A Profitability Assessment of Fast-charging Stations under Vehicle-to-grid Smart Charging Operation

Abstract

Along with the rapid development of vehicle-to-grid (V2G) technologies, additional economic benefits have come to light through effective energy interactions between electric vehicles (EVs) and power distribution grids. However, due to the uncertainty and heterogeneity associated with the EV behaviors, effectively quantifying the potential economic benefits from coordinated smart charging still remains challenging for charging service providers. In this context, this paper proposes a data driven approach of profitability assessment for fast-charging stations based on real-world operation data. Specifically, to identify the opportunistic timing, the regularities for EV charging behaviors and traffic mobility are characterized by coupling the session profiles and urban traffic profiles. Then an integer programming based profitability assessment approach is developed to calculate economic benefits through smart charging schemes. Under peak-shaving incentives from the grid, the flexibility of 0.7 million session profiles is explicitly investigated and the corresponding monetary gains are obtained. Lastly, analytical results and associated technical insights are reported by studying multiple influencing factors, e.g. climate and pandemic Covid-19. Case study results suggest that fast charging stations under coordinated charging scheme can yield a 20-30% profit increase as compared to uncoordinated circumstances.

Keywords: EV fast-charging, vehicle-to-grid, profitability assessment, peak shaving, cost-and-benefit analysis

1. Introduction

The world has seen an explosive expansion of electric vehicle (EV) sales, which amounted to 9% of the global vehicle market in 2021. As a pioneer economy in the EV market, the EV sales of China tripled relative to 2020 (from 1.1 to 3.3 million) [1]. In 2021, the number of publicly available EV charging points grew up by approximately 40%, approaching 1.8 million. Within such an accelerated trend of EV penetration, grid integration grows as common concern that limits the EV-related social benefits. Uncoordinated EV charging unexpectedly increases the burden of the grid operator to balance the demand and supply, thereby calling for added investment in peaking resources. Smart charging, or Vehicle-to-grid (V2G), involves coupling the smart grid and electric vehicles (EVs) in a way that provides benefits to both [2, 3] . Within this paradigm, EVs could act as flexible loads which could be guided through time-of-use electricity pricing or monetary incentives. As a result, smart charging could function in back-up electrical power provision [4, 5], load balancing support [6, 7], peak-load shaving [8, 9], thereby allowing a greater use of grid facility and lowering the operational cost.

With the technological readiness of smart charging, the literature on the quantification and valuing of smart charging programs has been gradually growing. Two main paradigms coexist in smart charging initialization: (1) through a long-term contract and (2) at each charging event. Long-term contracts have gained popularity in recent decades. In this mode, EV users will sign a contract with the utility that grants it the control of their charging sessions. A discount on the monthly electricity bill may be offered as a return. The users' willingness toward such contracts is studied in [10–13], and those findings indicate a promising prospect.

Though much work has been reported on valuing the smart charging programs with long-term contracts, still less is the knowledge of one-shot programs, a more flex-

*Corresponding author at: Department of Electrical and Electronic Engineering, Southern University of Science and Technology, Shenzhen, 518055, China. E-mail addresses:jiayw@sustech.edu.cn

ible instrument for smart charging initialization [14]. Besides, the effectiveness of long-term smart charging is reduced in non-residential charging scenarios. The one-shot paradigm supplements long-term contracts in non-residential charging stations (particularly fast-charging stations) and provides a more concrete and tangible entry point for smart charging participation. Concerning such contracts, consumers' price sensitivity in public charging stations is studied in [15, 16]. They are expected to be enthusiastic about a variety of smart charging programs, such as peak-shaving, renewable energy consumption, and so on. Specifically, in contrast to signing a long-term contract with a utility or aggregator, an EV user may need only accept an instant option on smart-charging participation offered by charging stations, which grants the charging station the right to reschedule his charging plan. Financial incentives, such as bonuses or discounts, are offered as a return to increase the willingness to accept potential players. Within this paradigm, it is envisioned that all players—the grid, the charging station, and the EV users—will benefit from smart charging.

In this regard, this particular paper aims to characterize and quantify the potential benefits produced by one-shot smart charging programs. In particular, we focus on the scope of fast-charging, a future paradigm for public charging. In 2021, over 1.8 million publicly accessible chargers were installed worldwide, of which more than 30% were fast chargers [1]. Compared to slow chargers, fast chargers feature an intensive energy exchange (typically over 50 kW) with the grid [17, 18]. Therefore, effective management of fast-charging could produce increased benefits for multiple parties engaged.

Designing and implementing effective smart charging programs necessitates a comprehensive understanding of the patterns of user behaviors and preferences. A common practice for generating such knowledge is exploiting the historical charging profiles, recorded by the charging stations or the grids. Following this spirit, we propose a data-driven approach for quantifying the smart-charging benefits from the perspective of a fast-charging station owner. To that end, we gathered over 0.7 million real-world charging session data from Shenzhen's largest fast-charging station. The raw data is cleaned and statistically characterized to reveal the opportunity of smart charging. Then, a data-driven scheme is proposed to evaluate the benefits of non-residential smart charging with peak-shaving service provision. Finally, the impacts of multiple influencing factors, such as seasonality and pandemic, are analyzed, thus providing managerial implications for the charging station owners.

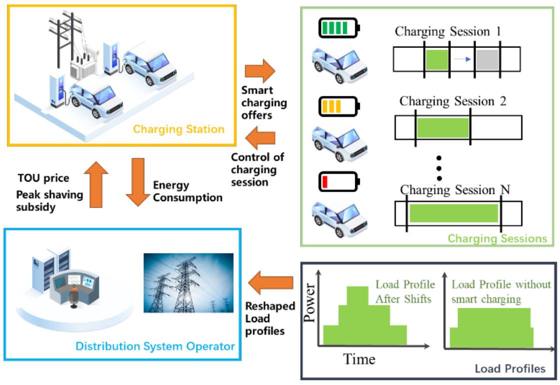

Figure 1: Interactions among multiple parties through smart charging

We contribute the literature by

- A characterization of EV charging and mobility patterns using a large real-world dataset of EV charging events spanning two years with over 0.7 million records.
- A mixed integer programming model for predicting the potential benefits of smart charging programs. In comparison to existing data-driven approaches [19, 20], this model is distinguished by a low computational burden and the ability to transfer energy in both directions.
- An exploratory data analysis of the representative factors influencing charging profiles and smart charging benefits.

The remainder of this paper is structured as follows. Section 2 details the related works. Section 3 describe and characterize the datasets. Section 4 presents a smart charging scheme for inferring benefits from session data. In Section 5, the influence of affecting issues is studied.

2. Related works

Planning for the EV charging demands and their impact on the existing grid facility have been a central task for grid operators. The challenge concerns the uncertainties and heterogeneity of users' recharging and driving behaviors, which are neither straightforward to analyze nor to quantify. Data-driven methods, which extract insightful information from historical data,have commonly been developed to deal with such issues. For example, Xydas et al. [21] characterize charging demand using a two-step statistical approach based on a charging event dataset of 22k records in the UK. Xu et.

al [19] couples the individual mobility in charging profile planning by combining datasets of mobile phone, census and charging sessions from the Bay area, USA. The results highlight the necessity of smart charging implementation. Powell et. al [22] uncovers the patterns of heterogeneous EV drivers using over 4 million EV charging sessions in California. It is revealed that 28% of the residential charging sessions align with the lowest price periods.

These papers, in general, provide valuable insights into charging demand patterns while focusing less on the design and implementation of effective smart charging programs. To do so, a precise understanding of the user behaviors and preferences, i.e., (i) daily mobility [19, 23], (ii) timing and duration concerning charging [24–26], and (iii) attitudes towards smart charging participating [10–12], is needed.

Several attempts have been made regarding this subject. In [27], the EV flexibility for providing spinning reserve are expressed as operational costs, environmental benefits and reduced wind curtailment. Kara et. al [20] define flexibility as idle time without charging and demonstrate that charging management can result in a 24.8% bill reduction. In [28], the extent to which energy use can be shifted is defined as a metric for quantifying flexibility. The study establishes the benefits of this flexibility in reducing carbon emissions. Regarding the transformer's health and the operator's electricity bill, the flexibility of EV charging is exploited through controlled charging and real data [29]. Long-term impact of smart charging is investigated using behavioral models and real-world data in [30], and the results suggest that smart charging could favor the grid in helping to integrate renewable generation, thus lowering the electricity price by 0.6–0.7% . [31] quantifies EV charging flexibility in two representative scenarios: peak shaving and load balancing.

While significant progress has been made in the slow and residential charging fields, significant gaps remain in the fast and non-residential fields. Understanding the flexibility characteristics, the users' behavior, and the influencing factors is an inevitable part of designing a realistic smart charging algorithm. We focus on quantifying and exploiting the potential values of non-residential EV charging based on the field data of EV charging.

3. Dataset Description

3.1. Studied Charging Station

In this section, we present the data collected and used in this paper. The data for our analysis was collected between 2020 and 2022 from the Minle P+R (parking + transfer) charging station, as shown in Fig. 2, the world's largest EV fast-charging station deployed at Longhua District, Shenzhen [32, 33]. The charging station, which covers an area of around 20 km^2, currently has 637 fast chargers that can service roughly 5 thousand EVs per day. Moreover, within walking distance of the Minle subway station, the station provides a rest space with lounge amenities to meet the demands of drivers.

The time-of-use (TOU) energy rate structure, one of the most well-known programs in demand response, have been widely practiced to encourage users to shift their power usage from peak to off-peak periods for peak shaving purpose. Currently, Shenzhen adopted a four-level TOU rate structure. In this framework, a day is divided into nine periods belonging with different charging price in Table 1.Ranging from 0.65 RMB/kWh to 1.55 RMB/kWh, the electricity price nearly tripled from the off-peak to the peak. High gaps between each price could offer energy users the possibility of reducing their electricity bills from altering parts of the flexible energy consumption like EV charging.

Table 1: Time-of-Use Price Structure

Label	Price	Duration
off-peak	0.65	0-8AM
shoulder	0.98	8-10AM, 0-2PM, 7-12PM
part-peak	1.25	10-11AM,2-3PM,5-7PM
peak	1.55	11-12AM,3-5PM

3.2. Charging Session data

Encoding the key information of the entire charging process, charging sessions play a central role in understanding the heterogeneity of EV users. In this paper, we collected over 0.7 million charging session data from MinLe (P+R) stations between 2020 and 2022. Those data are cleaned and structured into a format that is parameterized by the variables listed in Table 2. The majority of those could be directly extracted from the raw data, while others, like the average charging power, are calculated by simple rules or assumptions. As a preprocessing step, we filter out those records lasting less than 10 minutes as they have been considered irrelevant.

Now we portray the session data statistically to characterize the users' behavioral patterns and further seek to identify potential profitability and businesses value. The distribution and descriptive statistics are presented in Fig. 3 and Table 3. In terms of energy consumption, 90% sessions is characterized by a mean value of 33.2

Figure 2: The geographic location of the studied charging station.

Table 2: Parameters of individual charging events

Parameter	Meaning
i	Index of charging sessions
E_{chr}	Total electricity withdraw from the charger in kWh
B_{chr}	Bill of the charging session in RMB
T_{start}	Start time of the session
T_{end}	End time of the session
$\text{SOC}_{\text{start}}$	State of charge at the session beginning

kWh, the typical battery capacity of the majority of the current EV. Benefited from the fast-charging technology, 77.5% sessions are completed within a hour. Due to the diversity of vehicles, the charging power are scattered between 20 kW to 100 kW and centers around 38 kW. Compared to slow charging, fast-charging features much disturbance to the local grid. On the other hand, the extensive energy transferring may be exploited in smart charging programs. All concerned variables feature a unimodal and left-skewed distribution. That indicates the regularity of users' charging behavior : they tend to recharge the vehicles in the shortest time and with the least amount of money as possible. Note that the charging duration is the most dispersed variable, with a standard deviation of 24.5, and this implies a possibility to exploit the related flexibility.

3.3. Temporal Charging Patterns

The aggregated patterns of energy use (also known as daily load profiles) reflects the behavioral differences of EV users and could contribute to the understanding of their charging preferences. We construct daily load profiles from merging the session data and discretize them with a temporal resolution of 15-min intervals (starting at t=0 and ending at t=95), and Fig. 4 presents the average load profile for Minle (P+R) Station. The average load profiles with error bands are illstrated through solid and dashed lines. The background colors indicate the TOU rate.

Close inspection reveals a tri-modal pattern in terms of charging loads. These identified peaks, namely night (0-8AM), around noon (0-6PM), and afternoon/early evening (4-7PM), also align with the change in electricity prices. The noontime charge and the early evening are also aligned with lunch and the dinner break. The afternoon period is aligned with the afternoon shift schedule of EV drivers.

These patterns are also in line with the findings of [33]. For the first two peak periods, price seems to be the dominant factor affecting the charging behavior, and this indicates a high price sensitivity for fast charging. However, the third mode, as a contrary, illustrates a temporal alignment of the high-price period and the EV arrival.

Fig. 5 compares the charging modes in terms of duration per session and the total share of total sessions. It is clear that night is the most common periods for EV charging, accounting over 30% of total sessions, followed by afternoon charging (26.4%) and moon charging (19.2%). This pattern is also observed in charging duration. A longer duration means a longer potential

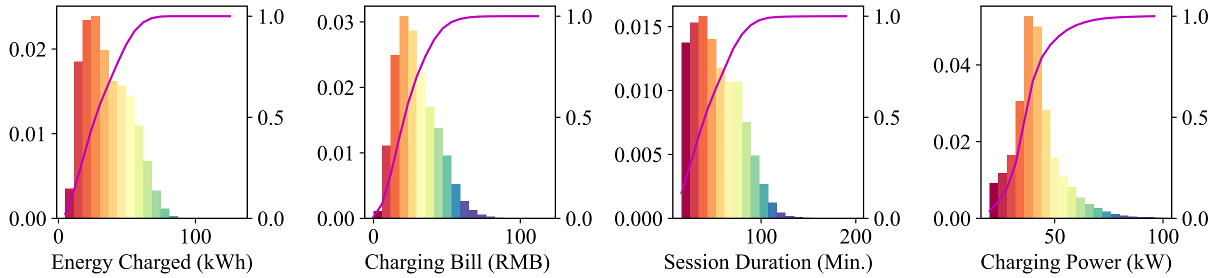

Figure 3: Histograms of session attributes.

Table 3: Descriptive statistics

Parameter	mean	std.	min	25% quantile	median	75% quantile	max	Skewness	Kurtosis
Energy Charged	35.81	16.35	5.01	22.44	33.20	48.23	131.56	0.43	-0.672
Bill	29.24	13.81	0.0	18.77	26.90	38.14	118.00	0.72	0.278
Duration	53.43	24.55	16.00	34.00	50.00	71.00	199.00	0.60	-0.022
Power	41.67	11.01	20.00	35.44	40.26	46.05	99.96	1.11	2.595

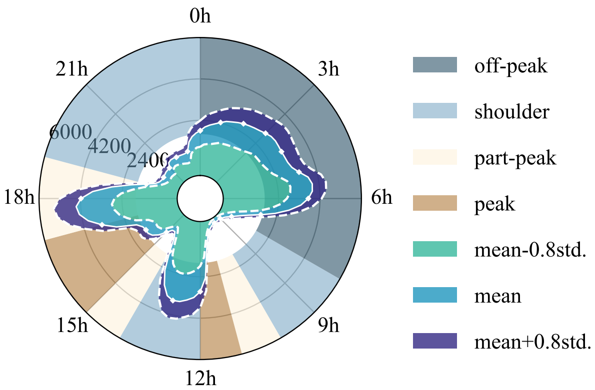

Figure 4: Average load profiles for Minle Charging Station.

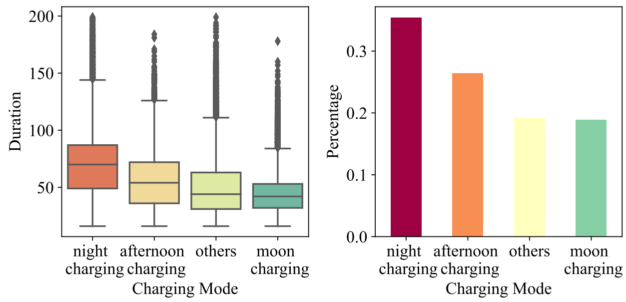

Figure 5: Characterization of charging modes.

idle time of vehicles. Besides, night charging typical last the longest time as the consequence of low recharging price. Compared with night charging and moon charging, we are more interested in afternoon charging, as this mode overlaps with a high-price period. This charging mode, if well managed, may be a main source of fast-charging flexibility compared to the other three.

3.4. Coupling PEVs energy demand and mobility patterns

According to the aforementioned discussions, EV charging behavior is classified into three distinct groups based on arrival. To further exploit the underlying factor, we collect historical data on urban mobility in the same region and conduct a comparison study, as illustrated in Fig. 6 The correlation analysis is then conducted using the constructed time series data to examine the distribution of correlation values between traffic speed and load profiles. The Pearson correlation coefficient (r), the most common way of measuring a linear correlation, will be computed within a specific rolling window to reveal the dynamics of the correlation, and the results will be presented in terms of a time series of r. The correlation value lies in the range of -1 to 1, with 1 indicating a strong positive correlation and -1 for a strong negative correlation. We compare the average daily load profile and traffic speed and identify an interesting pattern: the trend of traffic speed aligns with that of the load profile at most times, say 0AM-2:30PM and 20-24PM. However, they evolve contrarily at 2:30–20

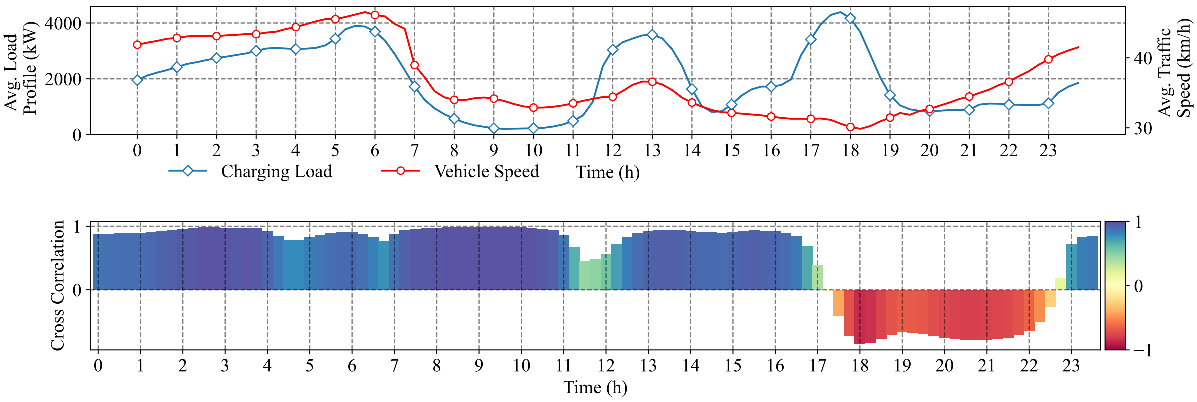

Figure 6: Relationships between EV charging and mobility.

PM, a mobility peak period in the evening. At such a period, the peaks of mobility and recharging are vitally overlapped. This pronounced peak in both may be caused by the regular behavior of both commuters and taxis. It is preferable for commuters to recharge on their way home, whereas taxis may do so to save time and energy wasted in traffic congestion. As a consequence of congestion, users may defer their departure and engage in other activities. In such cases, charging sessions are more flexible and this provides a chance for smart charging implementation.

From the perspective of facility operation, such a period is also opportunistic because it coincides with the high level of electricity prices. The benefit of implementing smart charging is twofold: the facility operator could save excessive costs by buying electricity from the grid and gain a subsidy by providing peak-shaving service.

From the above discussion, we recommend a smart charging implementation here. The EVs arriving in periods of peak demand are offered a one-shot contract, which grants the facility the right to control the charging power and adjust the departure time. During the effect duration, the facility first draws energy from the remaining battery storage at a constant power till the SOC drops to a predefined limit. Then the charging session comes to an idle state until the electricity price declines. The vehicles will be recharged using a high charging rate at a normal price till the end of the contract.

4. Smart Charging Scheme

In this section, we introduce the proposed smart charging methodology. In particular, we describe the general optimization strategy used to obtain the charging schedules for each charging session.

4.1. Problem Formulation

We lay out an infrastructure-specific charging scheme that maximizes the revenue from peak shaving by controlling the timing and power absorbed from and delivered back to the grid. Incorporating timing decisions into the optimization model is particularly challenging because of their implicit relationships between the objectives. In [20], the timing of controlled charging is modeled by introducing numerous binary incidence variables. By doing so, each session is rescheduled in a way that minimizes specific cost functions but without a reasonable time frame. The algorithm faces a scalability issue when dealing with millions of sessions.

Consider rescheduling a single session i with the original start time of T_{start}, end time of T_{end}, and energy consumption. The decision-maker aims to determine the power series in discrete time slots $[1, 2, ..., K]$ thereby optimizing a objective. For a typical session, an EV begins to draw power from the grid when plugged in and completes the process before it departs. However, the charging power could be managed in such a way as to suspend the charging at a high price and recover it when the price steps down. Further, if granted the ability to deliver power back to the grid, a vehicle could sell the extra electricity at peak times for the peak-shaving subsidy and complement the charging at off-peak times. Here, we split the energy interaction into two time series : charging power $P_t^{c,i}$ and discharging power $P_t^{d,i}$, $t = 1, 2, ..., K$. The most fundamental condition for session optimization is to ensure the expected battery power is fulfilled, that is

$$\sum_{t \in T} \left(P_t^{c,i} - P_t^{d,i} \right) = E_{\text{chr}}^i \tag{1}$$

Since $P_t^{c,i} > 0$ and $P_t^{d,i} > 0$ could note hold simultaneously, we introduce a set of logic conditions as

$$P_t^{d,i} \leq M\lambda_t^i \tag{2}$$

$$P_t^{c,i} \leq M(1 - \lambda_t^i) \tag{3}$$

$$\lambda_t^i \in \{0, 1\} \tag{4}$$

where λ_t^i is a binary variable indicating the direction of energy flow between the vehicle and the grid and M is a big real number. The controller charge the vehicle when $\lambda_t^i = 0$ and draw energy from it when $\lambda_t^i = 1$. The objective for smart charging is comprised of three parts: the energy purchase cost C_{purchase}, users' incentives C_{user} and the economic benefit from peak-shaving V_{peak}.

$$C_{\text{purchase}} = \sum_{i \in I} \sum_{t \in T} \pi_t^c P_t^{c,i} \tag{5}$$

$$C_{\text{user}} = \sum_{i \in I} \sum_{t \in T} \pi_t^{user,i} \left(P_t^{c,i} + P_t^{d,i} \right) \tag{6}$$

$$V_{\text{peak}} = \sum_{i \in I} \sum_{t \in T} \left(\pi_t^c + \pi_t^{ps} \right) P_t^{d,i} \tag{7}$$

where π_t^c and π_t^{ps} represent the TOU price and the peak-shaving subsidy, $\pi_t^{user,i}$ is the session-specific price, which also reflects the inconvenience made to the users because of smart charging participation. Since $\pi_t^{user,i}$ is related to the timing of arrival and departure, we design the price as a truncated second-order polynomial function of start and end time, that is

$$\pi_t^{user,i} \left(T_{\text{start}}^i, T_{\text{end}}^i \right) = \begin{cases} \mu \left(t - T_{\text{start}}^i \right)^2 & \text{if } t \leq T_{\text{start}}^i \\ \mu \left(t - T_{\text{end}}^i \right)^2 & \text{if } t \geq T_{\text{end}}^i \\ 0, & \text{otherwise} \end{cases} \tag{8}$$

where μ is a price coefficient that could be adjusted according to the realistic situation. The rule depicted in (8) reveals a fact that a higher price must be paid to incentivize users to adjust their arrival and departure to a large extent. Therefore, we could formally write the smart charging scheme as

$$\min_{P_t^{d,i}, P_t^{c,i}, \lambda_t^i} F = \quad C_{\text{purchase}} + C_{\text{user}} - V_{\text{peak}} \tag{9}$$

$$\text{s.t.}: \quad \text{Constraints} \quad (1) - (6) \tag{10}$$

The resulting formulation is a mixed-integer linear program (MILP) and could be trivially addressed by commercial solvers like CPLEX. The objective aims to reduce the operational cost from a stakeholder's perspective, subject to the users' energy requirements.

4.2. Optimization Results

The proposed smart charging scheme is tested under historical charging sessions. In Section 3.4, we have identified afternoon charging as the most profitable mode. Therefore, the sessions belonging to this scope are selected to test the proposed smart charging scheme. For each sessions, we record the resulting economic benefit in smart charging (B_{sc}) and aggregate them according to the date. Fig. 7 shows the distributions the optimization results.

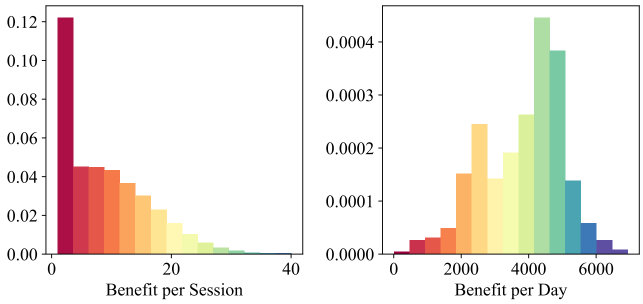

Figure 7: Distribution of benefits

5. Exploratory Data Analysis

5.1. Load Profile Trend Analysis

Fig. 8 illustrates the trend of daily energy consumption as well as the affecting issues. Analysis shows that the pandemic dominately contributes to the change in urban mobility, thereby influencing the trend of daily profiles. Another factor influencing energy use concerns the holiday. Holidays, represented by the spring festival, typically lead to a marked reduction in daily energy consumption. This finding arises from the fact that EV commuters are reduced during holidays.

5.2. The rescheduling results

Fig. 9 compares uncoordinated charging to the proposed smart charging scheme in terms of net revenue. The shaded areas represent the original and reduced trends of net monthly net revenue calculated in RMB in 2021, respectively. And the right axis displays the ratio of V2G benefit to net revenue. The results show that the proposed scheme could unlock a additional economic benefit ranging from 77,190 to 128,800 RMB per

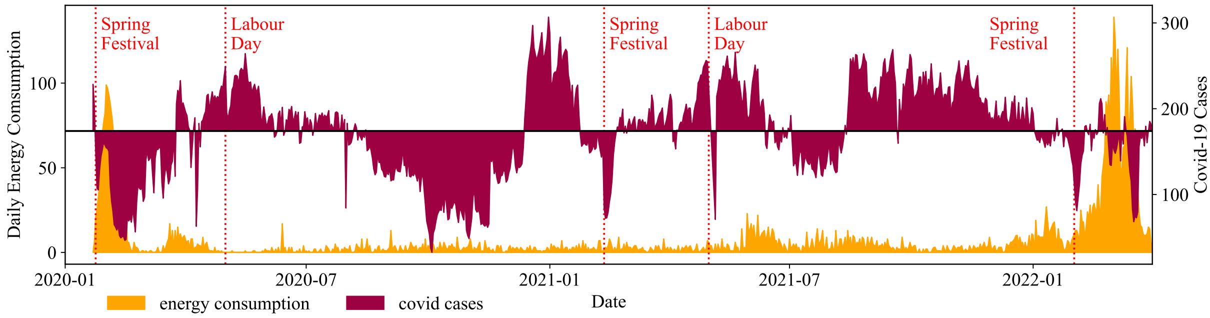

Figure 8: Trend of daily energy consumption

month, an 20%-30% saving on the original net revenue .

5.3. *Seasonal effects*

Seasonality is conventionally regarded as a critical factor driving the changes in energy use [34, 35]. According to the monthly ambient temperature, daily profiles are divided into three groups: (a) spring (March, April, and May) and fall (September, October, and November); (b) summer (June, July, and August); and (c) winter (December, January, and February). Fig. 10 presents the boxplots of key indicators of charging profiles.

Note that seasonal variation is significant, as charging sessions amount to 1307 per day in winter, 1564 per day in summer, and 1457 in spring and autumn. EVs generally consume less energy in winter (179.3 MWh per day) compared to the other seasons (195.6 MWh per day for summer and 196.7 MWh per day for spring and autumn). This could be interpreted as meaning that the energy used by the air conditioning system grows in line with the ambient temperature. The studied city features a monthly average temperature of over 10 degrees, and the additional energy consumed by the heating system is minor.

Regarding the smart charging benefits, seasonality also plays a significant role. The daily V2G benefits is 2933.76 RMB in winter, compared with 3991.64 RMB in summer and 3536.63 in spring and autumn. These trends indicate that summer is a much more opportunistic period for smart charging implementation than the others.

5.4. *Impact of COVID-19*

The COVID-19 pandemic has posed a structural impact on human society, thus reshaping the patterns of EV recharging and mobility [36, 37]. In this part, the impact of the pandemic spanning two years on the operation of the studied charging station is unveiled.

We divide the operational days into three groups according to the confirmed cases, which is an indicator of the lockdown. When the number of confirmed cases increases, the government tends to impose stricter mobility restrictions.Trip reduction is expected to reduce EV use and recharging, as shown in Fig. 11, where a discernible trend can be seen across all metrics.The results suggested that a small-scale COVID-19 outbreak (less than daily hospitalizations) could cause a 15% decrease in daily energy consumption and that the number grows up to 25% when the situation deteriorates even further. A similar variation exists in the monetary savings obtained through smart charging. The operator may suffer over half of the benefits gained in no-outbreak days when the confirmed case steps over 50.

6. Conclusion

In this paper, we quantify the potential benefits of smart charging to the station owner using real-world fast-charging data. An exploratory analysis of two distinct urban mobility and energy consumption patterns of electric vehicles was carried out. The Pearson correlation analysis shows an opportunistic period for smart charging implementation. We extend the proposed methodology by formulating a MILP problem for rescheduling the EV recharging and analyze its practicability. An average of 20% to 30% extra benefit in the monthly bill may be achieved after optimization. However, since they are strongly related to social and environmental factors, the benefits should be exploited using well-designed contracts or programs. These findings contribute to the understanding of the users' behavior and pave the way for designing effective smart charging schemes using charging session data.

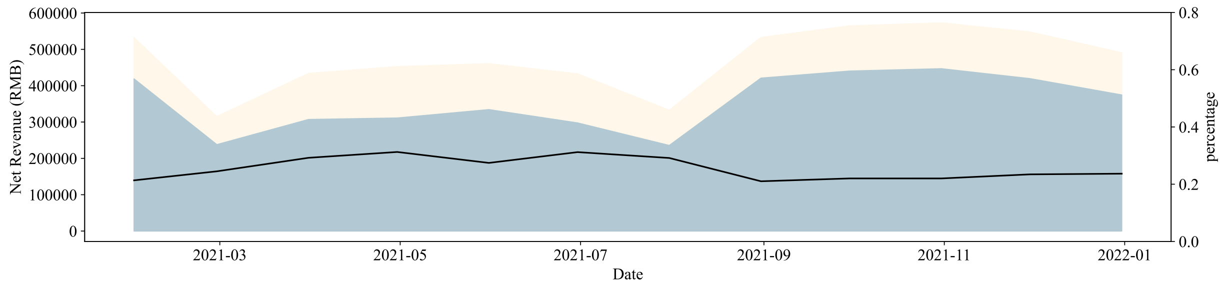

Figure 9: Daily bills and benefits for the owner in 2021.

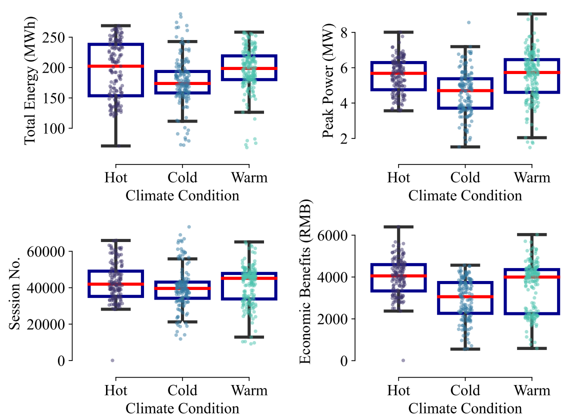

Figure 10: Impacts of climate.

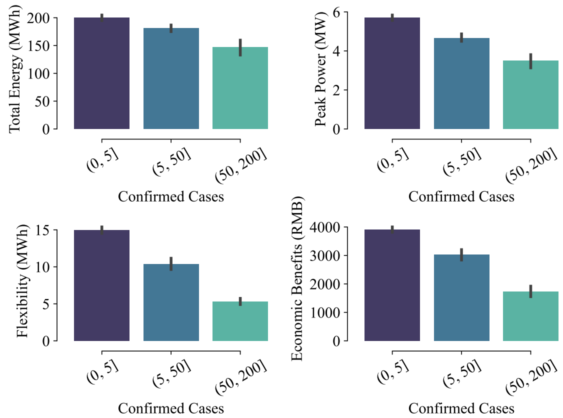

Figure 11: Impacts of the covid-19 pandemic.

This work can be expanded in a variety of ways. For example, the patterns of daily trips, energy consumption, and users' preferences are expected to be incorporated into the methodology. Another interesting scope concerns designing effective data-driven methods for managing and guiding EV fast-charging in the context of a grid environment with high-proportioned renewable energy generation.

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