separate meters for EV charging**		
Customer's charge		$10.00
Tier 1	500	$14.01
Tier 2	500	$29.16
Tier 3	405	$31.60
Tier 4	0	$0.00
Tier 5	0	$0.00
Community benefit charges		$7.25
Regulatory charge		$14.17
Time-of-use power supply charges		$47.68
EV charging basic charges		$30.00
EV charging power supply charges		$7.95
TOTAL BILL		$191.81

For each household n, we employ k-means clustering to partition $\{P^d_{n,t}\}_d$, the daily total electricity demand profiles, into k distinct clusters among all D samples where $d \in \{1, 2, \ldots, D\}$. The centroid of the most frequent cluster, $D_{n,t}$, is considered the most representative daily electricity demand profile of household n. Similarly, for each EV n, we employ k-means clustering to partition $\{X^d_{n,t}\}_d$, the daily EV charging power profiles, into k distinct groups among all D samples. The centroid of the most frequent cluster, $C_{n,t}$, is considered the most representative daily charging power profile of EV n.

It is worth noting that the number of clusters k is determined before clustering. We select the optimal k by finding the one that leads to the highest mean Silhouette Coefficient over all samples. This score is defined as:

$$SC = \frac{1}{D}\sum_{i=1}^{D}\frac{b_i - a_i}{\max\{a_i, b_i\}}$$

where a_i is the mean distance between the ith sample and all other samples within the same cluster and b_i is the mean distance between the ith sample and all other samples in the next nearest cluster (Rousseeuw, 1987).

5.2.2. A heuristic method for household travel pattern inference

The two clustering procedures provide us with the most representative daily electricity demand profile and the most representative daily EV charging profile. We introduce a heuristic approach to estimate the travel patterns of each household, including the arrival–departure times and the daily travel energy demand. These parameters related to travel patterns are crucial inputs for the optimization model outlined in Section 5.3.

Our approach leverages the characteristics of U.S. households' electricity load profiles during winter, which typically exhibit a morning peak and an evening peak. We can associate these peaks with household arrivals and departures, respectively (U.S. Energy Information Administration, 2021). Considering that this paper focuses solely on weekdays, we can safely assume that the weekday arrival and departure times do not vary substantially between winter and summer, as indicated by National Household Travel Survey (NHTS) data (U.S. Department of Transportation, Federal Highway Administration, 2017). Moreover, multiple studies have highlighted strong correlations between household energy consumption and travel patterns (Zhang and Qian, 2018; Sørensen et al., 2021; Movahedi et al., 2023).

Therefore, a "morning and evening peak" heuristic method is employed for estimating households' arrival and departure times for both summer and winter weekdays. Specifically, for each household, we use the difference between the original most representative daily electricity demand profile and its corresponding 6-day moving averages to identify the morning peak and evening peak. The estimation of the daily travel energy demand is more straightforward. It is directly calculated from the summation of the most representative daily charging energy profile, which can easily converted from the most representative daily charging power profile obtained from the clustering procedure.

The mathematical explanation of the two heuristic methods for travel pattern estimation are outlined below:

- For each household n, we calculate the difference $d_{n,t}$ between $D_{n,t}$ and its one-hour moving average $M_{n,t}$. Then, the time of departure t^d_n corresponds to the time of the largest $d_{n,t}$ before 12 P.M., while the time of arrival t^a_n corresponds to the time of the largest $d_{n,t}$ after 12 P.M.
- Similarly, for each EV n, we calculate the most representative daily charging energy profile $\tilde{C}_{n,t}$ from $C_{n,t}$ by adjusting the unit from kW to kWh considering that each time slot t corresponds to 10 min. Finally, D_n, the estimated energy needed to meet the daily vehicle miles traveled by household n, is obtained by summing up $\tilde{C}_{n,t}$ over T, the total number of time slots in a 24-hour day.

5.3. Optimization model formulation

Our computational workflow features a charging management optimization scheme based on the convex mathematical programming framework that meets system-wide objectives by minimizing the electricity cost. The model determines the time-of-use managed charging protocol and its objective is subject to (a) battery capacity constraints, (b) grid to vehicle power constraints, (c) EV energy demand constraints, and (d) charging flexibility. As shown in Section 4, electricity bills are higher when installing a separate meter for EV charging, if the charging behavior of the drivers does not shift accordingly or is not managed

Table 2
Variables and parameters used in our optimization framework.

Notation	Description	Notation	Description
Indices			
N	Set of EVs/households	T	Set of time slots in a 24-h day
T_n	Set of time slots, i.e., the time periods of each EV n parked at home	t	Time slot in a 24-h day
Parameters			
B	Battery capacity of EV (kWh)	D_n	Energy needed of EV n for completing the next trip
$c_{EV}(t)$	Time-of-use electricity cost per unit of EV charging energy ($/kWh)	$c_{RE}(t)$	Time-of-use electricity cost per unit of residential energy use ($/kWh)
A_n	Average of the summation of the max and min power consumption of a household n, set as a goal for valley-filling and peak shaving	$P_{n,t}$	Power consumption of household n during time slot t (kW)
p_n	Charging power to the EV (kW)	$Q^{(t)}$	Set of time slots prior to time t, $t \in T_n$
s^*	The number of the public DCFC station (default is 1)	t_n^a	Arrival time of the EV n
t_n^d	Departure time of the EV n	η	Charging efficiency
τ	Length of each time slot t, i.e., 10 min		
Variables			
$a_{n,t}$	Binary decision variable: whether an EV n is charging an each time slot t	$x_{n,t}$	Decision variable: power drawn from the grid by an EV n each time slot t (kW)

properly. To measure the benefits that households accrue when they optimize their charging behavior under time-of-use EV charging tariffs, we construct an optimization model to minimize the total electricity costs for all households by controlling the energy charged from the grid to EVs for each interval t. The modeling nomenclature is provided in Table 2.

The objective function describes a scenario in which there is a separate residential meter circuit attached to an in-home (garage or personal parking spot-installed) or a shared EV charging station. Thus, $c_{EV}(t)$, the time-of-use electricity rate for EV charging, is applied to the power drawn from the grid by an EV while $c_{RE}(t)$, a different time-of-use electricity rate, is used for the rest of the residential loads. The lower and upper boundaries of the energy charged to each EV's n battery is denoted as an inequality that needs to hold at each interval, as shown in constraints set (2). Charging power drawn from the grid $x_{n,t}$ to recharge an EV's battery has upper and lower bounds that should not be exceeded during each interval, as shown in constraints set (3). Constraints set (4) denotes that at the time of the vehicle's daily departure from home, the energy charged to the EV should be equal to the energy needed to conduct their daily vehicle miles traveled, essentially accounting for the driver's travel patterns.

$$\min \sum_{n\in N}\sum_{t\in T}\left(c_{EV}(t)\cdot x_{n,t} + c_{RE}(t)\cdot P_{n,t}\right)\cdot\tau \tag{1}$$

$$\text{s.t.}\quad 0 \le \sum_{t'\in Q^{(t)}} \tau\cdot x_{n,t'} \le 0.9\cdot B, \qquad \forall n\in N, \forall t\in T_n, \tag{2}$$

$$0 \le x_{n,t} \le p_n\cdot\eta, \qquad \forall n\in N, \forall t\in T_n, \tag{3}$$

$$\sum_{t\in T_n}\tau\cdot x_{n,t} = D_n, \qquad \forall n\in N. \tag{4}$$

$$x = \arg\min \sum_{n\in N}\sum_{t\in T} t\cdot x_{n,t} \tag{5}$$

$$x = \arg\max \sum_{n\in N}\sum_{t\in T} t\cdot x_{n,t} \tag{6}$$

$$x = \arg\min \sum_{n\in N}\sum_{t\in T}\left(x_{n,t} + P_{n,t} - A_n\right)^2 \tag{7}$$

$$A_n = \frac{\max(P_n) + \min(P_n)}{2}, \forall n\in N \tag{8}$$

$$\min \sum_{n\in N}\sum_{t\in T}\left(c_{EV}(t)\cdot x_{n,t}\cdot a_{n,t} + c_{RE}(t)\cdot P_{n,t}\right)\cdot\tau \tag{9}$$

$$\text{s.t.}\quad \sum_{n\in N} a_{n,t} \le s^*, \qquad \forall t\in T \tag{10}$$

$$\sum_{t\in T_n}\tau\cdot x_{n,t}\cdot a_{n,t} = D_n, \qquad \forall n\in N. \tag{11}$$

$$c_{EV}(t) = \begin{cases} \begin{cases} 0.4 & 2:00\text{ P.M. - }7:00\text{ P.M.} \\ 0 & 7:00\text{ P.M. - }2:00\text{ P.M.} \end{cases} & \text{June–September} \\ \begin{cases} 0.14 & 2:00\text{ P.M. - }7:00\text{ P.M.} \\ 0 & 7:00\text{ P.M. - }2:00\text{ P.M.} \end{cases} & \text{October–May} \end{cases} \tag{12}$$

$$c_{RE}(t) = \begin{cases} \begin{cases} 0.06605 & 3:00\text{ P.M. - }6:00\text{ P.M.} \\ 0.03025 & 6:00\text{ P.M. - }3:00\text{ P.M.} \end{cases} & \text{June–September} \\ \begin{cases} 0.03139 & 3:00\text{ P.M. - }6:00\text{ P.M.} \\ 0.02982 & 6:00\text{ P.M. - }3:00\text{ P.M.} \end{cases} & \text{October–May} \end{cases} \tag{13}$$

Our optimization model not only achieves the driver's cost minimization objective but also meets individual households' and the community's preferences (Flath et al., 2014; Yoon and Kang, 2017; Kontou et al., 2017; Sioshansi, 2012; Wu et al., 2020; Ioakimidis et al., 2018; Zhang et al., 2014; Wood et al., 2018; Xie et al., 2018) by adopting four secondary objectives: charging AFAP when the user arrives at home, charging ALAP before the user leaves, charging for valley filling and peak shaving residential load, and charging in a shared DCFC station defined by constraints (5), (6), (7)–(8), and (9)–(10). The AFAP case and the ALAP case serve entirely the needs of the drivers, which aim to charge when is the most convenient for them and allow their time to be used flexibly even though high peak loads during peak charging hours might potentially be detrimental to the distribution system operators. From the system's perspective, a uniform grid power profile would be beneficial for the stability and reliability of the utility grid, which is ensured by Eq. (7). This aims to flatten the net load's peaks and valleys by minimizing the squared difference between the summation of the residential power demand consumed and the power charged to the EVs and A_n for each interval. A_n is the average of the maximum and minimum of the residential power consumption, as shown in (8). Besides, the scenario where a shared DCFC station is installed in the community, instead of installing an EV charging station in each household, is considered as shown in (9). Under this shared charger scenario, (9) would substitute (1) as the objective function. The model would be subject to the same battery capacity and charging power constraint, in addition to the shared charging station capacity constraint and the updated energy demand constraint, as shown in constraint sets (10) and (11), respectively. The model is solved using Gurobi (version 10.0.1) (Gurobi Optimization, LLC, 2022), coded in Python (version 3.9.13).

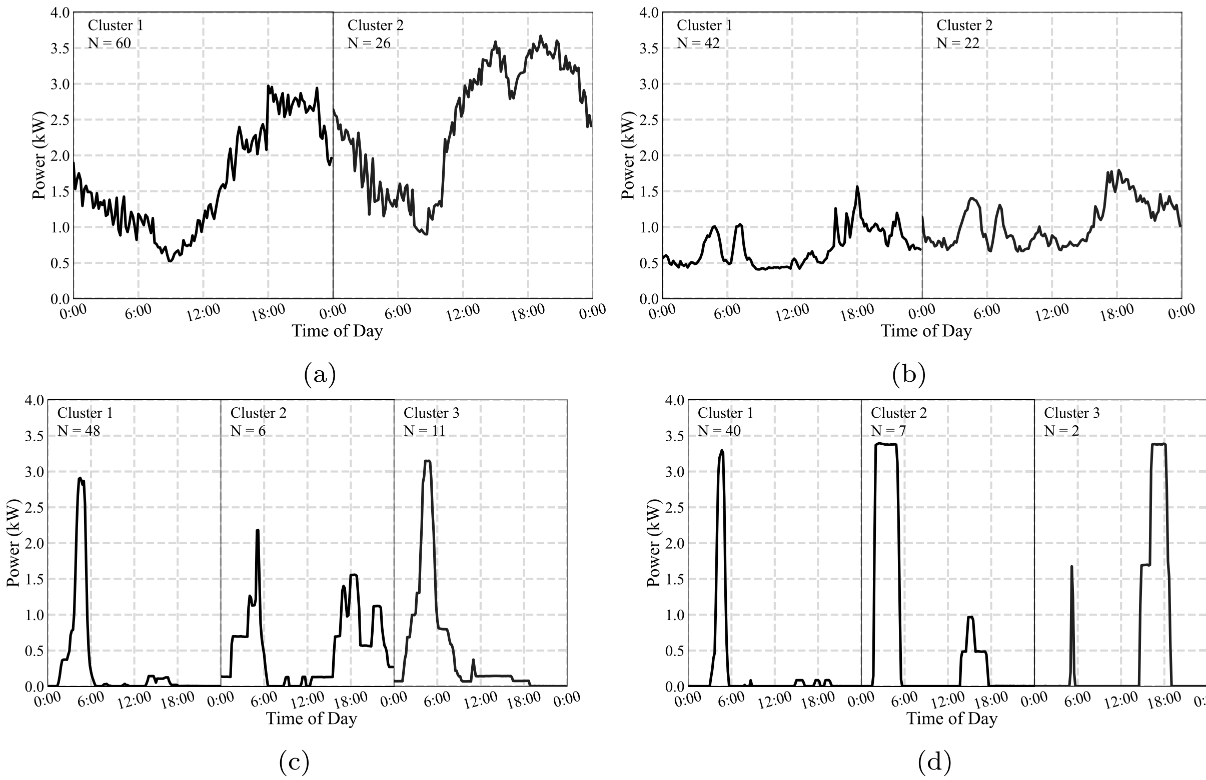

Fig. 5. The average of the electricity demand clusters in (a) summer weekdays and (b) winter weekdays, the charging power clusters in (c) summer weekdays and (d) winter weekdays of an indicative household using data from: Pecan Street Inc. Dataport.

6. Results and discussion

We apply the k-means clustering method and the charging management approaches to optimize the charging profiles of the share of households that own electric vehicles in Austin, Texas (Pecan Street Inc., 2020). We select the k-means clustering method over alternative approaches, such as k-medoids, based on its consistent and superior performance across a range of established clustering metrics. The Silhouette Score, Calinski–Harabasz Index, and Davies–Bouldin Index are widely recognized measures for evaluating clustering quality. Higher values for the Silhouette Score and Calinski–Harabasz Index indicate better clustering quality, while lower values for the Davies–Bouldin Index indicate better clustering quality. The Silhouette Score is defined in Section 5.2.1, and the Calinski–Harabasz Index and Davies–Bouldin Index follow literature definitions (Caliński and Harabasz, 1974; Davies and Bouldin, 1979). To provide a comparative analysis, we assess the performance of both the k-means clustering and k-medoids clustering methods using these metrics, and the results are presented in Table A.7 in Appendix. Travel patterns, the utility's electricity rate, and the charger type are essential factors that will influence the charging management outcomes. Thus, we conduct sensitivity analysis to evaluate the robustness of the model's outcomes.

6.1. Residential travel patterns analysis

Each of the households has unique travel patterns including the predicted charging time window (i.e., the time between the arrival to and departure from residences) and charging demand to satisfy the energy needed for the next trip. Taking an indicative household as an example, shown in Fig. 5, the optimal clusters of electricity demand profiles for summer and winter weekdays are found to be two, while the optimal charging power profiles of summer and winter weekdays are determined to be three. The summer electricity demand of Cluster 1 (Fig. 5(a) left panel) contains 60 daily profiles while that of Cluster 2 (Fig. 5(a) right panel) contains 26 daily profiles. Thus, Cluster 1 is the most representative daily electricity demand profile on summer weekdays of this particular household. The same logic is applied to generate the outcomes presented in the rest of the figures. The cluster averages of Cluster 1 in Figs. 5(b)–5(d) are, respectively, the most representative daily electricity demand profile on winter weekdays, the most representative daily EV charging profile on summer weekdays, and the most representative daily EV charging profile on winter weekdays of this indicative household.

Table 3
EV travel patterns of the average modeled households.

	t_n^a	t_n^d	D_n (kWh)
Summer	2 : 30 P.M.	8 : 10 A.M.	9.78
Winter	5 : 20 P.M.	7 : 00 A.M.	7.83

According to Section 5.2.2, the most representative daily electricity demand profiles are processed to calculate the arrival time and departure time while the most representative daily EV charging profiles are used to calculate the charging energy demand at home. Table 3 presents the estimated EV travel patterns on the weekdays of summer and winter for the households. Zhang et al. (2014) analyzes the vehicle stated travel behavior data from the 2009 National Household Travel Survey (NHTS) and suggests that the peak arrival at a residence occurs around 5 : 00 P.M. and the peak departure occurs at around 7 : 00 A.M.. This aligns our results with the actual travel patterns of U.S. households. A share of the households may not recharge their electric vehicles during the sample days we selected, which will not influence the management of charging profiles of the rest of the households.

6.2. Optimal charging schedule

Applying the optimization model to manage the charging schedule of households, we present the comparison of the aggregate EV charging

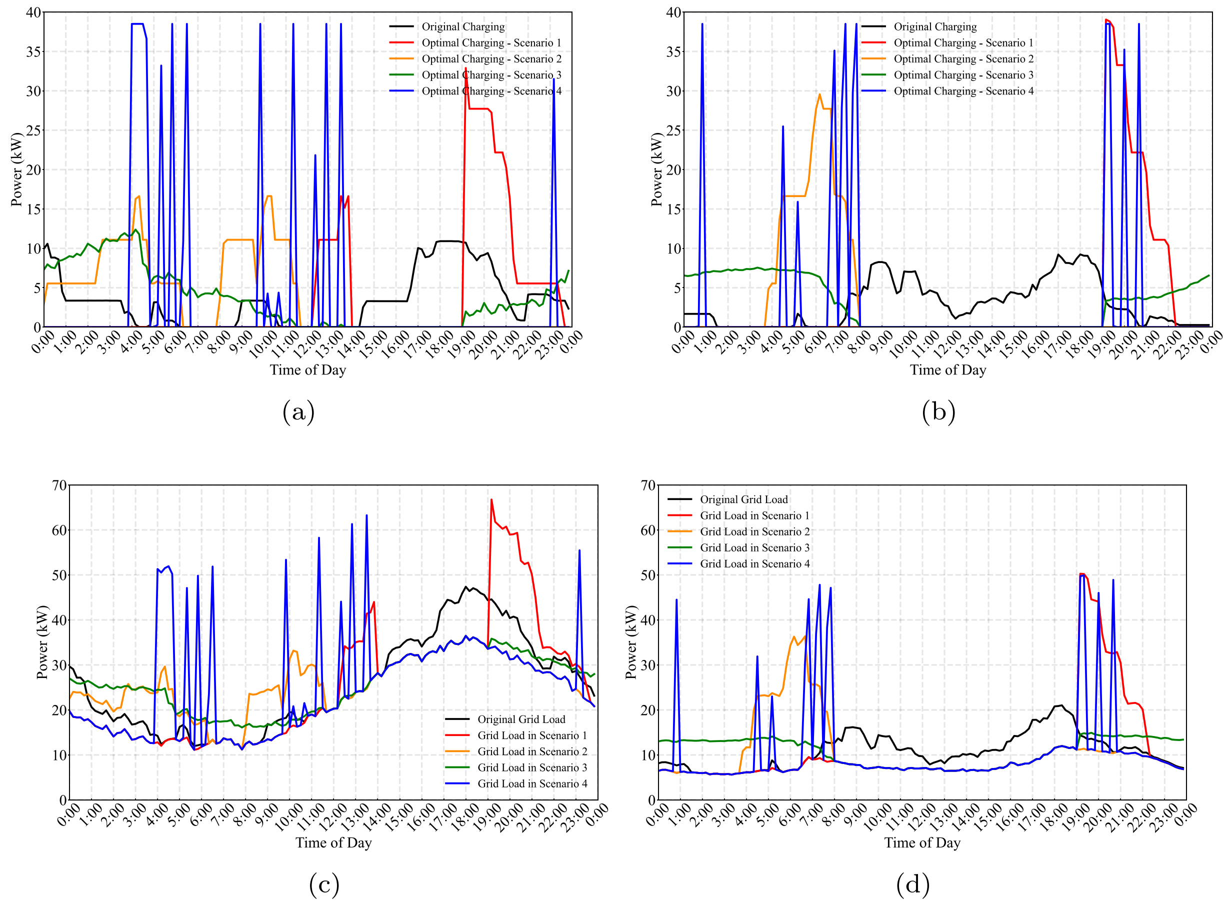

Fig. 6. EV charging schedule and grid load under the observed behavior and four alternative scenarios of managed charging (cost-minimizing charging scheme and four secondary objectives) on a summer weekday ((a) and (c)) and a winter weekday ((b) and (d)).

Table 4
Aggregate metrics of secondary charging management objectives on a summer weekday and a winter weekday (values in parenthesis).

Metrics	Scenario 1	Scenario 2	Scenario 3	Scenario 4
Average home profile costs ($)	2.20 (0.60)	2.20 (0.60)	2.20 (0.60)	2.20 (0.60)
Max charging power peak (kW)	4.34 (4.34)	4.34 (4.34)	1.59 (0.87)	38.50 (38.50)
Duration of charging power peak (min)	113.75 (82.22)	113.75 (82.22)	10.00 (10.00)	100.00 (60.00)
Peak load of the community (kW)	66.75 (50.27)	36.46 (36.36)	36.46 (14.92)	63.26 (49.89)
Average share of time charging over dwell time (%)	12.60 (11.08)	12.60 (11.08)	70.06 (88.16)	2.20 (2.05)
Average time that charging starts from home arrival (min)	82.50 (112.22)	915.00 (743.33)	82.50 (112.22)	460.00 (432.22)
Average time that charging stops from home departure (min)	716.25 (631.11)	0.00 (0.00)	0.00 (0.00)	31.25 (217.78)
Charger daily utilization (%)	7.56 (6.25)	7.56 (6.25)	49.38 (50.08)	12.50 (10.42)

profiles and grid load under the original charging plan and the optimal plan for electricity cost minimization while enforcing numerous secondary objectives (i.e., AFAP, ALAP, leveling grid power, and shared charging station) in Fig. 6. Figs. 6(a) and 6(b) illustrate the aggregated charging profiles in summer weekdays and winter weekdays under the original plan and four alternative scenarios. The charging behaviors captured under the original plan in the summer determine that the majority of charging takes place from 2 P.M. up until the morning of the next day. As for winter weekdays, charging generally occurs during the daytime and in the early evening from 7 A.M. to 8 P.M. in the original plan, which coincides with on-peak electricity demand hours. Avoiding charging during on-peak hours can decrease the electricity costs of the community. This is exactly what is achieved by all the optimal charging schemes implemented. Specifically, optimal charging behaviors under all four charging management scenarios are scheduled before 2 P.M. or after 7 P.M. All of the four optimal charging practices completely avoid on-peak hours charging. Therefore, the optimal charging schedule reduces the aggregated daily electricity costs from $32.39 to $19.80 on a summer weekday and $10.18 to $5.67 on a winter weekday.

Although both AFAP and ALAP can decrease the electricity costs and ensure that households exploit the dwell time flexibility offered at home to charge their EVs while meeting their daily driving needs, they do not necessarily follow a scheduling practice that can contribute to the grid's stability and reliability. From Figs. 6(c) and 6(d), even more peaks occur during the charging periods. The AFAP scenario results in a significant peak in the evening from 7 P.M. to 9 P.M., both in summer and winter. Similarly, the ALAP scenario results in several grid power peaks in the morning in summer and a remarkable peak in the morning in winter. The peak-shaving and valley-filling management, which aims to flatten the grid load curve, could mitigate the potential risk of high peak loads caused by EV charging. The solid green curves in Fig. 6 showcase the charging profiles and the grid load trends under the peak-shaving and valley-filling management. Charging is more uniformly distributed across all the available managing periods when the EVs are connected to the chargers. The peak in the afternoon and evening and the valley at night and in the morning are mitigated by this management strategy, as shown in Figs. 6(c) and 6(d).

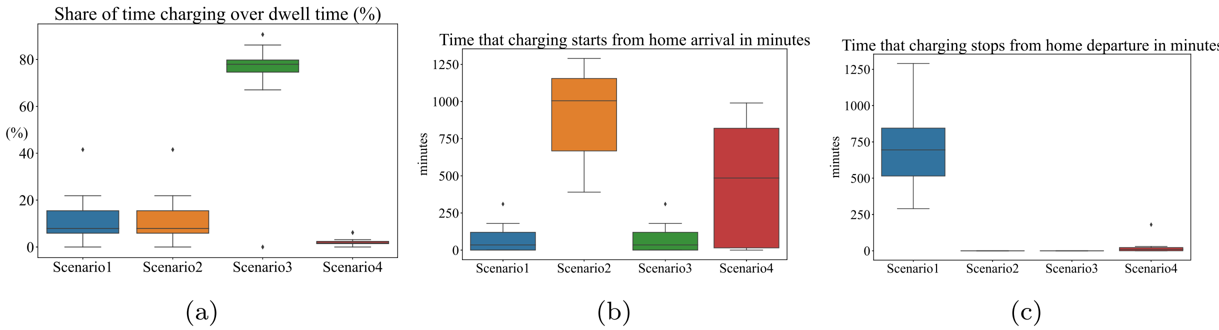

Fig. 7. Boxplots for (a) the share of time charging over dwell time, (b) the time that charging starts from home arrival, and (c) the time that charging stops from home departure on a summer weekday.

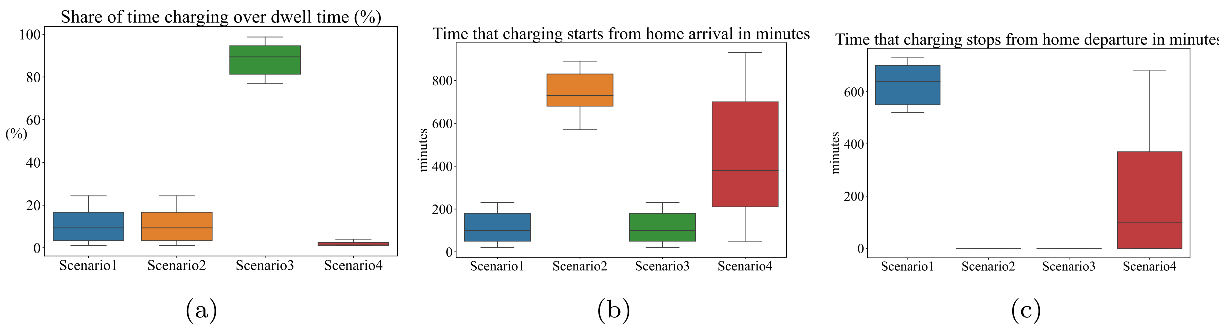

Fig. 8. Boxplots for (a) the share of time charging over dwell time, (b) time that charging starts from home arrival, and (c) time that charging stops from home departure on a winter weekday.

As for the scenario when only one public DCFC station is installed in the whole community with sharing capabilities, the resulting optimal charging periods are much shorter compared to the other three secondary objectives, allowing households for even more time flexibility over their vehicles. The shorter charging period is a result of the higher level of charging power (50 kW versus 7.2 kW) offered by the DCFC. However, the peak load of DCFC is an apparent drawback of this charging practice. Figs. 6(c) and 6(d) indicate that while the grid load under DCFC is certainly higher than the one under the peak shaving and valley filling scheme, it is not much different from the grid loads under the AFAP and the ALAP case, especially the former. This is because charging under the AFAP case coincides with the increased residential load from other units in the late afternoon when the household vehicles return home. Additionally, one should not ignore the high demand charge associated with the DCFC station, which may not be billed for residential electric service. According to the electricity tariff, the demand charge depends on the monthly max grid usage in a fifteen-minute interval. A 10 kW bound of demand charge is typically set and the demand charge will be billed if the peak demand exceeds this bound (Austin Energy, 2020). If the demand charge is taken into consideration, the daily electricity for the DCFC scenario will go up to \$25.17 and \$11.05 on a summer weekday and a winter weekday, respectively. Under such a scenario the optimal electricity cost of operation even exceeds the original cost. Therefore, the high demand charge of a DCFC station is an important factor to consider when the residential community is comparing a shared public DCFC station with lower-level EV chargers at individual households. Moreover, the higher operation and infrastructure cost of the shared DCFC station should be taken into consideration. Installing one public DCFC station might be more economically viable for a larger community where costs can be distributed between a greater share of residential units and their electric vehicle drivers.

Table 4 summarizes the trade-offs of optimal charging schedules under each scenario. The average daily home profile costs are the same in all 4 scenarios, further illustrating that all 4 scenarios reach optimality and achieve cost minimization. The max charging power peak per day of each household is primarily affected by the power level of the charger. The max charging power peaks of scenarios 1, 2, and 4 are close to or equivalent to their respective power levels after taking power efficiency into consideration (5.5 kW for level 2 charging and 38.5 kW for DCFC). These 3 scenarios aim to utilize the maximum level of charging power available whereas scenario 3 is designed to lower the max charging power peak. The peak shaving effect of scenario 3 is evident as scenario 3 also has the minimum value in the duration of charging power peak and the average peak load for the community. In comparison, scenarios 1, 2, and 4 have at least 100 continuous minutes staying at the charging peak power during a day, and the average community peak loads of scenarios 1 and 4 are over 60 kW on a summer weekday and over 49 kW on a winter weekday. It might be surprising that the average community peak load of scenario 2 is close to that of scenario 3. However, this is reasonable as we investigate further the optimal schedule of scenario 2: the majority of the charging occurs during the late night and early morning when the residential grid load is usually low.

The share of time charging over dwell time is a measure of flexibility. Scenario 4 gives drivers the highest degree of flexibility as it only requires around 2% of charging time over dwell time on both a summer weekday and a winter weekday. According to Figs. 7(a) and 8(a), the degree of flexibility of scenario 4 is the least variable among the four scenarios. Scenarios 1 and 2 also allow the drivers for a high level of flexibility as both scenarios occupy less than 13% of the household vehicle's dwell time for charging. However, this level of flexibility can vary by households, where the share of time charging over dwell time range from almost 0% to close to 30% on both a summer weekday and a winter weekday. Relatively, scenario 3 provides the least level of flexibility as the charging time is spread over the dwell time in order to achieve the peak shaving and valley filling goal. The share of time charging over dwell time can vary from 70% to more than 90% on both a summer weekday and a winter weekday. In addition, the time that charging starts from home arrival and the time that charging

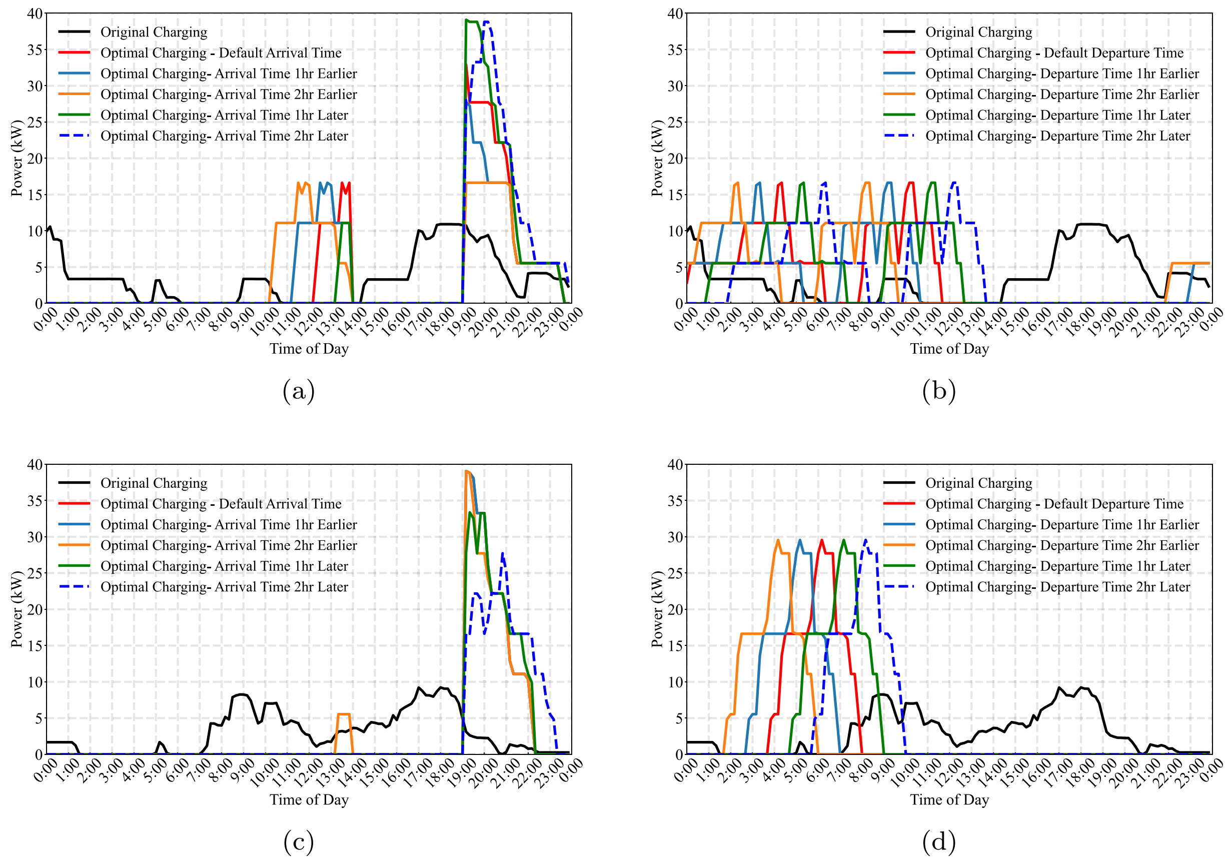

Fig. 9. Sensitivity analysis on time of arrival and time of departure when (a) charging AFAP on a summer weekday, (b) charging ALAP on a summer weekday,(c) charging AFAP on a winter weekday, and (d) charging ALAP on a winter weekday.

stops from home departure can measure the "convenience" of each scenario. Convenience could suggest that other trips can be added in the commuting trip prolonging the commuting time and impacting either the arrival at home in the evening hours or the departure from home in the morning hours. According to Figs. 7(b), 7(c), 8(b), and 8(c), the level of convenience is highly variable in general on both a summer weekday and a winter weekday. This can be explained by the fact that the metrics that measure convenience depend highly on the commute time, which differs by household. The results suggest that there is a trade-off between the time that charging starts from home arrival and the time that charging stops from home departure. While scenario 2 provides the highest level of convenience before the start of charging after the driver arrives at home, the time that charging stops from home departure under scenario 2 is 0 on average, indicating that the drivers cannot depart until the very last minute. In contrast, scenario 1 only provides limited free time before charging begins but offers the highest level of convenience after charging stops. As for scenario 3, the level of convenience is the least among the four scenarios, which is consistent with the measures of the level of flexibility. The level of convenience under scenario 4 is highly varied by households. An explanation for this significant variability is that only one or limited number of EVs can charge at the same time under scenario 4. Thus, households that charge at a later time slot are likely to have lower levels of convenience. Finally, the charger utilization over 24-h exhibits a similar pattern to that of the measure of flexibility. A noticeable difference is that scenario 4 has higher charger utilization compared to scenarios 1 and 2. This may be due to the fact that the same public charger is shared by multiple households one at a time in scenario 4.

6.3. Sensitivity analysis

Time-of-use electricity price, travel patterns of drivers, as well as the charger's power level, are expected to influence the optimal residential charging scheduling. The following section conducts sensitivity analyses to evaluate the robustness and feasibility of the modeling outcomes under the uncertainty of the aforementioned parameter.

6.3.1. Sensitivity analysis: Travel patterns

Travel patterns, including the arrival and departure times and the demand for travel energy, define the time window available to manage charging behaviors and the volume of energy needed to complete charging. Specifically, travel patterns of the households are key influencing factors of the charging schedule under the AFAP and ALAP scenario. Figs. 9 and 10 present a sensitivity analysis of the travel patterns and aim to determine the effects of variations in travel patterns on the optimal charging schedules under the AFAP and ALAP scenario. All of the scenarios under different travel patterns reach their respective optima. Fig. 9(a) demonstrates the sensitivity analysis on the arrival time. As the arrival time of the households' vehicles shifts from two hours earlier to two hours later than the estimated arrival time, it is apparent that the AFAP optimal charging schedules shift accordingly. Despite the shifts in scheduled charging time, the shapes of the optimal charging schedules are similar. Similar shifts in optimal charging schedule can be seen in Fig. 9(b), where a sensitivity analysis is conducted on the departure time. Under the ALAP case, the charging time is dependent on the departure time of the households. Thus, as the departure time shifts two hours later than the estimated departure time, the optimal charging schedules shift accordingly.

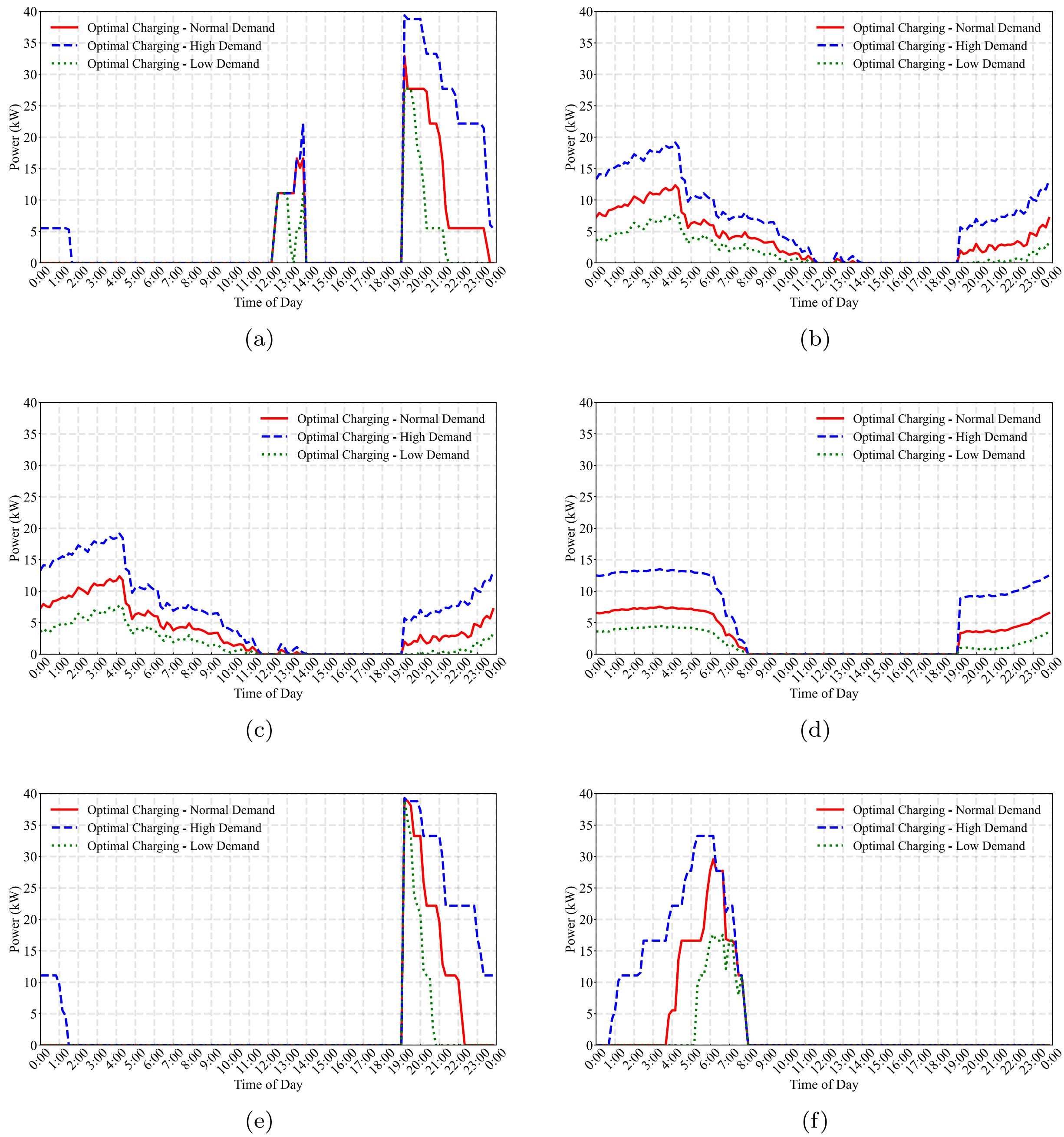

Fig. 10. Sensitivity analysis on the energy volume for travel when (a) charging AFAP on a summer weekday, (b) charging ALAP on a summer weekday, (c) charging for valley filling and peak shaving grid load on a summer weekday (d) charging for valley filling and peak shaving grid load on a winter weekday, (e) charging AFAP on a winter weekday, and (f) charging ALAP on a winter weekday.

In real-life scenarios, the actual energy demand for daily household travel, which is an input to our proposed optimization framework, might deviate from our estimated energy demand obtained from the average of the household's most representative EV charging profile. To further test the robustness of our model a sensitivity analysis is conducted, examining various energy demand levels.

The level of energy volume cannot exceed 90% of the battery capacity since the model assumes that only one trip per day is made by every household, and every household only charges once at home. Empirical evidence shows that home charging is preferred by current EV adopters and could be one of the cheapest and most convenient charging options (Hardman et al., 2018). Fig. 10 presents the optimal EV charging schedules of low demand (half of the base case demand), base demand, and high demand (double of the base demand but less than the capacity of the vehicle battery) under secondary objectives 1, 2, and 3. It can be observed that the optimal charging schedules under all three energy levels are able to preserve the optimal cost by scheduling EV charging during off-peak hours. As the charging energy volume increases, the charging curve has greater peaks. In addition, the profiles of the optimal charging schedules are almost identical to each other under different demand levels. We can safely conclude that the proposed optimization model is able to work well within a reasonable range of charging demand levels.

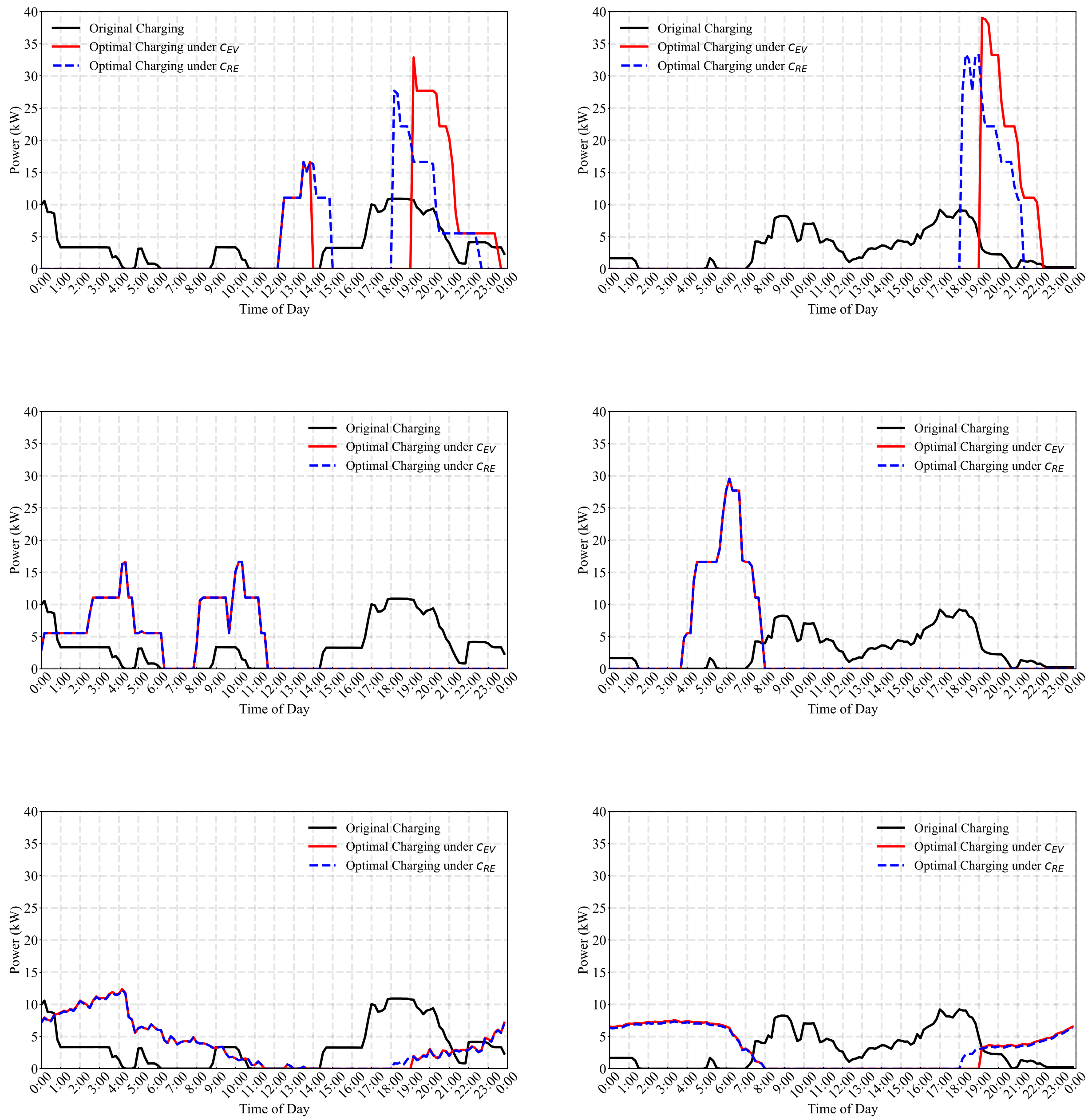

Fig. 11. Sensitivity analysis on cost function with the optimal EV charging schedules on (a) a summer weekday when charging AFAP, (b) winter weekday charging AFAP, (c) summer weekday when charging ALAP, (d) winter weekday when charging ALAP, (e) summer weekday when charging for valley filling and peak shaving grid load, and (f) winter weekday when charging for valley filling and peak shaving the grid load.

6.3.2. Sensitivity analysis: Utility rates

This section compares the scenario of EVs charging demand being treated as another residential plug load compared to our main scenario where a separate meter for EVs is installed. Under the alternative scenario, $c_{RE}(t)$, the time-of-use electricity rates for residential services will be applied to the power drawn from the grid by an EV, instead of $c_{EV}(t)$.

As shown in Fig. 11, the optimal EV charging schedules under two different cost functions achieve cost minimization successfully as both schedules avoid their respective peak hours (3 P.M. - 6 P.M. under $c_{RE}(t)$ and 2 P.M. - 7 P.M. under $c_{EV}(t)$). When charging AFAP (Figs. 11(a) and 11(b)), the optimal charging schedules under $c_{EV}(t)$ have higher peak loads compared to the optimal charging schedules under $c_{RE}(t)$. Under $c_{EV}(t)$, the optimal charging schedules avoid a long period of peak hours, thus more charging is scheduled to take place immediately after the peak hours end. When charging ALAP (Figs. 11(c) and 11(d)), the optimal charging schedules under two cost functions are the same because charging is scheduled in late night and morning, therefore not conflicting with the peak hours. Under secondary objective 3 (which aims to flatten the grid load curve), the optimal charging schedules are almost the same since charging is spread throughout the day despite the difference in peak hours.

Table 5 presents a comparison of the optimized aggregated daily electricity costs of the households used in our analysis under the two time-of-use cost functions. It can be seen that higher cost reductions can be achieved under $c_{EV}(t)$. This can be explained by the fact that the cost difference between on-peak and off-peak hours is larger under $c_{EV}(t)$. Firstly, the on-peak hour electricity rates under $c_{EV}(t)$ are higher.

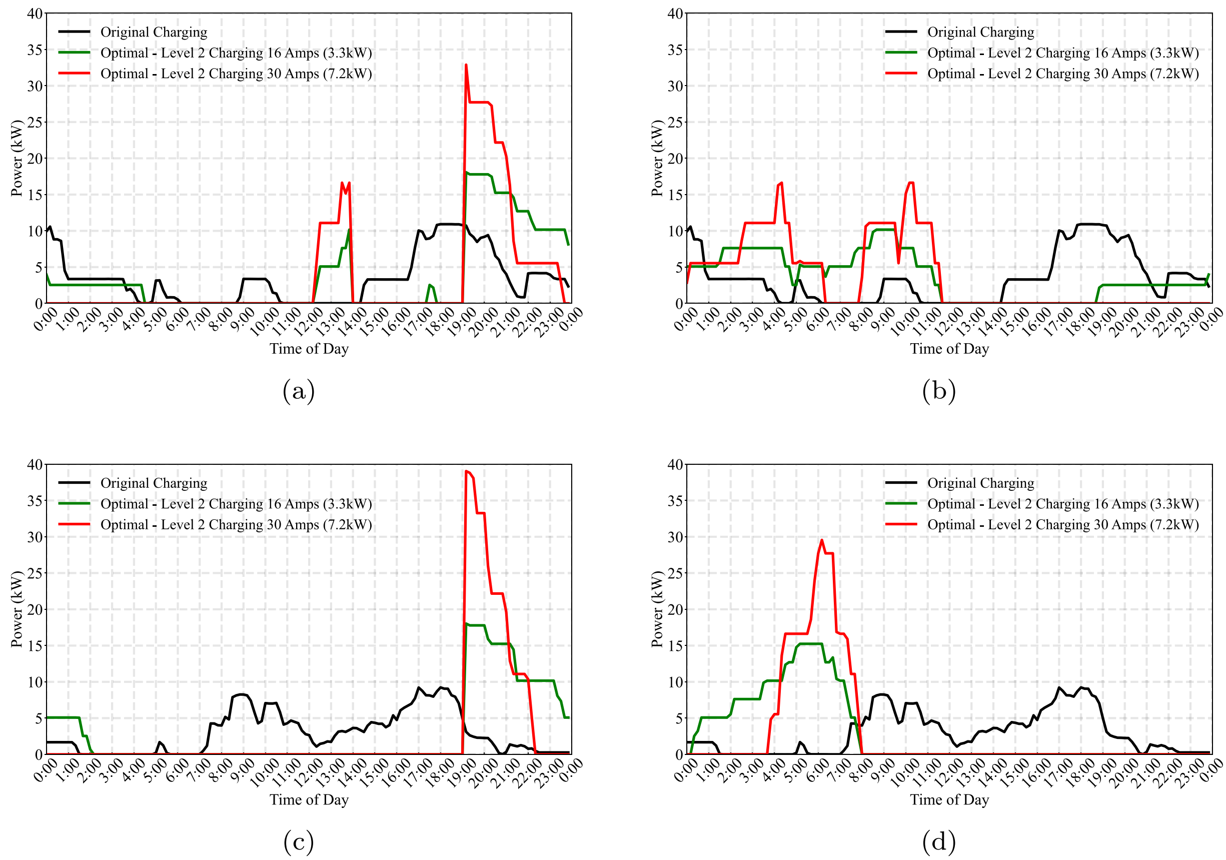

Fig. 12. Sensitivity analysis on charging power when (a) charging AFAP on a summer weekday, (b) charging ALAP on a summer weekday, (c) charging AFAP on a winter weekday, and (d) charging ALAP on a winter weekday.

Table 5
Time-of-use daily electricity costs ($) of the original plan and the optimal plan for the analysis households.

Scenario	Original cost ($)	Optimal cost ($)	Cost reduction (%)
Summer weekday with $c_{EV}(t)$	32.39	19.80	38.87%
Summer weekday with $c_{RE}(t)$	22.94	22.46	2.14%
Winter weekday with $c_{EV}(t)$	10.18	5.67	44.30%
Winter weekday with $c_{RE}(t)$	7.81	7.77	0.38%

Consequently, under unmanaged charging where most charging takes place during on-peak hours, the original electricity price is reasonably higher under $c_{EV}(t)$. Secondly, the off-peak hour rate under $c_{EV}(t)$ is set to be 0. In our optimized charging schedules, all the on-peak hours are avoided, thus, the portion of the electricity costs are minimized to 0 under $c_{EV}(t)$. Even though on-peak hours are shorter under $c_{RE}(t)$, the demand for charging is not high enough to schedule charging during on-peak hours.

6.3.3. Sensitivity analysis: Charging power

Fig. 12 consists of four subgraphs showing the effects of different charging power on the optimal EV charging schedules under the AFAP and the ALAP scenario. Charging for valley filling and peak shaving grid load is not included in this discussion because the change in charging power does not have an impact on the optimal charging schedule. Level 2 charging with 16 Amps and level 2 charging with 30 Amps are considered.

It can be observed that the optimal charging schedules have similar patterns (i.e., charging around the same time) and the optimal charging schedule using a level 2 charger has a more flattened curve, as expected. The level 2 charger with 16 Amps results in a low charging rate and under a managed optimal charging schedule the on-peak hours cannot be entirely avoided, resulting in a short period of charging during the on-peak hour at around 5:30 P.M. when charging AFAP on a summer weekday 12(a). Thus, the electricity bill under 16 Amps level 2 charger is more expensive. However, one should not ignore the higher fixed cost associated with installing a 30 Amps level 2 charger, which will require a greater period of usage to accrue benefits of the charging cost reduction.

7. Conclusion

In this paper, we characterize the EV charging patterns of a sample of Austin households and estimate the electricity costs under alternative electricity rates. Household travel patterns are inferred by applying k-means clustering along with a heuristic method to households' daily energy consumption profiles while the electricity bills under different pricing scenarios present us an incentive to optimize the EV charging schedules. In order to maximize the benefits for households, we propose an optimization framework that not only achieves the objective to minimize the total electricity costs but also meets households' and their community's preferences by adopting four secondary objectives: charging AFAP when the EV user arrives at home, charging ALAP before the user leaves, charging for valley filling and peak shaving of the residential load, and charging in a shared DC fast charging

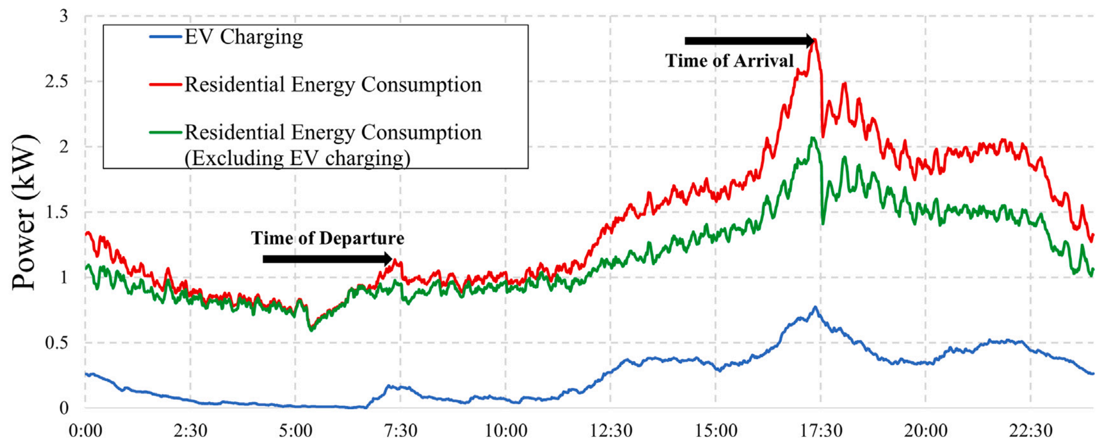

Fig. A.13. Daily electricity consumption of an indicative household in Austin, TX.
Source: Pecan Street Inc. Dataport (Pecan Street Inc., 2020).

station. We demonstrate that under the optimal EV charging management, electricity cost reductions can be achieved through managing EV charging to avoid on-peak hours. Under all four secondary objectives, the optimal charging schedule reduces daily total electricity costs by 38.87% on a summer weekday and by 44.3% on a winter weekday. While charging AFAP, ALAP, and in a shared DCFC station allow drivers to have greater flexibility and free (no charging) downtime despite high peak loads, charging for valley filling and peak shaving of the grid load not only achieves the same cost reduction but also flattens the load curve. We show that charging for valley filling and peak shaving the grid load is effective in reducing the peak load, which is important for maintaining the stability of the distribution infrastructure and reducing the charging and maintenance costs. The price behind maintaining grid load stability is that this charging management scenario requires a longer hour of charging. Thus, the level of flexibility and convenience is likely to be lower for the drivers compared to those of other charging management scenarios. Furthermore, we identify several important parameters (i.e., travel patterns, utility rates, and charging powers) of the optimization model and conduct sensitivity analyses based on these parameters. The model is proven rigorous and the results robust under a variety of settings and scenarios.

This study is not without limitations. First, due to limited data availability, we only focus on a small subset of households in Austin, whose charging behaviors might not be representative of all EV owners. Home EV charging behavior can exhibit heterogeneity (Sørensen et al., 2021). Future research should investigate the effect of managed charging schemes given access to a larger sample of EV household data. The framework we use can be tailored to different regions, such as other states in the U.S. and regions in Europe and Asia that are experiencing electrification of their transportation system. Although the exact numerical results may not be applicable to residences in other places, likely due to the difference in power profiles, level of charging, individual travel patterns, electricity pricing, etc., the relative policy insights into managed charging schemes under various charging preferences gained in this study will still apply. Future studies should also account for additional sensitivity parameters exploration, such as external temperature, that might affect the travel pattern inference and EV's battery performance and optimization procedure employed in this study, as more granular data is collected.

Future work on this topic can further enhance the proposed methodology by incorporating new user-imposed constraints. For example, future applications can consider users' comfort levels. This could exclude the scenario of ALAP, since users might face unexpected events during the day and might not want to take the risk of waiting till the last minute to finish charging their vehicles. Furthermore, this work can be expanded by accounting for people with pro-environmental preferences, e.g. a cleaner grid that includes energy generated from solar panels installed at residential premises or renewable energy use. Beyond environmental considerations, EV drivers through vehicle-to-grid (V2G) technologies can be considered as prosumers, providing services to the grid. Willingness to participate in such services and provision programs, as well as benefits accrued from V2G need to be further modeled and studied (Noel et al., 2018).

CRediT authorship contribution statement

Tinghan Ye: Conceptualization, Methodology, Formal analysis, Data curation, Software, Visualization, Writing – original draft. **Shanshan Liu:** Methodology, Data curation, Software, Writing – review & editing. **Eleftheria Kontou:** Conceptualization, Methodology, Supervision, Funding acquisition, Writing – review & editing.

Data availability

The data that has been used is confidential.

Appendix

By leveraging the average daily energy consumption of a household, the travel patterns of the household owners can be deduced, as shown in Fig. A.13. For instance, the second arrow identifies the peak usage of the day which could correspond to the time of arrival of the household owners at home. During the night, the household energy consumption gradually decreases. In the early morning, the energy consumption increases again, reaching a temporary peak value around 7:30 A.M. After that, energy consumption profiles are uniform, indicating that the household residents are not in. Therefore, we can hypothesize that 7:30 A.M. could be the departure time as represented by the blue arrow on the left-hand side. While we infer the travel patterns of the household here by just looking at the graph, we propose an algorithm in Section 5.2.2 that can automate this travel pattern inference process and be applied to all households.

Table A.6
Residential electricity billing rates based on 2021 Austin electric tariff.

Panel A: Flat rate	
Basic charges ($/month)	
Customer	$10.00
Energy charges ($/kWh)	
0–500 kWh	$0.02801
501–1000 kWh	$0.05832
1001–1500 kWh	$0.07814
1501–2500 kWh	$0.09314
Over 2500 kWh	$0.10814
Power supply adjustment charge ($/kWh)	
Billed kWhs	$0.03078
Community benefit charges ($/kWh)	
Customer assistance program	$0.00154
Service area lighting	$0.00124
Energy efficiency services	$0.00238
Regulatory charge ($/kWh)	
Billed kWhs	$0.01009

Panel B: Value-of-solar rider rate	
Rate schedule type	**Value-of-solar rate ($/kWh)**
Non-demand	$0.09700

Panel C: Time-of-use power supply charges		Summer (June through September)	Non-summer (October through May)
Power supply charges ($/kWh)			
Weekdays			
	Off-Peak	$0.03025	$0.02982
	Mid-Peak	$0.03025	$0.02982
	On-Peak	$0.06605	$0.03139
Weekends			
	Off-Peak	$0.03025	$0.02982
Power supply periods:			
Weekdays			
Off-Peak		10:00 P.M.–7:00 A.M.	
Mid-Peak		7:00 A.M.–3:00 P.M., 6:00 P.M.–10:00 P.M.	
On-Peak		3:00 P.M.–6:00 P.M.	
Weekends			
Off-Peak		Entire day	

Panel D: PEV charging station charges		Summer (June through September)	Non-summer (October through May)
Basic charges ($/month)			
Delivery			
	Demand (<10 kW)	$30	$30
	Demand (>10 kW)	$50	$50
Power supply charges ($/kWh)			
Weekdays			
	Off-Peak	$0.00000	$0.00000
	On-Peak	$0.40000	$0.14000
Weekends			
	Off-Peak	$0.00000	$0.00000
Time periods:			
Weekdays			
Off-Peak		7:00 P.M.–2:00 P.M.	
On-Peak		2:00 P.M.–7:00 P.M.	
Weekends			
Off-Peak		Entire day	

Table A.7
Clustering quality metrics 95% confidence intervals.

Scenario	Silhouette score		Calinski–Harabasz index		Davies–Bouldin index	
	k-means	k-medoids	k-means	k-medoids	k-means	k-medoids
Summer residential	0.17 ± 0.07	0.15 ± 0.07	20.18 ± 11.28	18.80 ± 11.60	2.20 ± 0.49	2.35 ± 0.59
Summer charging	0.34 ± 0.18	0.34 ± 0.18	71.08 ± 109.25	71.37 ± 109.20	1.22 ± 0.45	1.16 ± 0.40
Winter residential	0.28 ± 0.10	0.24 ± 0.11	17.19 ± 6.24	15.89 ± 6.34	1.69 ± 0.38	1.89 ± 0.42
Winter charging	0.32 ± 0.14	0.31 ± 0.16	13.95 ± 8.26	12.69 ± 6.13	1.28 ± 0.21	1.34 ± 0.44

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