MONASH University

WP1.2 Technical modelling of electrification of transport profiles Milestone Report: EV charging profile extraction and aggregation for PV customers

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DISCLAIMER AND ACKNOWLEDGEMENT

Acknowledgement and Disclaimer:

This research is part of a program of fourteen projects, which have variously been funded and supported under C4NET's Enhanced System Planning collaborative research project. While conducted independently, the authors acknowledge the funding and in-kind support of C4NET, its members and supporters, and its ESP project partners.

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In addition to the current team members, we would like to acknowledge Ryan Wang and Xiangrui Li for their early efforts that contributed to some of the content included in this report.

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EXECUTIVE SUMMARY

This report introduces a framework for analysing and modelling electric vehicle (EV) charging patterns specifically for customers who have installed solar photovoltaic (PV) systems. As the adoption of rooftop PV increases, understanding the EV charging behaviours of PV customers becomes increasingly relevant and crucial for the energy transition. This report examines EV charging profiles for customers with PV installation from both an individual and aggregated perspective. From the individual perspective, EV charging disaggregation is performed using smart meter data. From the group perspective, we construct the aggregated EV charging profiles across different types of chargers for PV customers.

For the disaggregation task, our focus is on extracting EV charging load from overall household electricity load using their smart meter data. Disaggregating EV charging profiles without ground truth data is is particularly challenging, especially when PV generation is present but data on the PV generation is unavailable. It is also important to note that several factors, such as the presence of batteries, changes in EV ownership and charging location, are not considered due to the lack of necessary data. In addition, common factors like potential impacts of COVID on load and the usage of EVs, as well as the lack of information on customers' activities, usage of appliances, possible installation of batteries, may affect the disaggregating results in this work. Besides these, PV generation poses additional challenges to the disaggregating task, while the available dataset only shows the electricity purchase and PV feed-in without including PV generation amount. The upgrade of PV systems over time is not visible to our analysis due to the lack of necessary data. To perform disaggregation for PV customers, the used method involves identifying PV customers and applying statistical filtering techniques to extract EV charging profiles from other household energy usage. Critical assumptions include stable non-EV energy consumption behaviour and consistent solar PV generation capacity over 2020-2022. To further enhance reliability of the result, our approach accounts for variability in customer behaviour and extreme weather conditions, ensuring that the extracted EV charging profiles are as accurate as possible.

Implementing our disaggregation approach on smart meter data first involves a series of data refinement steps, such as eliminating incomplete or inconsistent data entries. Further filtering of the dataset is applied to identify EV customers and exclude those without solar PV installations. By differentiating energy consumption between two years for the same PV customer, we were able to identify the EV charging load. A travel behaviour filter is applied to ensure that only realistic and consistent charging patterns are included. The weekly sampled EV charging profiles, along with meter load data and verification on extreme weather days, which assist to make the framework more effective and reliable. Additionally, further analysis of EV charging behaviour on weekdays versus weekends provides valuable insights into individual charging habits.

It is important to note that while our disaggregation toolbox is functional, it may not fully capture EV charging profiles for PV customers during the daytime due to the absence of solar PV generation data. Our method relies on smart meter data, but the specific solar PV generation occurring behind the meter, which could contribute to EV charging, is unknown. The accuracy could be potentially enhanced with the inclusion of

residential solar PV generation data if it could be made available. Additionally, after classifying customers by charger type, we found that most customers identified in the dataset use 2.3kW chargers at home, with only a small number using 3.7kW or 7.4kW chargers. As a result, we recognize that the disaggregated EV charging profiles for the 3.7kW and 7.4kW chargers may not fully capture a variety of charging patterns due to the limited sample size.

For the aggregation task, we model the collective EV charging consumption of PV customers using a probability distribution approach that accounts for key factors such as charger types, charging segments, and the temporal distribution of charging events. This method enables the capture of variability in EV charging behaviours across different customer groups and time periods, which adds to the reliability of the representation. For PV customers, we define four charging segments: morning-only, daytime-only, evening-only, and multi-charging, the last of which includes at least one daytime charging event as it is a particularly interesting behaviour for PV customers. We then calculate the probability density distribution for each segment across three different types of chargers. By integrating the probability distribution of each segment, we derive the aggregated EV charging profiles.

Comparing the aggregated meter load derived through non-PV customer's data, we found that installing solar PV systems may to some extent alter the residential energy consumption patterns. This is because EV customers with solar PV systems may tend to take advantage of the solar PV generation during daytime to charge their EVs. Their EV charging consumption at night times (especially during night peak hours) is therefore partially shifted toward the daytime periods. As a result, integrating solar PV systems for EV customers, on the one hand, benefits customers from using solar PV generation instead of purchasing electricity from the grid, on the other hand, helps peak load shaving for the grid. In addition to such a comparison between non-PV customers and PV customers, we also conducted a synthetic analysis to examine the impacts of more daytime charging on both aggregated EV charging profiles and aggregated meter load.

The results provide the insights in the following three aspects: 1) Reduction in peak load: The primary impact of shifting EV charging from evening to daytime is the reduction of evening peak load. As the evening typically experiences high residential electricity consumption, reducing the additional burden of EV charging can significantly alleviate strain on the grid during this time; 2) Better utilisation of solar PV energy: By shifting charging to daytime, when solar PV generation is at its peak, customers can optimise the use of their PV systems, effectively charging their EVs with clean energy. This not only promotes the use of renewable energy but also reduces dependence on grid electricity, which may be more costly and less environmentally friendly during peak periods; and 3) Shaping EV charging profile: Increased daytime charging leads to a more even distribution of load throughout the day. This balanced load profile aids in optimising the operation of the electrical grid, potentially reducing the need for infrastructure upgrades and lowering overall electricity costs.

Moreover, the aggregated EV charging profiles provide the following insights related to peak intensity, duration, and potential solar PV usage. For instance, the 7.4kW charger consistently exhibits the sharpest and highest peaks across all segments. In comparison, the 3.7kW charger shows slightly broader peaks, while the 2.3kW charger has the most gradual peaks and slower declines.

Additionally, we analyse the impact of solar PV generation on the aggregated EV charging profile through a synthesised analysis, demonstrating that PV system installations can significantly reduce the EV charging consumption from the grid during daytime hours.

This report presents detailed data analysis and advanced modelling techniques for EV charging profiles in particular for PV customers. These findings could provide useful insights into future charging management and grid upgrade in the presence of solar PV.

GLOSSARY OF TERMS/ABBREVIATIONS

PV	Photovoltaic
EV	Electric vehicle
DNSP	Distributed network service provider
NMI	National meter identifier
PDF	Probability density function

1. Introduction

The electrification of transportation, combined with the integration of photovoltaic (PV) systems, marks a critical step toward reducing greenhouse gas emissions and achieving sustainability goals. Effective modelling of EV charging profiles, particularly for households with PV systems, is vital to ensuring that the grid can meet growing consumption while optimising the use of renewable energy. Driven by the need to better understand EV charging profiles when residential solar PV is accessible, this report shifts its focus to customers with PV installations, utilising both disaggregation and aggregation methods to provide an analysis of EV charging patterns for PV customers.

In the disaggregation task, we aim to identify and extract EV charging load from overall household energy consumption using the rule-based methodology based on smart meter data, which has been documented in the milestone report on "EV charging profile extraction methodology and results". Similarly, this process involves extensive data wrangling and preparation for PV customers in the dataset, as well as the integration of external data sources, such as travel behaviour reports, EV charging rates, and temperature data from the Bureau of Meteorology to account for the influence of extreme weather on charging profiles. It's worth noting that the knowledge of EV charging power, travel behaviour, and weather data used in our method settings was independently sourced from government reports and research works, such as [1] - [6], [11]. By disaggregating EV charging from meter data, this analysis offers insights into individual charging behaviours for customers with PV. However, the lack of solar PV generation data may lead to lower accuracy of EV charging extraction especially during daytime. The inclusion of behind-the-meter solar PV generation data is expected to enhance the accuracy of the results, if such data could be made available.

In the aggregation task, we model the aggregated EV charging consumption of PV customers, focusing on its uniqueness posed by distributed solar PV generation and possible distinctions compared to that of non-PV customers. By developing an aggregated probability distribution model, we categorise PV customers' EV charging profiles into four distinct segments: morning-only, daytime-only, evening-only, and multi-charging (with at least one daytime charging session as it's of particular interest to observe PV customers' charging behaviours). Additionally, we explore various charging scenarios, including the impact of different charger types and potential future upgrades to higher-powered chargers. This enables us to assess how aggregated consumption may evolve as more customers adopt faster chargers and adjust their charging habits to align with solar PV generation. We also analyse the effects of PV generation on aggregated EV charging profiles during daytime hours through synthetic solar PV generation data.

By combining detailed disaggregation techniques with aggregated modelling, this report offers a perspective on EV charging patterns for PV customers. The insights from this report could be useful for future charging management, grid infrastructure planning, and the integration of renewable energy sources.

2. EV charging extraction in the presence of PV

2.1 Recap on EV charging profile extraction: dataset, assumption, and methodology

2.1.1. Input dataset overview

The datasets used in this study include smart meter data, EV rebate program data, and daily temperature data, each providing key insights into electricity usage, program participation, and weather impacts.

Smart Meter Dataset: This dataset contains half-hourly electricity usage data from smart meters installed at customer premises, spanning from January 2020 to March 2023, with variations in the end dates. Note that, in this report, our focus has shifted toward customers with solar PV installation. We have filtered out all PV customers from the smart meter dataset through one column namely "HAS_PV_SUM". The values of PV customers in this column should not be equal to zero.

Fig. 1 visualises the weekly meter load of a sampled PV customer. The negative values of meter loads indicate that there is excessive solar PV generation which is exported back to the grid. However, the exact solar PV generation is behind-the-meter and thus unknown to us, which poses great challenges in extracting EV charging profiles for PV customers, as customers may use the behind-the-meter solar PV generation to charge their EVs, which may not be reflected through the smart meter loads. The data include periods affected by COVID-19 lockdowns in Melbourne, which likely influenced consumption patterns. Key components include:

- Customer Identification: Anonymised unique identifiers for each customer.
- Customer Classification: Identifies customer types (business, industry, residential) to analyse specific consumption patterns.
- Timestamp: Date and time of data recording to track usage over time.
- Channel Records: Data on energy imported from and exported to the grid, highlighting bidirectional flows and distributed generation impacts.
- Electricity Usage: Detailed time-series of electricity consumed or exported, measured in kWh.

EV Rebate Program Dataset: This dataset identifies customers participating in the EV rebate program, distinguishing EV owners from the broader customer base. Key components include:

- Customer Identification: Anonymised unique identifiers consistent with the smart meter dataset.
- Program Participation Status: Indicates customer involvement in the EV rebate program.

In addition, some DNSPs provide geographic identifiers (4-digit postcodes) and limited data on PV installation sizes for certain customers, scattered across the smart meter and EV rebate datasets.

Daily Temperature Dataset: To assess the impact of extreme weather on EV charging patterns, temperature data from all weather stations in Victoria were collected from the Bureau of Meteorology. Only daily maximum and minimum temperatures are available. In particular, variations in data formats, missing values, inconsistencies, and discrepancies across different DNSPs are addressed in the data wrangling section.

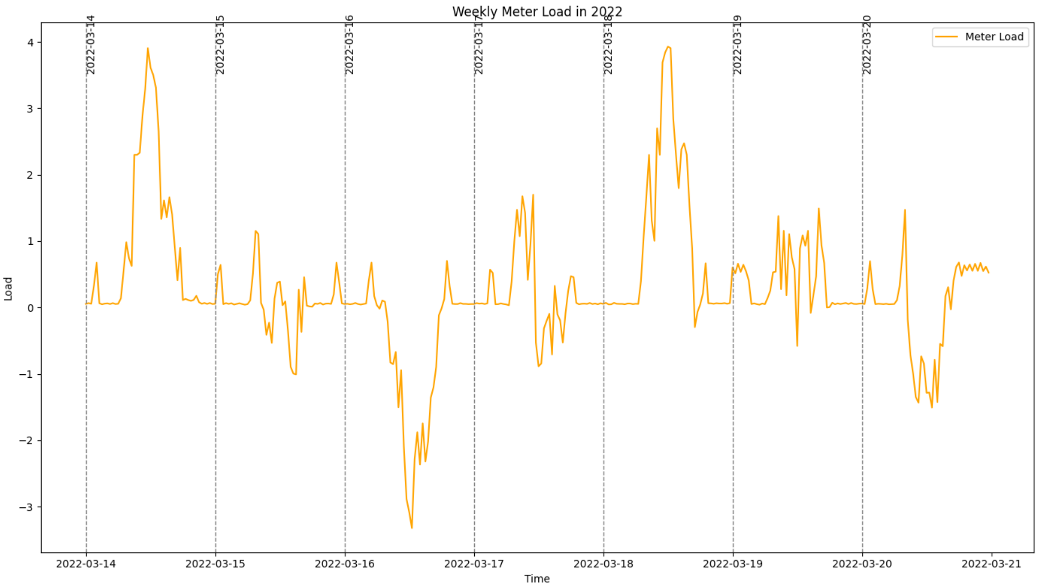

Figure 1 Weekly meter load visualisation of a sampled PV customer

2.1.2. Data wrangling and key assumptions

Although data adhere to the NEM12 format, inconsistencies and anomalies can arise during storage and processing. We performed data wrangling on raw data, including EV rebate and meter data, to ensure data consistency and reliability in the analysis of EV data. Key issues and solutions are outlined below.

- Date and Time Inconsistencies: Different DNSPs used varying date formats (e.g., DD/MM/YY vs. MM/DD/YY) and time zones (AEST vs. UTC), complicating data processing. We standardised all date and time formats to ensure consistency.

- Column Name Inconsistencies: Column names varied across DNSPs, particularly for customer identifiers, classification, meter channels, and timestamps, hindering data merging. We standardised column names and order across all datasets.

- Missing and Duplicate Data: We identified duplicates and missing values, such as repeated meter readings and missing quarters of data, which could distort analysis. Key columns, like NMI_classification, were sometimes missing, affecting customer categorisation. We removed duplicates and focused on complete data.

- Semantic Errors: Misclassifications of customer types (e.g., residential customers showing industrial-level consumption) and issues with battery storage variability were common. We cross-verified classifications, identified outliers, and excluded customers with large batteries by comparing PV installation sizes with export channel data.

- Weather Station Matching: To link customers with relevant weather stations, we matched weather station locations to postcodes using suburb boundaries from DataVic, ensuring each customer was aligned with a nearby weather station for accurate extreme weather assessments.

Moreover, our technical methodology relies on key assumptions to improve the reliability and robustness of the analysis, enhancing the interpretability and validity of our findings while acknowledging limitations, presented as follows.

- Stable Appliance Energy Consumption: We assume that the energy consumption of non-EV appliances, including water heaters, remains consistent at the same date and time over three consecutive years for each customer.

- Consistent PV Size and No Abnormal Output: This assumption is particularly made for PV customers in this analysis. For PV customers, we assume that PV size remains the same and its output is similar on the same date and time points over three years, without having any significant system changes or failures. Note that in this dataset, we do not have any extra information about these PV customers except for their feed-in amount.

- Regular EV Charging Events: We focus on customers with consistent charging patterns, excluding those with sporadic, short-duration signals likely to be noise, to ensure reliable EV charging data.

2.1.3. EV charging extraction methodology

The proposed toolbox integrates data from smart meters, the EV rebate program, weather data, and travel behaviour profiles to extract EV charging data by analysing increased load consumption between two periods: before and after customers owned EVs. The approach compares daily energy consumption in half-hour intervals over two years—one without EVs and the next with home EV charging—to identify the additional power usage attributable to EVs.

The analysis begins with a rule-based model that evaluates energy consumption, using statistical methods to filter outliers and focus on typical patterns. It then examines the increased energy consumption to identify potential EV charging curves, distinguishing them from other sources. Due to limitations such as the impact of COVID-19 and household devices like batteries possibly installed, accuracy may be affected.

A machine learning model, incorporating a knowledge base of typical EV charger levels, clusters the detected charging curves to identify common charging behaviours across customer segments. It refines detection to minimise false positives and ensure reliable EV charging identification.

The final step validates EV charging profiles against travel constraints derived from travel behaviour, confirming alignment with realistic EV usage. Weather conditions and battery usage can affect consumption, and extreme weather days are analysed using daily temperature data to verify EV charging patterns. Model parameters, such as buffers and travel profiles, are adjustable for specific conditions, enhancing adaptability and accuracy.

Fig. 2 illustrates the complete toolbox framework, detailing data flow and analysis steps. The following subsections will outline the rule-based model's filters and mechanisms.

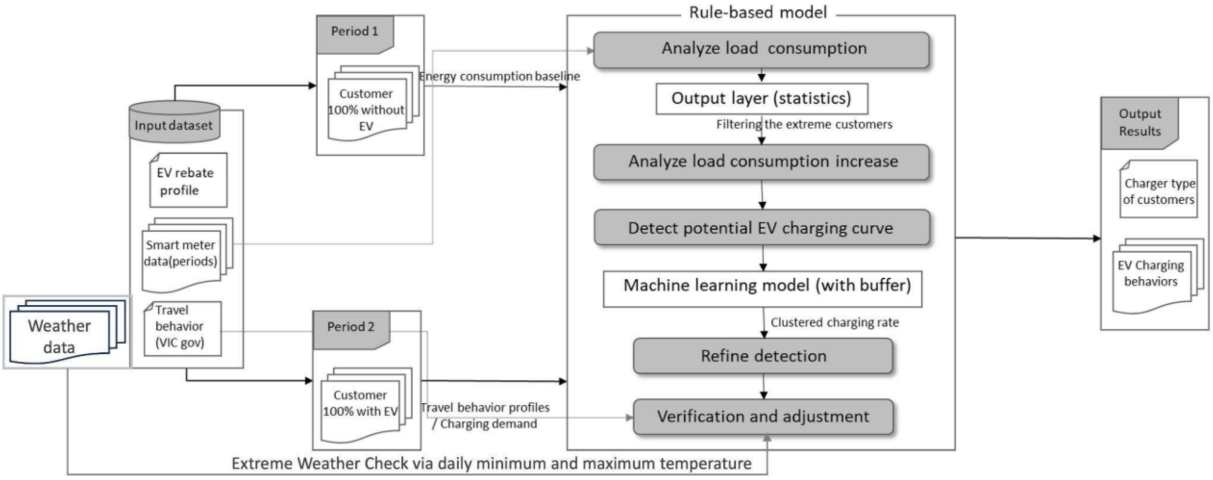

Figure 2 Framework of the proposed toolbox

The detailed explanation of the proposed toolbox/methodology can be found in our previous milestone report on "EV charging profile extraction methodology and results", including the following components.

1. **Smart Meter Data Preparation**: We cleaned the smart meter data by standardising date-time formats, unifying column names, and addressing missing or duplicate data. Semantic errors, such as mislabeling customer classifications, were corrected to ensure data consistency and reliability for subsequent analysis.

2. **EV Customer Identification**: EV customers were identified by merging the EV rebate program data with the smart meter data, aligning customer identifiers to create a dataset that links EV rebate participation with detailed energy usage patterns.

3. **Energy Consumption Differentiation**: We compared energy consumption between periods without EVs and periods with EV adoption to isolate the impact of EV charging. By calculating the load balance and analysing the differences in energy use, particularly for PV customers, we identified increased energy attributed to EV charging. A filter excluded brief power spikes unrelated to EV charging, ensuring effective EV charging data.

4. **Meter Load Data Alignment:** Instead of matching data by calendar dates, we aligned meter load data between 2020 and 2022 based on the same day of the week, improving the accuracy of EV charging disaggregation by accounting for weekday and weekend variations.

5. **Outlier Detection for Consistent Consumption**: We applied statistical methods, including the three-sigma rule, to filter out customers with unstable consumption patterns, ensuring observed increases in energy usage were due to EV charging and not other high-energy appliances.

6. **EV Charger Type Inference**: Using the K-means clustering algorithm and a knowledge base of typical EV charger levels, we grouped similar charging events to infer potential charger types. A noise term was introduced to adjust for inaccuracies and ensure reliable EV charging disaggregation.

7. **Refining EV Charging with Travel Behaviour Filter**: By integrating travel behaviour data, we refined charging profiles to match actual EV usage. Calculations based on annual travel distances and charging rates allowed for more accurate estimations of energy requirements and charging patterns.

8. **Extreme Weather Verification**: Using daily temperature data, we identified extreme hot and cold days and examined the impact on EV charging. EV charging profiles were compared against normal weather patterns, and adjustments were made if charging deviated significantly during extreme weather days.

2.2. EV charging disaggregation results

This section presents the EV charging disaggregation results for customers with PV system installation, including a general overview of the disaggregation from the perspective of different kinds of chargers, customers' weekly charging pattern investigation, and discussions on the weekday and weekend EV charging behaviours.

2.2.1. Disaggregation overview

The following analysis provides insights into the dedicated datasets after implementing various data processing steps. After meticulously applying our data filters, we identified the valid residential EV customers with solar PV installation. The total number of identified customers is 447. The identified charger levels are 2.3 kW, 3.7 kW, and 7.4 kW. After data wrangling including the removal of incomplete, inconsistent, and erroneous data, the overall customer number for those with residential PV systems is 705. After the filters developed in Section 2.1.3, including the load pattern consistency filter, travel behaviours filter, and the charging frequency filter, the number of customers drops down to 447. These levels provide a detailed understanding of the charging rates, showing how different power levels are utilised. This information is crucial for extracting EV charging profiles and for managing and balancing local energy consumption.

Customers' charging behaviours can be influenced by the charger's power rate. This variance in charging rates, aligned with the number of customers for each type, distinctly contributes to the overall load on the power grid. For example, Fig. 3 illustrates the distribution of customers by their type of charger. The pie chart shows that 82.1% of the customers use 2.3 kW chargers, 7.4% use 3.7 kW chargers, and 10.5% use 7.4 kW chargers, with the number of customers being 367, 33, and 47, respectively. The average EV charging consumption per day is 9.9 kWh across all PV customers.

More importantly, it is worth noticing that, after classifying each customer to a specific type of charger, the majority of customers use 2.3kW charger to charge their EVs at home, while a small number of customers use 3.7kW or 7.4kW chargers. Therefore, we acknowledge that the disaggregated EV charging profiles for customers with these two kinds of chargers may not represent the general EV charging profiles for 3.7kW or 7.4kW charger due to limited sample size.

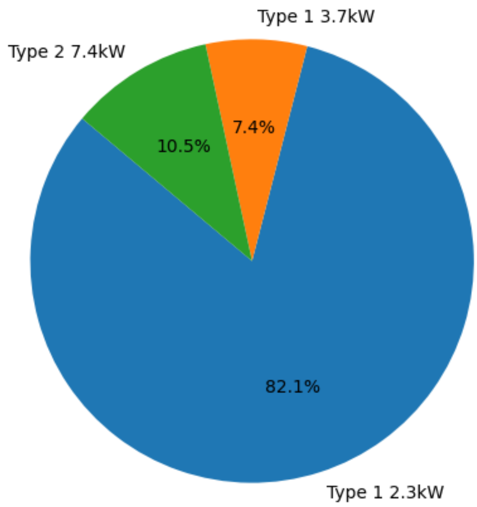

Figure 3 Distribution of EV customers with PV by their using types of chargers (Note that this mix does not necessarily reflect the actual mix in the real world as the processed data can be biased due to limited sample size)

2.2.2. Weekly meter load and EV charging visualisations

The following samples illustrate disaggregated EV charging profiles for customers using different types of chargers (with partially masked NMI). These profiles reflect different charging events on a weekly time scale and include customers using different levels of chargers. All the following visualisations start from Monday. Also, the blue and orange lines represent the disaggregated EV charging load and the smart meter load, respectively. Note that the negative values of the meter load indicate that the customer exports the excessive PV generation back to the grid.

- 2.3kW charger:

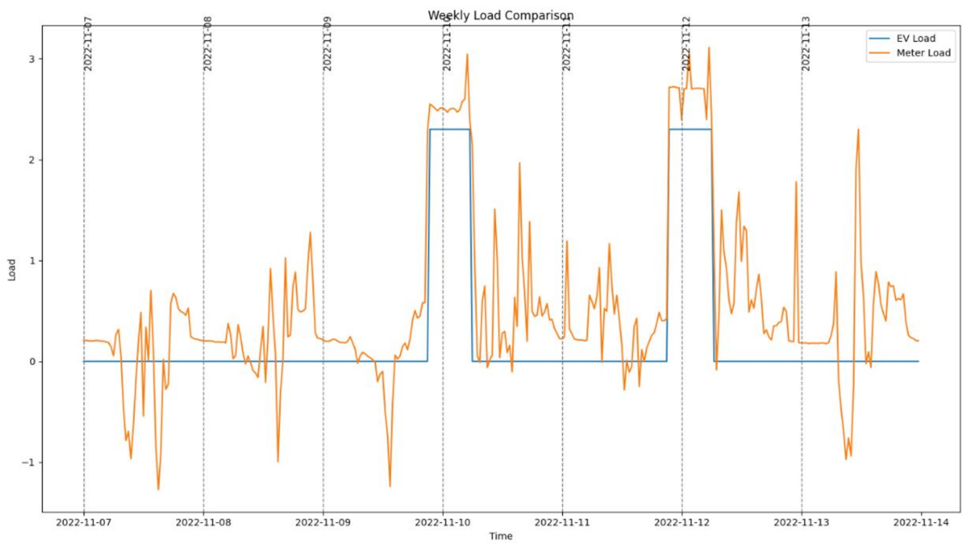

Figure 4 Weekly meter load and EV charging for customer using 2.3kW charger 1Dxxxx48E from 2022-11-07 to 2022-11-14

- 3.7kW charger

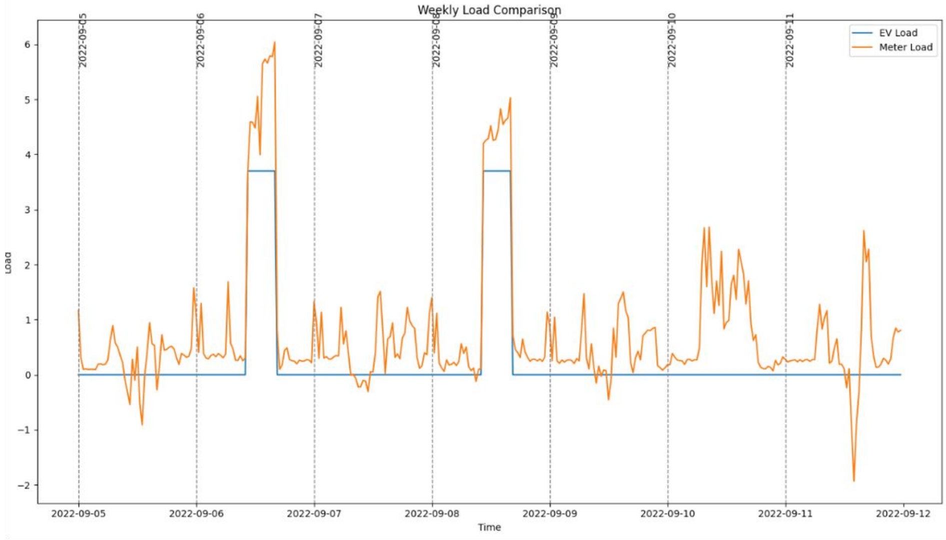

Figure 5 Weekly meter load and EV charging for customer using 3.7kW charger 0116xxx481144D84 from 2022-09-15 to 2022-09-12

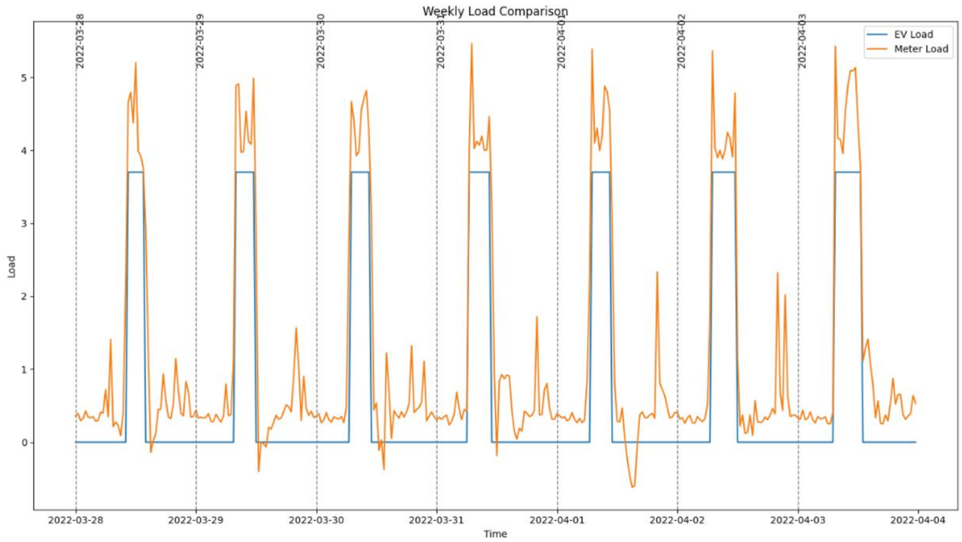

Figure 6 Weekly meter load and EV charging for customer using 3.7kW charger 37F0E8xxx0169D0A3C95 from 2022-03-28 to 2022-04-04

- 7.4kW charger:

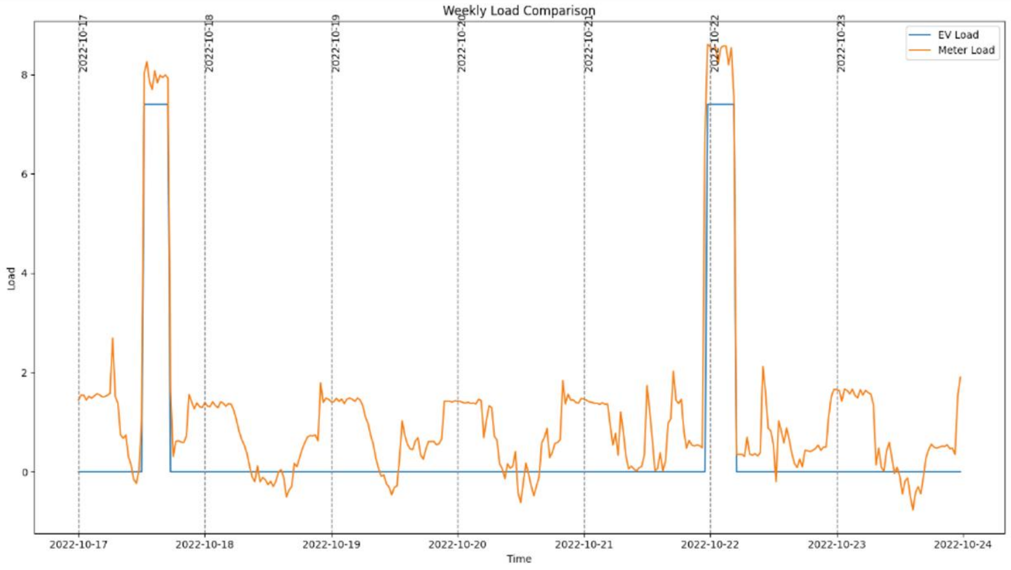

Figure 7 Weekly meter load and EV charging for customer using 7.4kW charger 0AA18xx3DACB17B0AFC from 2022-10-17 to 2022-10-24

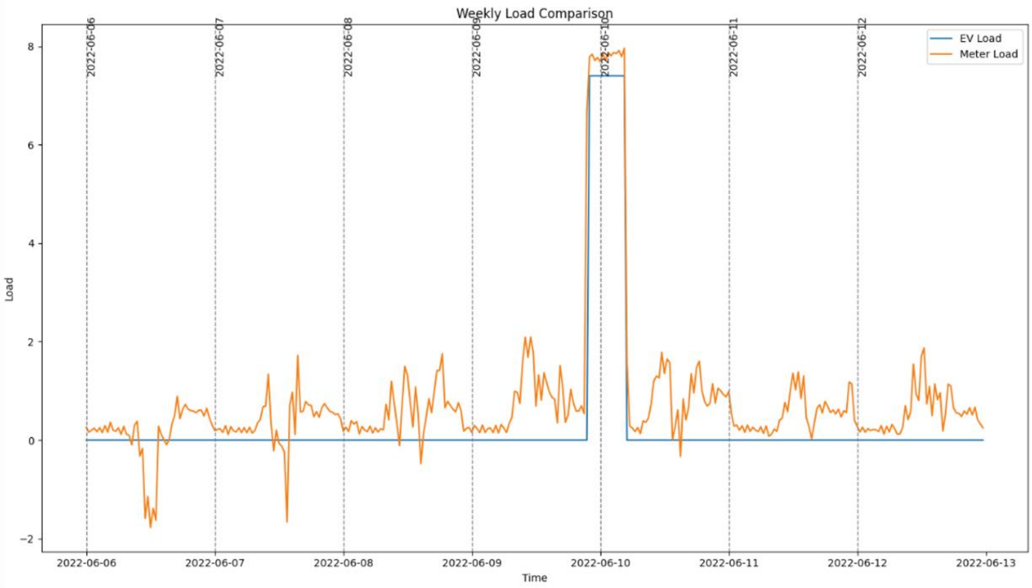

Figure 8 Weekly meter load and EV charging for customer using 7.4kW charger 8ECCB233xxxxxx5761 from 2022-06-06 to 2022-06-13

The above illustrations across 2.3kW, 3.7kW, and 7.4kW chargers highlight a key difference with the 7.4kW charger. As charger capacity increases from 2.3kW to 7.4kW, the EV load has a more substantial impact on the overall meter load. For instance, the 2.3kW charger has a relatively small effect on the total load, whereas the 7.4kW charger significantly contributes to the meter load, often aligning with the highest peaks.

Moreover, higher capacity chargers lead to more pronounced and consistent peaks in the total load. The 7.4kW charger, in particular, generates substantial spikes in overall load, suggesting that EV charging becomes more regular and synchronised with the total meter load as charger size increases. This trend aligns with findings showing that, for high-powered chargers, EV charging accounts for over 90% of the overall energy uplift between 2020 and 2022.

Again, we would like to emphasise that, for disaggregated EV charging profiles using 3.7kW and 7.4kW chargers, due to the small number of corresponding customers, the above weekly meter load and EV charging profiles may be influenced by specific customers' daily electricity usage patterns and may not be representative enough.

2.2.3. Weekday and weekend EV charging analysis

We calculate the average EV charging energy consumption for each day of the week, with the results presented in Table 1. These findings are consistent with a relevant research work done by the University of Queensland [13], which indicates that EV drivers typically drive longer distances on weekends and shorter, primarily commuting distances on weekdays. Our results suggest that customers tend to charge more on Fridays, possibly in preparation for long-distance weekend driving. Additionally, there is a noticeable increase in charging at the beginning of the week, particularly on Tuesdays, which may be due to EVs needing to recharge after weekend travel for regular weekday commuting.

Table 1 Average EV charging energy consumption for each day of week

Day of Week	Average EV Energy Consumption
Monday	9.78 kWh
Tuesday	10.58 kWh
Wednesday	9.50 kWh
Thursday	9.07 kWh
Friday	9.42 kWh
Saturday	9.37 kWh
Sunday	9.07 kWh

Note that our disaggregation toolbox may not fully capture the EV charging profiles for PV customers due to the absence of solar PV generation data. Our method relies on smart meter data, but the specific solar PV generation occurring behind the meter, which could contribute to EV charging, is unknown. Therefore, we would like to acknowledge that the statistics above may not reflect the actual EV energy consumption at each day of week in the real-world and could be biased due to the lack of solar PV generation data.

2.3 Validation on disaggregated EV charging profiles

2.3.1. Validation 1: Energy uplift between 2020 and 2022 w.r.t. EV charging

The detailed proportions of energy uplift attributed to EV charging for the three types of chargers are shown in Table 2.

Table 2 Energy uplift proportion caused by EV charging for three types of charger

Charger Type	Customer Number	EV Charging Proportion in Energy Uplift
2.3kW	367	66.46%
3.7kW	33	69.48%
7.4kW	47	70.46%

Given the lack of solar PV generation data for customers with PV installations, we further validate the effectiveness of our disaggregation toolbox by analysing the ratio of EV charging to the overall energy uplift during periods without PV generation. To isolate these periods, we set default parameters for PV generation times between 8 a.m. and 6 p.m. Note that this time window is an approximation without considering the varying sunrise and sunset times but would capture the major time periods when PV systems generate power. We consider the time between 8 a.m. and 6 p.m. as the PV generation period and summarise the ratio of EV charging to energy uplift during non-PV generation periods in Table 3.

It's important to note that sunrise and sunset times vary by season, so the 8 a.m. and 6 p.m. parameters can be adjusted for more accurate identification of PV generation periods. In Table 3, we observe that our disaggregated EV charging data accounts for a larger proportion of the energy uplift during non-PV generation periods. This further demonstrates the effectiveness of our disaggregation approach in identifying EV charging events and supports our assumption that the energy uplift between 2020 and 2022 is primarily driven by the adoption of EVs. The gap in the results of Table 2 and Table 3 is primarily caused by PV generation during daytime that the method may miss some EV charging profiles when PV generation supplies EV charging.

Table 3 Energy uplift proportion caused by EV charging for three types of charger during non-PV generation periods (from 6pm to 8am)

Charger Type	Customer Number	EV Charging Proportion in Energy Uplift
2.3kW	367	78.83%
3.7kW	33	81.41%
7.4kW	47	88.30%

2.3.2. Validation 2: EV charging under extreme weather days

To assess the effectiveness of our disaggregation method under extreme weather conditions, we provide sample data of meter loads and EV charging over a one-week period, including days with extreme weather. For example, in Fig. 9, 2022-12-03 and 2022-12-04 are two extremely hot days, as indicated by the red line representing the daily maximum temperature. Our disaggregation does not attribute the additional daytime power increases (up to 6kW) to EV charging. Given the high temperatures, the spikes in meter load are more likely due to increased cooling consumption.

Similarly, Fig. 10 presents another example. Our disaggregation model excludes the spike observed during the daytime on 2022-12-05 from EV charging, as the short duration of the power increase suggests it is unlikely to be related to EV charging.

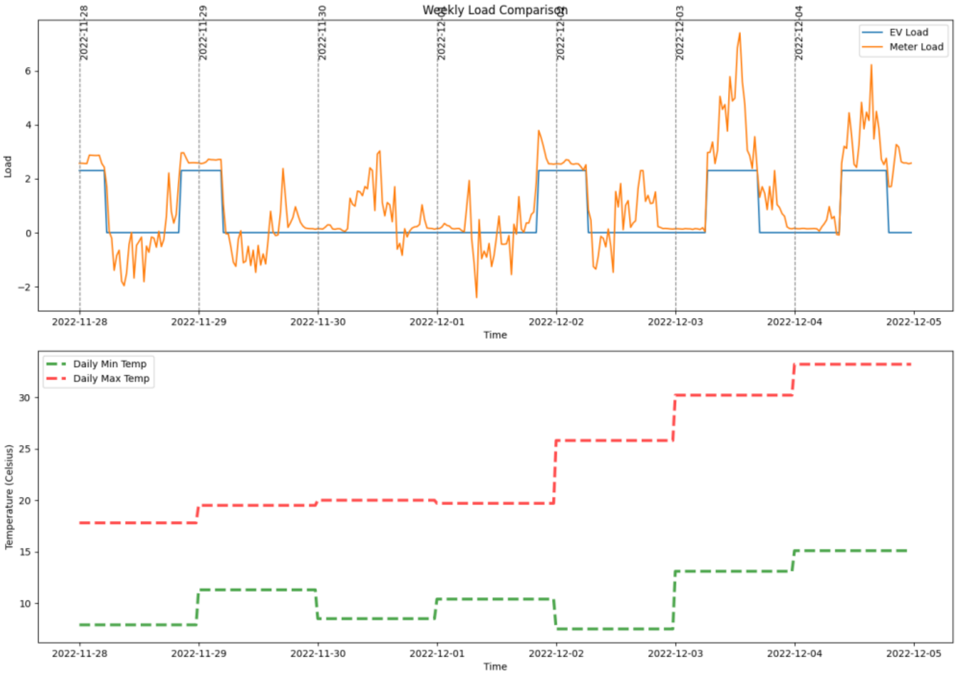

Figure 9 Meter loads and EV charging from 2022-11-28 to 2022-12-05 (2022-12-04 and 2022-12-05 are extreme hot days for this customers)

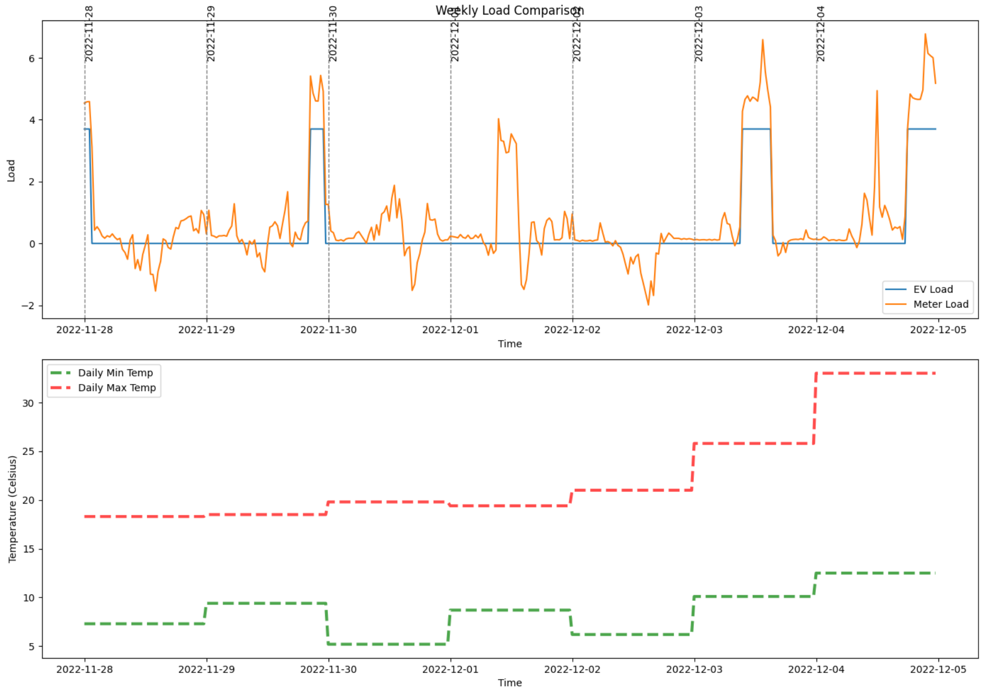

Figure 10 Meter loads and EV charging from 2022-11-28 to 2022-12-05 (2022-12-05 are extreme hot days for this customers)

The two examples above demonstrate that: 1) our disaggregation model does not capture additional load as EV charging, particularly on extreme weather days, and 2) our model carefully examines meter loads during extreme weather conditions to avoid mistakenly identifying heating or cooling loads as EV charging.

It is important to note that identifying the impact of extreme weather on EV charging load is challenging, as each customer may exhibit different EV charging behaviours, daily load profiles, and varying power consumptions from heating and cooling appliances.

2.3.3. Validation 3: Examining the impacts of kettle load and heat pump consumption on EV charging profiles

In addition to verifying the disaggregated EV charging profiles under extreme weather conditions, we also ensure that our extracted EV charging load is not impacted by short-duration power increases, such as those caused by kettles, or other load increases from heat pumps. As mentioned in Section 2.1.3, our disaggregation toolbox filters out EV charging events that do not last for at least one hour. Consequently, short-term power spikes, such as those from kettle usage, are excluded from the EV charging profile.

For heat pump energy consumption, our disaggregation approach compares the 2020 load with the 2022 load. We assume that hot water consumption patterns remained relatively stable and that hot water usage was already present in the 2020 load. Therefore, the most significant increase in power consumption observed in 2022, compared to 2020, is attributed to EV charging, especially since the customers in this study applied for EV rebates in 2021, between the two periods.

In Fig. 11, the blue dashed rectangle highlights load increases/jumps lasting only for a single 30-minute interval, and our EV charging profile is not affected by these brief power spikes which could be caused by kettle load and other similar loads. In Fig. 12, we observe that variations during the identified EV charging period are minimal, while heat pump loads typically exhibit periodic patterns of cyclic increases and decreases. This example demonstrates that our disaggregated results do not mistakenly classify those periodic and cyclic loads, potential from heat pump, as EV charging events.

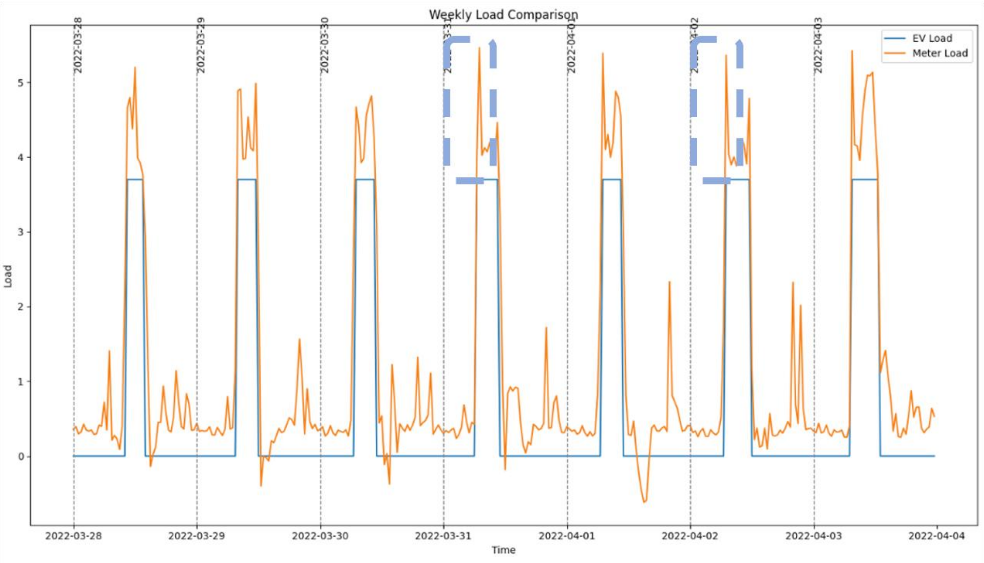

Figure 11 Potential kettle load not captured as EV charging by our disaggregation model

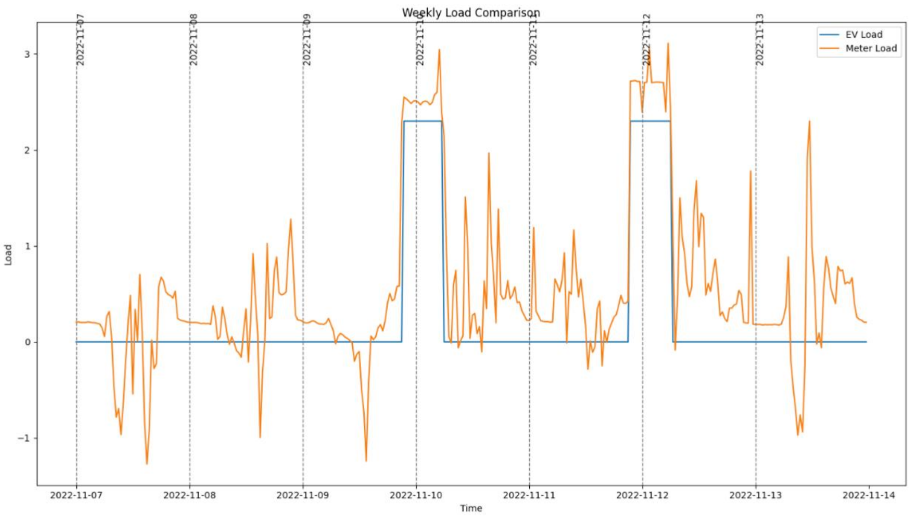

Figure 12 2.3kW charger charging profile

3. EV charging profile aggregation for PV customers

3.1. Overview of EV profiles for PV customers

Based on the EV charging data extracted from our toolbox, we conducted a descriptive analysis focusing on the distribution of charger types, the number of customers using different charger types, the average weekly charging frequency, and the average weekly EV-related energy consumptions.

Our toolbox identified three types of EV chargers: 2.3kW, 3.7kW, and 7.4kW chargers. As shown in Fig. 3, which illustrates the distribution of PV customers by charger type, 82.1% of customers use 2.3kW chargers, 7.4% use 3.7kW chargers, and 10.5% use 7.4kW chargers, with corresponding customer counts of 367, 33, and 47, respectively. The average EV charging consumption per day across all PV customers is 9.93 kWh.

Compared to the statistics of non-PV customers summarised in our previous disaggregation report, the proportions of 3.7kW chargers and 7.4kW chargers relatively increases. But the majority of PV customers based on the filtered dataset still use 2.3kW chargers. We would like to first acknowledge that this charger mix may not reflect the real-world charger mix due to the limited sample size. Moreover, as the solar PV generation data behind the meter is unavailable, it is a naturally challenging task to disaggregate EV charging profiles from only the smart meter dataset. Therefore, we recommend that it would be better to be cautious about the usage of the disaggregated EV charging profiles for PV customers, especially during daytime.

As mentioned in the EV charging disaggregation report, it is important to note that the majority of customers use 2.3kW chargers for home charging, while only a small number use 3.7kW or 7.4kW chargers. Therefore, we recognize that the disaggregated EV charging profiles for customers with the 3.7kW and 7.4kW chargers may not fully represent the typical charging patterns for these types of chargers due to the limited sample size. Gathering more data from customers using 3.7kW and 7.4kW chargers would improve the robustness and accuracy of the results.

We further examine the average weekly EV charging frequency and the average EV charging weekly consumption (kWh), as presented in Table 4. The average weekly charging frequency across three charging rates is 3.37, with corresponding average EV weekly consumption being 61.91kWh.

Table 4 Groups of charger types and relevant weekly EV charging information (Note that the charger mix does not necessarily reflect the actual mix in the real world as the processed data can be biased due to limited sample size)

Charger type and charging rate (kW)	Number of customers	Average weekly charging frequency	Average EV weekly consumption (kWh)
Type 1 – 2.3	367	3.52	57.97 kWh
Type 1 – 3.7	33	3.18	72.57 kWh
Type 2 – 7.4	47	1.55	54.61 kWh

Table 4 provides an overview of customers with solar PV installations, focusing on three different types of chargers and their respective charging rates: 2.3 kW, 3.7 kW, and 7.4 kW. For each charger type, it presents the number of customers, the average weekly charging frequency, and the average EV weekly consumption (kWh). For the 2.3 kW charger, there are 367 customers, with an average weekly charging frequency of 3.52 times and an average EV weekly consumption of 57.97 kWh. The 3.7 kW charger has 33 customers, who charge their EVs 3.18 times per week on average, leading to an average weekly consumption of 72.57 kWh. The 7.4 kW charger is used by 47 customers, with a significantly lower average weekly charging frequency of 1.55 times and an average EV weekly consumption of 54.61 kWh. It is worth noting that the average weekly charging frequency and average EV weekly consumption are relatively low for customers using the 7.4 kW charger. This might be attributed to the limitations of the extracted EV charging profiles, which are based on smart meter data. Unfortunately, we currently do not have access to the solar PV generation data for each customer, as this information is behind the meter and unavailable at this stage. This missing solar PV data could potentially impact the accuracy of the charging profiles and EV consumption measurements.

To better understand the daily charging patterns of customers with solar PV installations, we analysed and created distribution charts showing the number of charging days per week, as depicted in Fig. 13. The results reveal that the highest proportion of PV customers charge their vehicles on 2 days per week, with a value of approximately 0.30. This indicates that a significant portion of PV customers prefer to charge their EVs twice a week. After this peak, there is a gradual decline in the proportion of customers as the number of charging days increases: 3 days per week has the second-highest proportion, slightly below 0.30, followed by 4 days per week with a lower proportion than 3 days, and 5 days per week showing an even smaller proportion, continuing the downward trend.

A small portion of PV customers, approximately 0.05, charge their vehicles only 1 day per week. Similarly, only around 0.05 of PV customers charge their vehicles every day (7 days per week), indicating that daily charging is uncommon among the majority of PV customers. The chart highlights that most PV customers prefer to charge their EVs between 2 to 4 days per week, with fewer customers engaging in either more frequent or less frequent charging patterns.

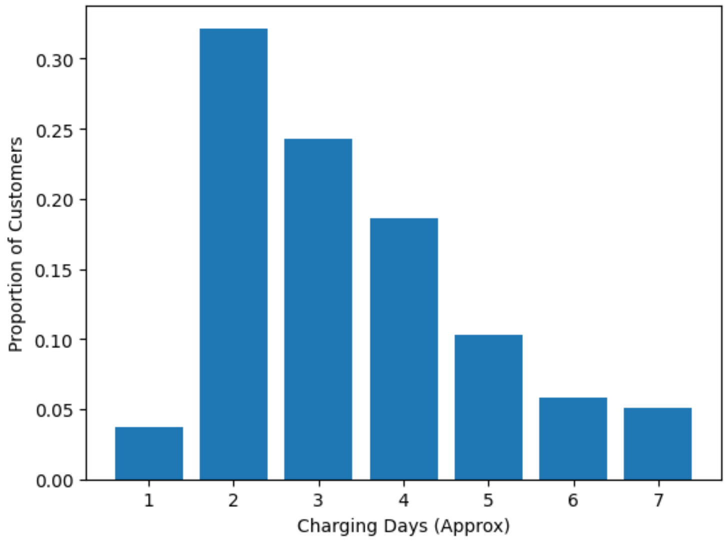

Figure 13 Charging frequency (approximate days) in one week for all PV customers

3.2. Charging pattern segmentation analysis for PV customers

3.2.1 Charging events

Different customers have varying charging patterns, in other words, different customers may have different preferences for charging periods. Analysing the distribution of their charging periods is crucial for effective segmentation. After completing the segmentation, we can estimate the charging distribution for each segment.

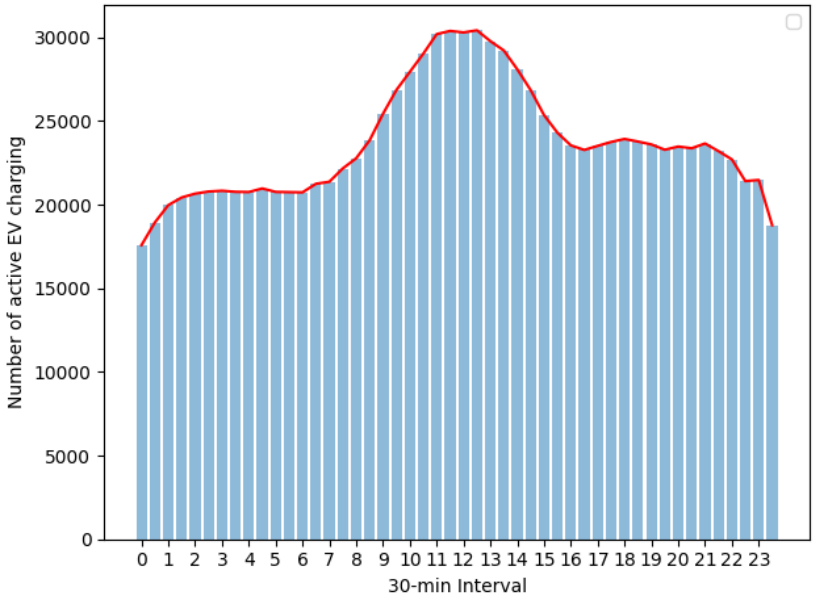

Figure 14 The number of active charging across a day

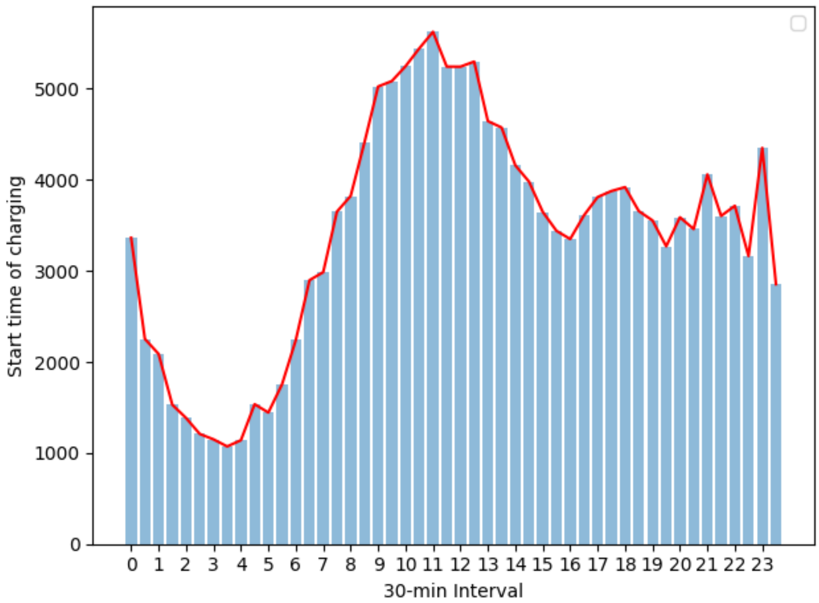

Figure 15 The start time distribution of charging events

We conducted a statistical analysis of the charging periods for all DNSPs. Fig. 14 shows the number of active charging across a day. Specifically, for each charging session, the number of active charging is counted for the whole period of hours. Fig. 15 further illustrates the distribution of the start time of charging. Based on the above two figures, we can observe that PV customers prefer daytime charging with a higher number of active charging and more charging sessions starting from daytime.

3.2.2. Charging patterns in different segmentations

We segment all charging events to estimate the probability distribution for each segment using our sample data. In this context, a session is defined as one day, and a complete charging cycle is considered a charging event. A session may consist of multiple charging events, which can occur in different time segments such as the morning, daytime, and evening.

To capture the potential influence of solar generation during daytime hours, particularly the tendency of PV customers to charge their EVs using solar power, we introduce an additional segment. This new segment represents sessions with multiple charging events that include at least one daytime charging event. By doing so, we aim to better understand and reflect the charging behaviours of customers who take advantage of solar energy for their EV charging during peak sunlight hours.. We define the segments[1] as follows:

- **Morning Charging Segmentation**: If all charging events in a session occur between 12 am and 8 am, this session is categorised under the morning charging segmentation.
- **Daytime Charging Segmentation:** If all charging events in a session occur between 8 am and 4 pm, this session is categorised under the daytime charging segmentation.
- **Evening Charging Segmentation**: If all charging events in a session occur between 4pm and 12am.
- **Multi-Charging with Daytime Charging Segmentation**: If multiple charging events occur within one charging session and at least one charging event can be considered daytime charging, this session is categorised under the multi-charging with daytime charging segmentation.

It should be noted that this classification is a hard classification. For instance, if a charging event begins at 6 am and ends at 10 am, any data from the segment between 8 am and 10 am would be ignored under this classification. Such a hard classification could result in some loss of charging data. To address this limitation and enhance the accuracy of our modelling, we adopted a soft classification approach.

In the soft classification method, for charging events like the one starting at 6 am and ending at 10 am, the entire event is categorised under the morning charging segmentation. This method ensures that all relevant data points are included, minimising the potential for data omission. By using this approach, we can capture a view of EV customers' charging behaviour throughout different times of the day, which allows for a more reliable construction of EV charging profiles.

[1] The segmentation criteria outlined here are defined specifically for this study. They can be adjusted according to the characteristics of the dataset and the specific requirements of the analysis. While we focus on one day as a session, the insights gained from this analysis can be extended to understand charging behaviours over slightly longer periods.

Once all sessions are categorised into the respective segments, we estimate the probability density function (PDF) for each segment individually. These segments include charging events that take place in the morning, daytime, and evening, with an additional segment for sessions with multiple charging events, including at least one daytime event to account for solar PV generation usage.

Within each segment, we consider three different types of chargers: 2.3 kW, 3.7 kW, and 7.4 kW. For each charger type, we estimate their probability density function individually, ensuring that our analysis accounts for the variation in charging behaviour across different charger capacities. This approach provides a more accurate and detailed understanding of how EV customers with solar PV installations charge their vehicles at various times of the day.

For example, in the morning charging segmentation, to estimate the probability density function (PDF) for 2.3 kW chargers, we begin by counting the number of charging events that occur at each hour of the day. This allows us to construct a dictionary that stores the count of charging events for each of the 24 hours.

Next, we calculate the total number of charging events that occur in a day for the 2.3 kW chargers. To obtain the probability density function, we divide the count of charging events at each hour by the total number of charging events for the day. This results in the PDF, which represents the likelihood of charging events occurring at different hours for customers using 2.3 kW chargers in the morning charging segmentation.

We apply the same method to estimate the probability density functions for other segmentations (e.g., daytime, evening, and multi-charging with daytime charging) and charger types (3.7 kW and 7.4 kW). By doing so, we can compare charging behaviours across different times of the day and charger types, gaining a more granular understanding of how customers with solar PV installations charge their EVs. This detailed analysis helps to create more reliable EV charging profiles based on real charging events.

The approach can be summarised as:

- **Calculate Total Charging Events**: Compute the total number of charging events in a day for each segmentation and charger type.
- **Estimate Probability Density Function**: For each hour, divide the count of charging events by the total number of charging events. This ratio represents the probability density function for the specific charger type in the given segmentation.
- **Repeat for Other Segmentations and Charger Types**: Apply the same process to estimate the probability density function for 3.7 kW and 7.4 kW chargers in the morning, evening, and morning-evening charging segmentations.

There are examples of estimating the probability density of charging events for the 7.4 kW charger data in the morning only, daytime only, evening only, and multi-charging with daytime charging segmentations, as given from Fig 16 to 19.

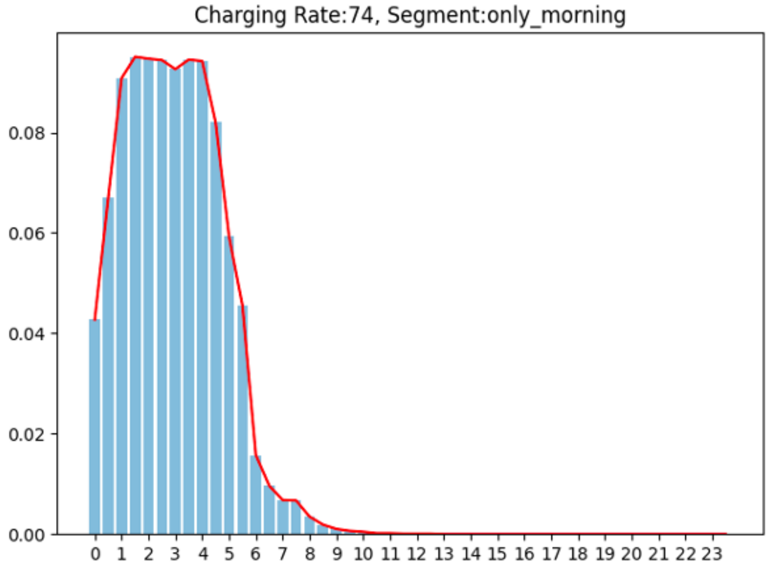

Figure 16 PDF for morning charging segmentation

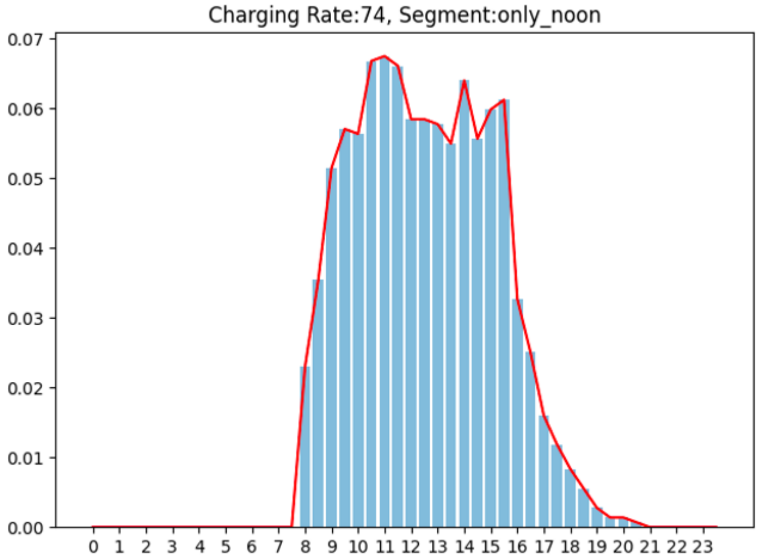

Figure 17 PDF for daytime charging segmentation

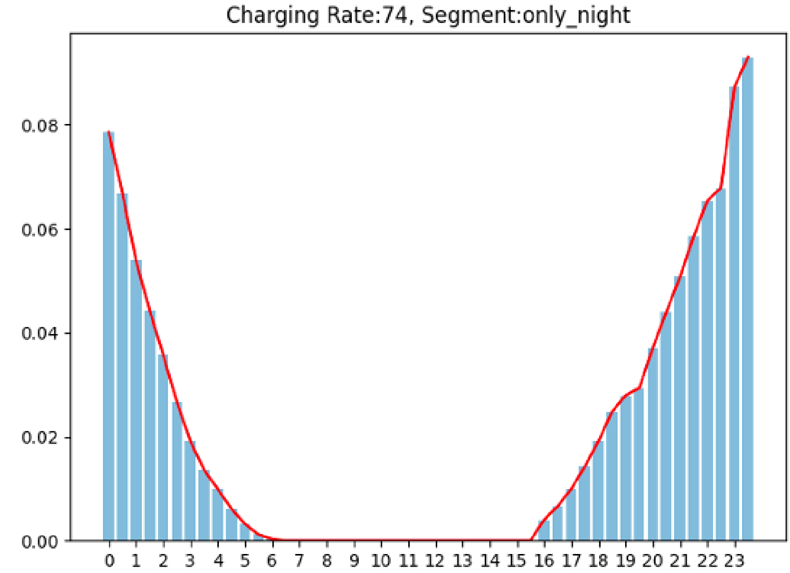

Figure 18 PDF for evening charging segmentation

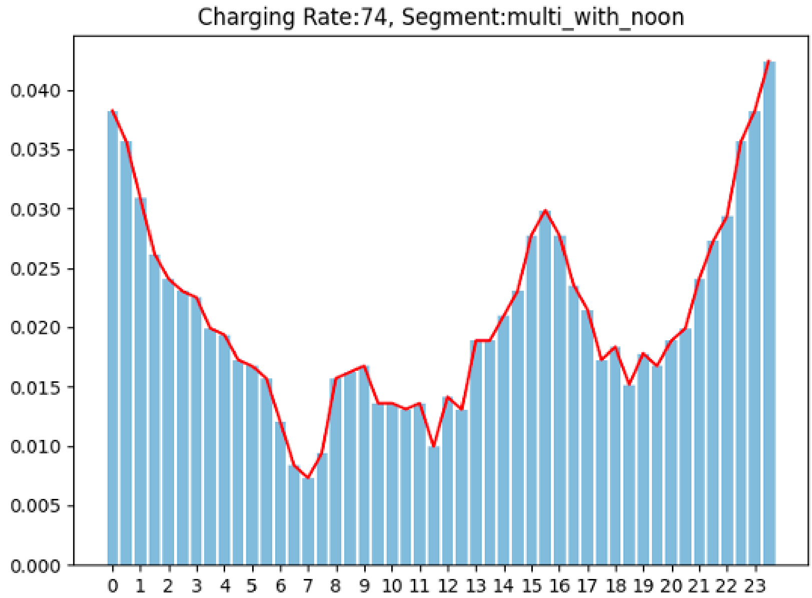

Figure 19 PDF for multi-charging with daytime charging segmentation

3.3. EV profile modelling for PV customers

To model the charging consumption profile, we utilise an aggregated probability distribution approach. This method integrates various factors that influence charging consumption, including different types of chargers customers use, the segmentation scenarios (e.g., morning, daytime, evening, and mixed), and the temporal distribution of charging events. In this approach, the aggregated probability distribution forms the foundation for modelling EV charging consumption. This distribution is derived by considering multiple segments of EV customers and their corresponding charging events, capturing the variability in charging behaviours across different customer groups and time periods. By doing so, we are able to build a detailed representation of overall charging consumption.

The details of our aggregation approach have been presented in the previous aggregation report for non-PV customers. Note that our charging segmentation for PV customers is slightly different from non-PV customers. Both non-PV and PV customers have morning-only, daytime-only, and evening-only charging segments. For PV customers, we propose one more charging segment (with multiple charging events within a day), i.e., the multi-charging with daytime charging segment, with the aim of investigating customers' EV charging behaviours with solar PV generation. Below is a summary of our probability-distribution-based approach. Please refer to our previous aggregation report for non-PV customers for more technical details.

A key component of this approach is the probability density function (PDF) for charging events, which models the likelihood of charging occurring at different times within each scenario. The PDFs capture the temporal distribution of charging consumption, reflecting how it fluctuates throughout the day. For example, PDFs may show peaks in the evening when customers return home or during the day due to solar PV power charging, allowing us to represent diverse charging behaviours. The aggregation process combines contributions from all scenarios and charger types over defined time steps, capturing temporal variability and the interaction of factors influencing charging consumption. This method ensures our models reflect real-world usage patterns, providing a detailed understanding of how home charging consumption is shaped by different variables.

The aggregation model is formulated as

$$X_{n,t} = m_n \sum_{k \in K} \quad p_{n,k} \times P_{n,k,t} \times r_n, \forall n \in N, t \in T \quad (1)$$

where

- X: Aggregated probability distribution of charging consumption
- m_n :Number of customers, and the subscript is used to distinguish the number of customers using a specific type of charger.
- T: Set of time step index , for example, it represents one day in our case.
- N: Set of obtained types of chargers used by customers, for example, it contains three different types in our case.

- K: Set of obtained scenarios of segmentation clustered and aggregated by customers, for example, it contains three different segmentations in our case.
- $p \in [0,1]$: Percentage of scenarios of segmentation associated with the population of customers using a specific type of charger
- $P_{n,k,t}$: Probability density of charging events in corresponding scenarios of segmentation.
- r: Charging rate of a specific type of charger.

This aggregation captures:

- **Temporal Aggregation**: By integrating the PDFs, we identify peak and off-peak charging times.
- **Charging Rate Impact**: Different chargers affect energy consumption and consumption profiles.
- **Weighted Contributions**: Each scenario's contribution is weighted by its probability, reflecting the combined effects of various charging patterns.
- **Scenario Integration**: Demand is calculated by summing contributions from all scenarios..

For individual customer analysis, the model refines to:

$$X_t = \sum_{n \in N} \quad \sum_{k \in K} \quad \frac{m_n}{N} \times p_{n,k} \times P_{n,k,t} \times r_n, \forall t \in T \quad (2)$$

This allows us to assess how individual behaviours aggregate to influence overall demand.

Moreover, EV usage is often closely tied to commuting patterns, suggesting that the day of the week is a critical factor in understanding charging behaviour. For instance, weekdays may see higher demand for charging compared to weekends due to regular commuting schedules.

To address these interdependencies, we have incorporated scenario analysis in the subsequent sections of our study. This analysis allows us to explore how various factors—such as seasonal conditions, temperature fluctuations, and weekly commuting patterns—influence the overall charging demand. By accounting for these influences, we aim to provide a model of EV charging behaviour that reflects real-world dynamics.

3.4. Case Study

In this section, based on disaggregated data for customers with PV from the previous section, we will perform segmentation for three types of chargers separately, and then carry out the aggregation. The proportions of each charging segment are shown in Table 5. From the table, customers with 2.3kW chargers have a relatively high proportion of daytime-only charging, potentially taking advantage of the installed PV systems. However, this segment's proportion drops for customers with 3.7kW and 7.4kW charger as we observe. Note that this result may be affected by the lack of solar PV generation information and a smaller size of customers. A detailed discussion of the results, including each segment's PDF for all three types of chargers will be presented in this section.

Table 5 Proportions of each charging segment

	2.3kW charger	3.7kW charger	7.4kW charger
Morning Only	8.80%	23.24%	35.30%
Daytime Only	43.91%	18.35%	10.03%
Evening Only	23.42%	44.17%	50.61%
Multi-Charging with daytime Charging	23.88%	14.24%	4.05%

3.4.1. Customers using 2.3kW charger

The PDFs of four kinds of charging segments for customers using 2.3kW chargers are depicted from Fig. 20 to Fig. 23. We first briefly describe each segment's distribution and then make a comparative analysis among these segments.

For the morning charging segment in Fig. 20, the probability density starts high, with a peak around 1 AM to 3 AM. The density tapers off quickly after 5 AM, although there is still some probability extending towards daytime. The presence of charging events around daytime likely reflects some overlap between early morning sessions and longer-lasting charging sessions due to the solar PV system's contribution during daylight hours, allowing some flexibility in charging patterns.

For the daytime charging segment in Fig. 21, the distribution peaks significantly around 11 AM to 2 PM, aligning well with the period of maximum solar PV production. The higher concentration of charging events during this time indicates that customers with solar PV installations prefer to charge during peak sunlight hours, likely to maximise the use of solar PV energy. The density falls sharply after 4 PM, but some sessions extend into the evening, possibly due to charging sessions starting late in the afternoon.

For the evening charging segment in Fig. 22, there is a distinct bimodal pattern, with one peak around 5 PM and another near 11 PM. The charging behaviour could be driven by customers starting their charging sessions either when they return home from work (early evening) or later in the evening, possibly to utilise cheaper off-peak electricity rates. Despite the solar PV installation, these customers likely rely on the grid during the night.

For the multi-charging with daytime charging segment in Fig. 23, the distribution shows a broad peak centred around noon (solar PV peak production), with residual probability densities in the morning and night hours. This indicates a mixed charging behaviour where customers may charge during the day to leverage solar PV energy and in the early morning or evening hours for other charging needs.

Comparing the four charging segments for 2.3kW chargers, here are several insights.

- The daytime-only segment shows a clear concentration of charging during peak solar hours (11 AM to 2 PM), which may indicate that customers with solar PV installations are optimising their charging sessions to take advantage of their solar PV production. This pattern contrasts with the morning-only segment, where customers likely start their charging sessions before solar PV generates, relying more on grid power.
- In both the morning-only and daytime-only segments, there is residual charging extending beyond the segment boundaries, indicating some flexibility in charging times. The morning-only segment shows some overlap into the daytime period, likely due to the longer duration of charging sessions that overlap with the start of solar PV production, whereas the daytime-only segment occasionally extends into the evening hours, possibly when customers initiate charging late in the afternoon.
- The night-only segment demonstrates bimodal peaks, likely influenced by customer work schedules and utility rate structures, particularly in relation to off-peak pricing. PV systems have less impact on night-time charging behaviour since solar PV production is unavailable.
- The multiple-with-daytime segment illustrates mixed behaviours, with charging spread across different times of the day. The daytime peak stands out, suggesting that solar PV energy still plays a significant role in these charging patterns. However, the morning and night peaks indicate that some customers may need additional charging outside the solar PV peak hours, possibly for longer trips.

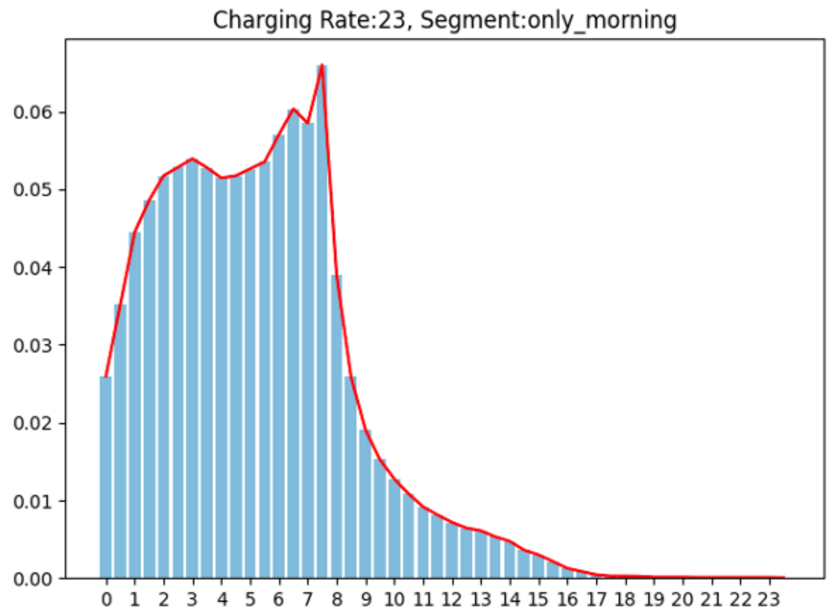

Figure 20 PDF for morning charging segmentation for 2.3kW charger

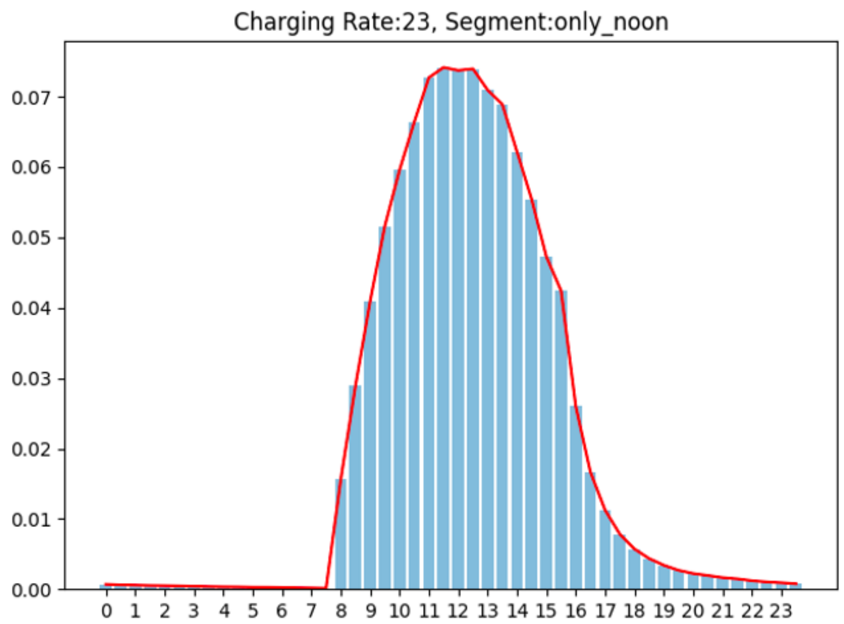

Figure 21 PDF for daytime charging segmentation for 2.3kW charger

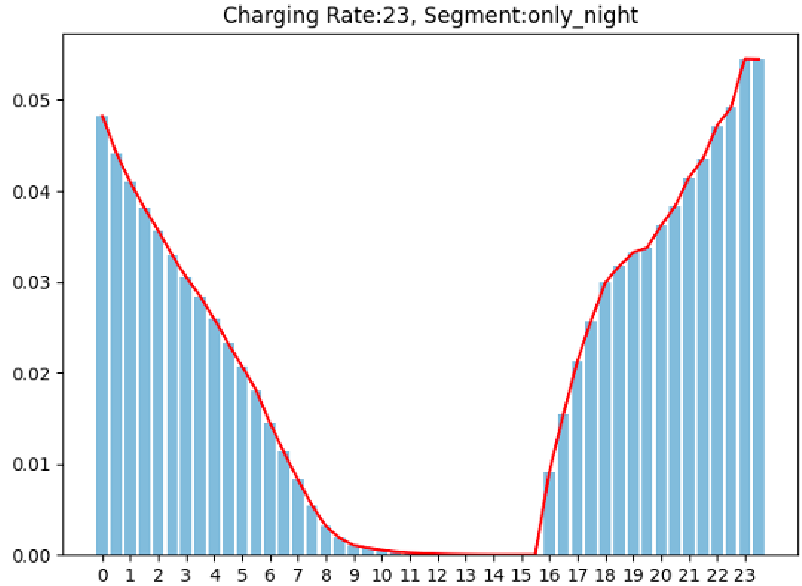

Figure 22 PDF for evening charging segmentation for 2.3kW charger

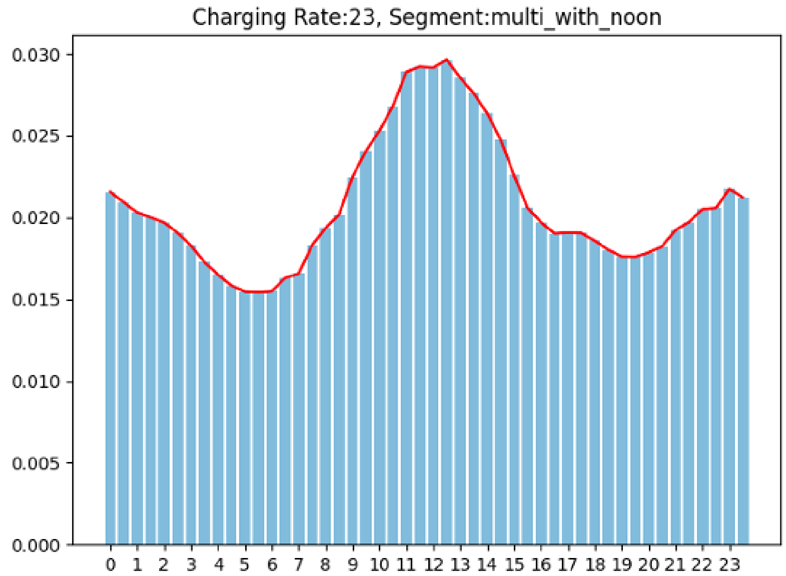

Figure 23 PDF for multi-charging with daytime charging segmentation for 2.3kW charger

3.4.2. Customers using 3.7kW charger

The PDFs of EV charging using 3.7kW charger under different charging segments are presented from Fig. 24 to 27. For the morning charging segment in Fig. 24, the distribution has a noticeable double peak, one around 1 AM and another around 5 AM. The high peaks indicate that customers using the 3.7kW charger can complete their charging faster than those using the 2.3kW charger, but they are still charging early in the morning, likely to maximise off-peak electricity rates before the solar generation starts. The sharp drop-off after 8 AM reflects the conclusion of morning charging sessions.

For the daytime charging segment in Fig. 25, the peak density is concentrated between 11 AM and 2 PM, aligning closely with peak solar PV production hours. The curve is sharper compared to the 2.3kW charger, indicating that customers with the 3.7kW charger are finishing their sessions faster. The higher density during peak sunlight hours suggests that customers with solar PV installations prefer to charge when their PV systems are most productive.

For the evening charging segment in Fig. 26, the night-only segment for the 3.7kW charger displays a bimodal distribution, with peaks around 6 PM and another significant peak close to midnight. These sharp peaks suggest that customers are either initiating charging immediately after returning home or shortly before bed, completing their sessions more quickly due to the higher charging power of the 3.7kW charger. Despite the lack of solar PV power at night, this charging behaviour reflects a reliance on grid power, likely optimised for off-peak rates.

For the morning-evening charging segment in Fig. 27, this figure shows a broad distribution with multiple peaks, indicating that charging events are distributed throughout the day, with a particular concentration around solar PV production hours (midday). However, this pattern also reflects evening and early morning charging, suggesting that customers with solar PV installations are supplementing their daytime charging with additional sessions in non-peak hours, possibly to meet higher energy consumptions or because they anticipate longer driving distances.

Comparing the four charging segments for 3.7kW charger, as well as those of 2.3kW charger, we found several insights discussed below.

- Efficiency and peak timing: the 3.7kW charger consistently shows sharper peaks and faster drop-offs across all segments, reflecting the higher power delivery compared to the 2.3kW charger. In the morning-only segment, for example, the double peak seen in the 3.7kW charger is more distinct, reflecting faster completion of sessions. In the daytime-only segment, the concentration of charging during solar PV peak hours is more pronounced for the 3.7kW charger, showing a greater alignment with solar PV production;

- Distribution speed: the 2.3kW charger displays broader distributions with more overlap into adjacent time periods due to its slower charging speed. The 3.7kW charger, by contrast, has more concentrated distributions with sharper rises and falls, reflecting the ability to complete charging sessions more quickly. This is particularly visible in the night-only segment, where the 3.7kW charger exhibits a clear bimodal pattern with sharper peaks compared to the more gradual distribution seen with the 2.3kW charger;

- Solar PV power usage: both chargers show a clear preference for charging during peak solar PV production hours in the daytime-only segment, but the 3.7kW charger exhibits a faster rate of completion. This suggests that customers with the 3.7kW charger are better able to take full advantage of their solar PV systems' production by completing their charging during these hours;

- The residual charging effects, where charging sessions extend beyond the primary segment, are more prevalent with the 2.3kW charger. For example, in the multiple-with-daytime segment, the 2.3kW charger shows more lingering charging into adjacent periods, whereas the 3.7kW charger completes these sessions faster, resulting in less residual activity beyond the intended charging window.

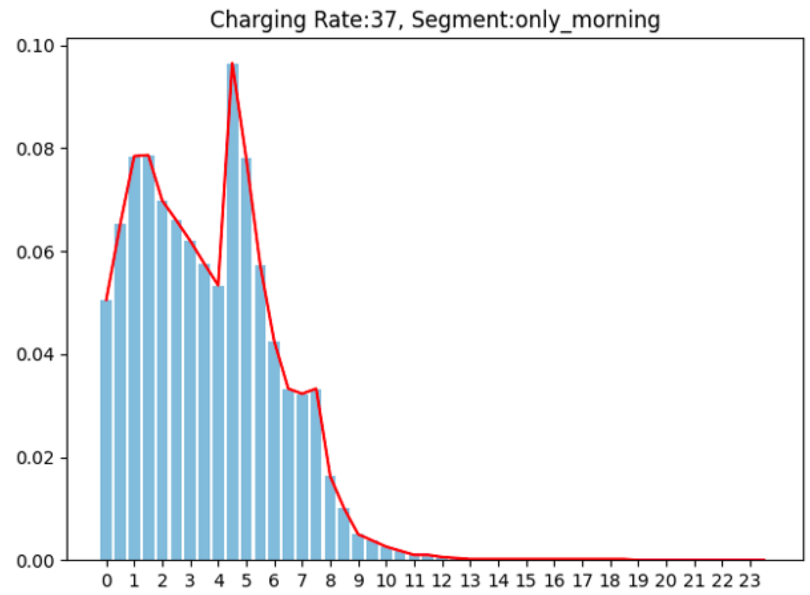

Figure 24 PDF for morning charging segmentation for 3.7kW charger

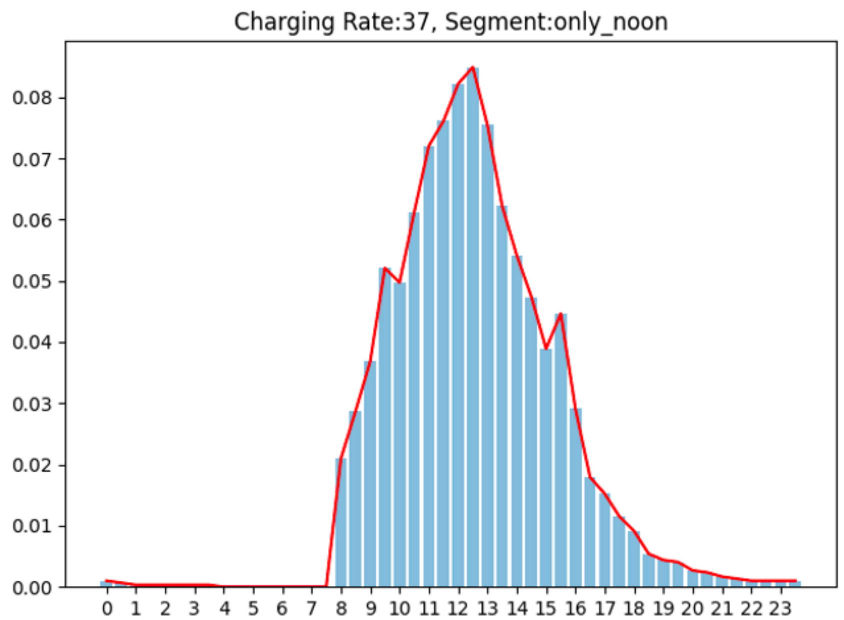

Figure 25 PDF for daytime charging segmentation for 3.7kW charger

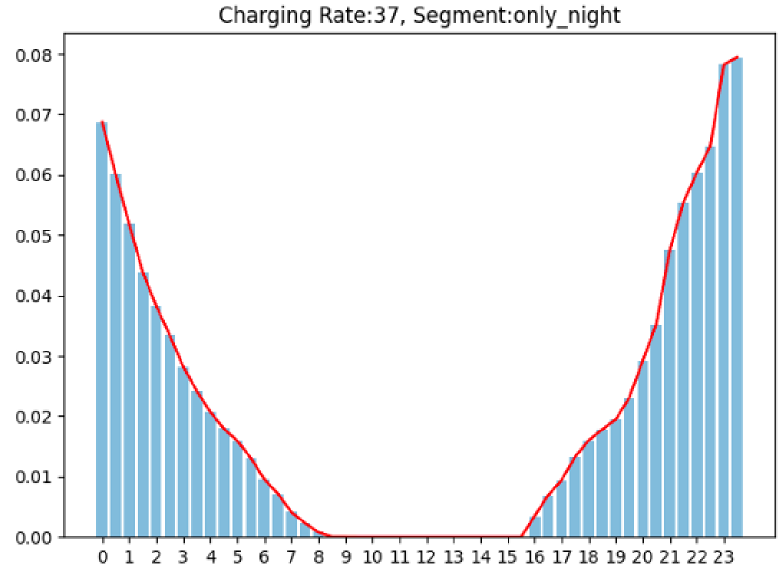

Figure 26 PDF for evening charging segmentation for 3.7kW charger

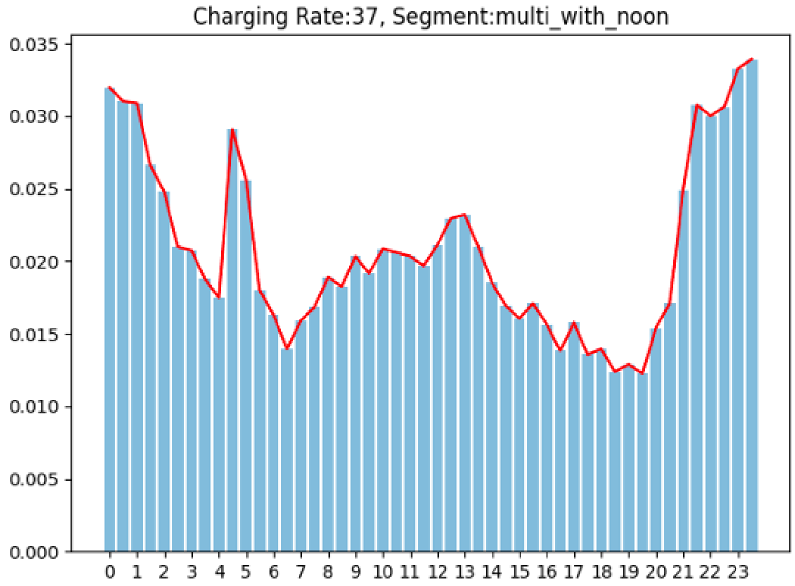

Figure 27 PDF for multi-charging with daytime charging segmentation for 3.7kW charger

3.4.3. Customers using 7.4kW charger

The PDFs of EV charging using 7.4kW charger under different charging segments are presented from Fig. 28 to 31. For the morning charging segment in Fig. 28, this figure represents charging sessions occurring between 12 AM and 8 AM. The distribution exhibits a high and sharp peak around 2 AM, with the density dropping rapidly after 4 AM. This pattern suggests that customers using the 7.4kW charger are completing their charging sessions much faster than those with lower-rated chargers. The sharp decline after 5 AM reflects the quick completion of charging sessions before the start of the solar PV generation window, indicating a reliance on grid power during early morning hours.

For the daytime charging segment in Fig. 29, this plot represents the distribution for charging events occurring between 8 AM and 4 PM. The charging behaviour is heavily concentrated between 10 AM and 2 PM, corresponding to peak solar PV production hours. The sharp peak indicates that customers using the 7.4kW charger maximise their charging efficiency during these hours. The rapid rise and fall around the peak suggest that customers can charge quickly and efficiently during midday solar PV production, allowing them to fully utilise their solar-generated electricity.

For the evening charging segment in Fig. 30, the night-only segment for the 7.4kW charger displays a bimodal distribution with peaks around 6 PM and another prominent peak close to midnight. This reflects a distinct charging behaviour, where users begin charging either upon returning home or before going to bed, and the sessions complete rapidly due to the high power delivery. The sharpness of these peaks shows that customers with the 7.4kW charger can efficiently charge their vehicles during non-solar hours, likely taking advantage of off-peak electricity rates.

For the morning-evening charging segment in Fig. 31, this figure shows a relatively broad distribution, with multiple peaks throughout the day. The largest peak occurs around 12 PM, reflecting solar PV charging during peak production hours. However, additional peaks in the early morning and late evening suggest that some users charge at times other than peak solar hours, possibly to meet unexpected driving needs or to take advantage of lower electricity prices during off-peak periods.

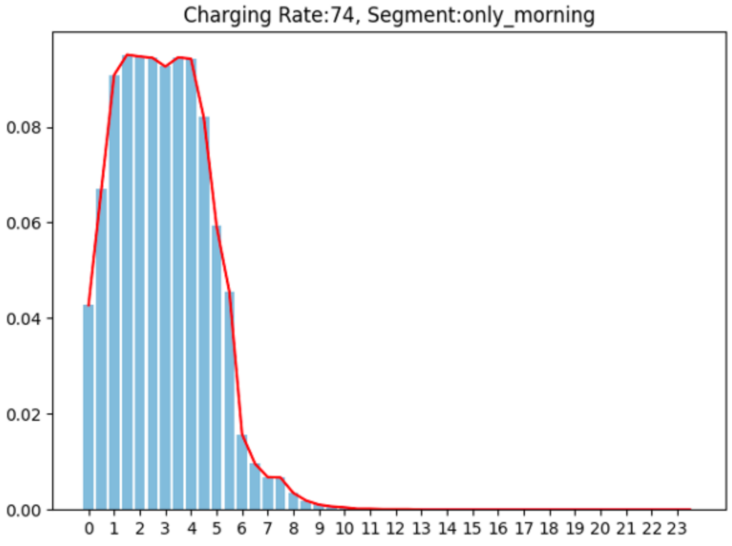

Figure 28 PDF for morning charging segmentation for 7.4kW charger

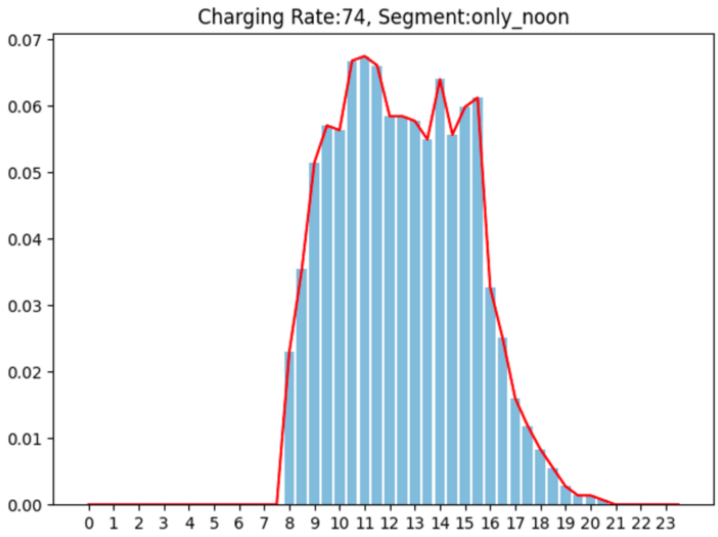

Figure 29 PDF for daytime charging segmentation for 7.4kW charger

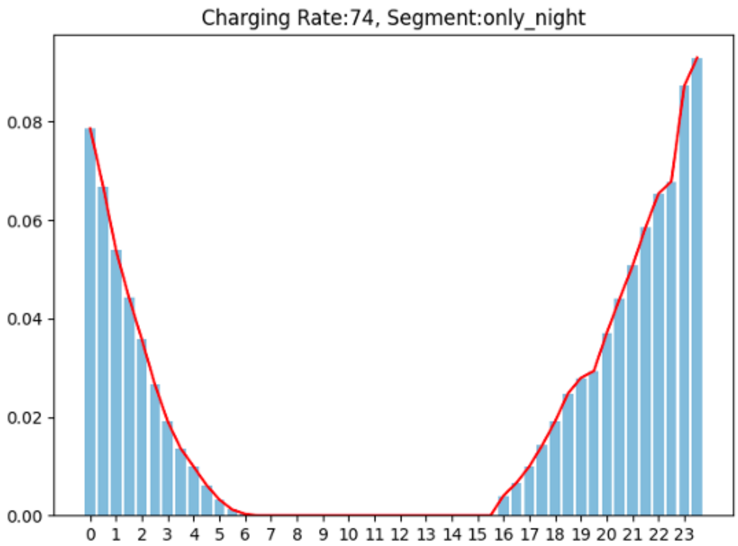

Figure 30 PDF for evening charging segmentation for 7.4kW charger

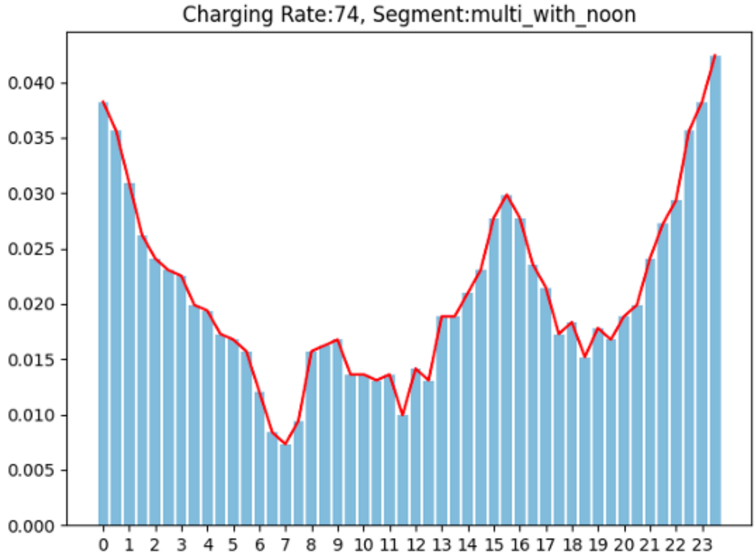

Figure 31 PDF for multi-charging with daytime charging segmentation for 7.4kW charger

We summarise the comparative analysis among 2.3kW, 3.7kW, and 7.4kW chargers below from several key factors of the probability distribution.

- **Peak Intensity and Duration**: The 7.4kW charger consistently exhibits the sharpest and highest peaks across all segments, reflecting the fastest charging times. In comparison, the 3.7kW charger shows slightly broader peaks, while the 2.3kW charger has the most gradual peaks and slower declines. This indicates that the 7.4kW charger allows for much quicker charging sessions than the lower power chargers, with users completing their sessions in shorter bursts.

- **Distribution Spread**: The distribution spread for the 7.4kW charger is the narrowest, especially in the morning-only and daytime-only segments, indicating efficient and rapid charging sessions within a limited time window. In contrast, the 2.3kW charger shows much wider spreads, reflecting longer charging sessions that bleed into adjacent time periods. The 3.7kW charger represents an intermediate case, with distributions that are narrower than the 2.3kW but wider than the 7.4kW.

- **Solar PV Usage:** The daytime-only segments for all three chargers show a preference for charging during peak solar hours. However, the 7.4kW charger is the most effective in concentrating charging during these hours due to the faster charging speed, allowing users to maximise solar PV energy usage. The 2.3kW charger, on the other hand, shows more residual charging beyond the peak solar window, reflecting longer charging times that extend into the afternoon.

- **Bimodal Patterns**: In the night-only segments, the 7.4kW charger shows sharper and more distinct bimodal peaks compared to the other two chargers. The 3.7kW charger also displays a bimodal distribution but with broader peaks, while the 2.3kW charger has the most gradual bimodal pattern, reflecting longer charging durations and more overlap between peaks

- **Multiple Charging**: The multiple-with-daytime segment shows more evenly distributed charging across different times of the day for the 7.4kW charger. In comparison, the 2.3kW charger shows more charging residuals outside the primary daytime peak, suggesting longer charging sessions extending into other periods. The 3.7kW charger falls in between, with more concentrated daytime peaks but still some extended charging outside the peak solar hours.

3.4.4. Scenario analysis on aggregated EV charging consumption per customer

Following Equation (2) defined in Section 3.3, we can derive the aggregated EV charging consumption based on our current charger mix: 367 customers with 2.3kW charger; 33 customers with 3.7kW charger; and 47 customers with 7.4kW charger, which is then averaged over the year. The corresponding proportion for three types of chargers are 82.1% for 2.3kW charger, 7.4% for 3.7kW charger, and 10.5% for 7.4kW charger. Once again, we would like to acknowledge that the charger mix extracted from the data used in this research does not necessarily reflect the actual mix in the real world as the processed data can be biased due to limited sample size.

We then average such aggregated EV charging consumption based on the total number of customers (i.e., 447 for PV customers), with results illustrated in Fig. 32. The pattern of this aggregated EV charging consumption per user aligns with the study by the University of Queensland [13], where customers with PV installation are more likely to charge their EVs during daytime.

To analyse how the aggregated EV charging consumption varies in the future with customers possibly upgrading their chargers from 2.3kW to 3.7kW or 7.4kW, we synthesise several scenarios with different charger mix: 1) 2.3kW – 33.3%, 3.7kW – 33.3%, 7.4kW – 33.3%; 2) 2.3kW – 20%, 3.7kW – 40%, 7.4kW – 40%; 3) 2.3kW – 10%, 3.7kW – 45%, 7.4kW – 45%; 4) 2.3kW – 0%, 3.7kW – 50%, 7.4kW – 50%, and 5) 2.3kW – 0%, 3.7kW 30%, 7.4kW – 70%, 6) 2.3kW – 0%, 3.7kW – 100%, 7.4kW – 0%, and 7) 2.3kW – 0%, 3.7kW – 0%, and 7.4kW 100%. The aggregated EV charging consumption per customer for all these seven scenarios are shown from Fig. 34 to Fig. 40.

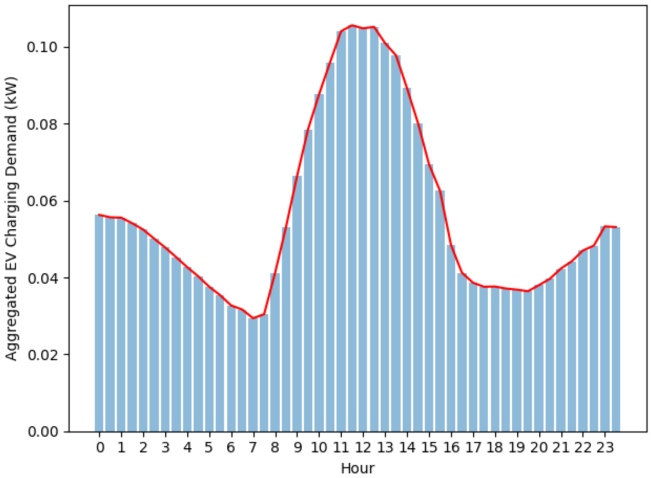

Figure 32 Aggregated EV charging consumption per customer based on current charger mix (2.3kW – 82.1%, 3.7kW – 7.4%, 7.4kW – 10.5%)

In Fig. 32, i.e., our current charger mix, the charging consumption is relatively low, with a peak around midday, likely reflecting the fact that 2.3kW chargers dominate the market. The high proportion of 2.3kW chargers explains why the midday peak is notable, since 43.91% of their charging occurs during the daytime-only segment.

Also, we compare the aggregated meter load profiles for both non-PV and PV customers shown in the orange and blue lines in Fig. 33, respectively. To perform a fair comparison, the aggregated meter load profiles for these two types of customers are sampled and aggregated based on the charger mix of PV customers, i.e., 82.1% of 2.3kW chargers, 7.4% of 3.7kW chargers, and 10.5% of 7.4kW chargers.

Compared to the meter load profiles of non-PV customers, the meter load profiles of PV customers present two key differences: 1) the meter loads during daytime (especially between the sunrise and the sunset) is lower than those of the non-PV customers; and 2) the meter loads during night peak hours also are lower than those of the non-PV customers. For the former difference, it is reasonable for PV customers to have lower meter load, since PV generation is behind-the-meter and thus invisible through the smart meter load dataset. PV customers during daytime can utilise the solar PV generation, thereby purchasing less electricity from the grid and leading to the decline of meter load as shown in the profiles. The latter difference suggests that the installation of solar PV systems can somehow influence residential energy consumption patterns. This shift occurs because EV customers with solar PV systems may prefer to charge their EVs during the day to take advantage of solar PV power. As a result, their nighttime EV charging consumption, especially during peak hours, is partially shifted to daytime periods. Consequently, integrating solar PV systems for EV owners not only enables them to use solar PV energy instead of relying on grid electricity but also aids in reducing peak load on the grid.

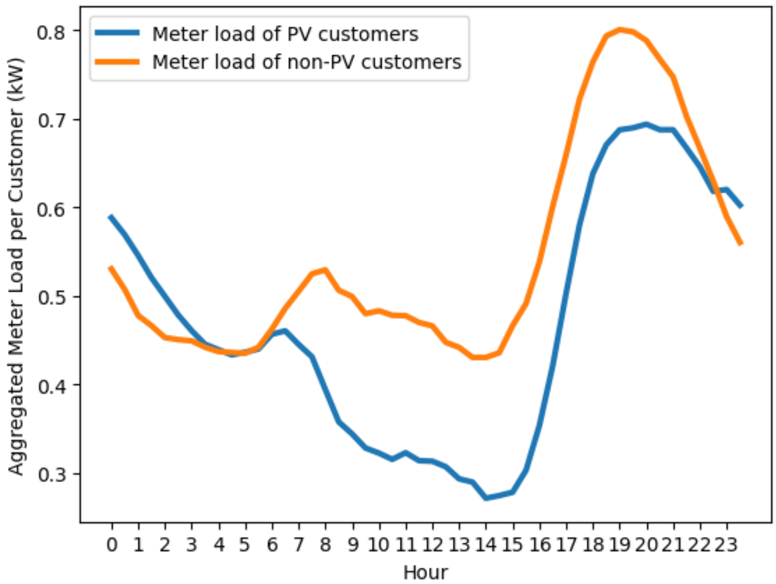

Figure 33 Aggregated meter load profiles per customer for both non-PV and PV customers based on charger mix of PV customers (2.3kW – 82.1%, 3.7kW – 7.4%, 7.4kW – 10.5%)

The following Fig. 34 represents scenarios in which customers increasingly adopt higher-powered chargers. The aggregated EV charging consumption becomes progressively more pronounced, especially during evening and early morning hours, as the percentage of 3.7kW and 7.4kW chargers increases. Also, as the proportion of 2.3kW chargers decreases, the aggregated charging consumption during the midday hours also decreases significantly. This is because the 3.7kW and 7.4kW chargers have lower daytime-only charging segments (18.35% and 10.03%, respectively). Thus, as higher-powered chargers become more prevalent, the midday peak flattens. This low proportion of daytime-only and multi-charging with daytime charging segments may be due to the lack of solar PV generation data. Such solar PV data is behind-the-meter and invisible in the smart meter dataset. Given that utilising solar PV generation to charge EVs results in less-purchased electricity from the grid, it is challenging to derive the EV charging profiles for PV customers during daytime. In Section 3.5, we conduct a synthetic analysis via tuning the probability density distributions of all the charging segments and investigate the impacts of PV generation on the average EV charging consumption.

More importantly, we would like to acknowledge that the solar PV generation data is not available, making it difficult to detect EV charging events that may occur during the day. As a result, some EV charging activities may be missing from the aggregated profiles, particularly for the high-powered chargers, which have a lower daytime-only segment. This limitation could potentially skew the interpretation of charging patterns, leading to an underestimation of daytime consumption.

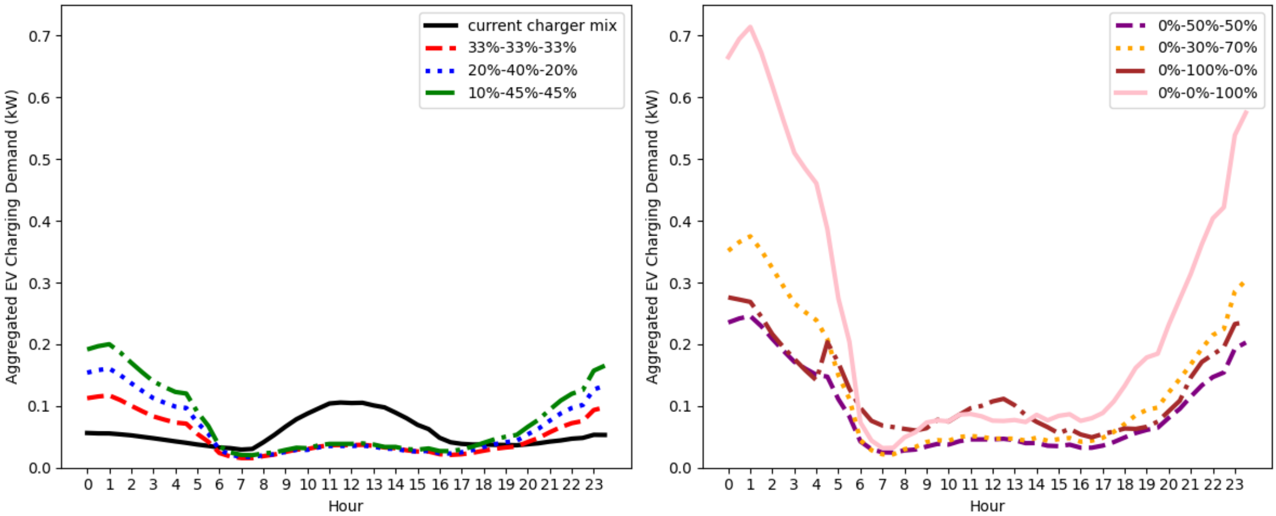

Figure 34 Aggregated EV charging consumption per customer in all eight scenarios

3.5. Analysis of PV impacts on aggregated EV charging profiles

As the solar PV generation is behind-the-meter and unknown to us at the current stage, to evaluate the impacts of solar PV generation on the aggregated EV charging profiles, we use the solar home electricity data publicly from [14], containing 300 homes' solar PV generation data across multiple years. We take 5kW as the capacity for a PV system as a synthetic case study. We then use those homes with 5kW solar PV within the dataset to calculate the PDF of the solar output.

The average solar PV generation profile for a 5kW solar PV system based on the derived PDF is shown in Fig. 35, exhibiting a symmetric bell shape. Solar PV generation starts at zero, increases gradually to peak around midday, and then decreases symmetrically until sunset. This profile is the aggregate of all seasonal variations and represents the average solar PV generation pattern.

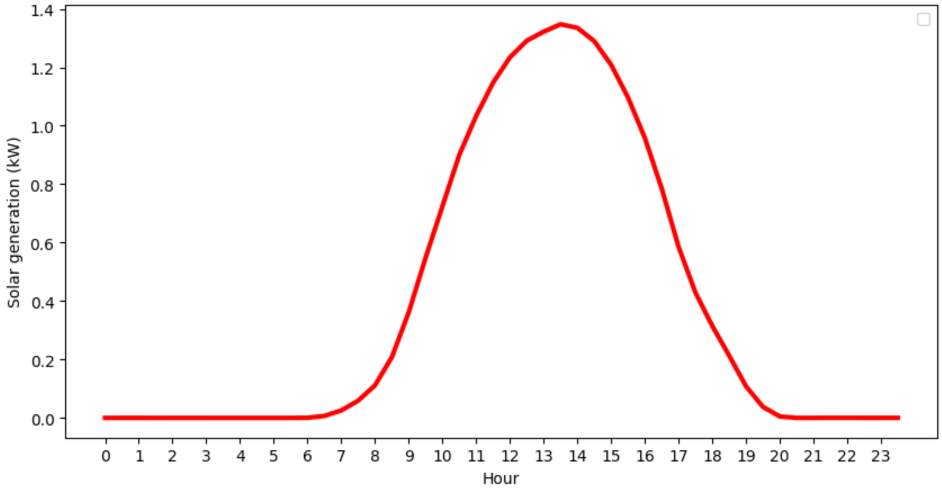

Figure 35 Average solar PV generation profile for 5kW PV system

Following the same aggregation approach detailed in Section 3.3, we incorporate the previous aggregated EV charging consumption per customer with such aggregated solar PV generation data base on the current PV customers (with the number of 447) and eight different charger mixes as mentioned in Section 3.3., including the current charger mix for the filtered PV customers (i.e., 82.1% of 2.3kW, 7.4% of 3.7kW, and 10.5% of 7.4kW), scenario 1 – 33.3% of 2.3kW, 33.3% of 3.7kW, and 33.3% of 7.4kW, scenario 2 – 20% of 2.3kW, 40% of 3.7kW, and 40% of 3.7kW, scenario 3 – 10% of 2.3kW, 45% of 2.3kW, and 45% of 7.4kW, scenario 4 – 0% of 2.3kW, 50% of 3.7kW, and 50% of 7.4kW, scenario 5 – 0% of 2.3kW, 30% of 3.7kW, and 70% of 7.4kW, scenario 6 – 0% of 2.3kW, 100% of 3.7kW, and 0% of 7.4kW, and scenario 7 – 0% of 2.3kW, 0% of 3.7kW, and 100% of 7.4kW.

The average EV charging profiles per customer before and after considering PV impacts for all eight charger mixes are shown in Fig. 36, which all indicate that the installation of PV systems to a great extent shapes EV customers' charging profiles. Again, as discussed in Section 3.4.4., midday aggregated charging consumption also significantly drops with the decreasing proportion of 2.3kW chargers. This is because 3.7kW and 7.4kW chargers have lower daytime-only charging segments (18.35% and 10.03%, respectively), leading to a flattened midday peak as higher-powered chargers become more common. The low proportion of daytime-only charging may be due to the absence of solar PV generation data, which is behind-the-meter and not visible in the smart meter dataset. Since solar-powered EV charging reduces grid electricity usage, deriving accurate EV charging profiles for PV customers during daytime is challenging. Also, our current charger mix in the filtered PV customer dataset does not necessarily reflect the actual mix in the real world as the processed data can be biased due to the limited sample size.

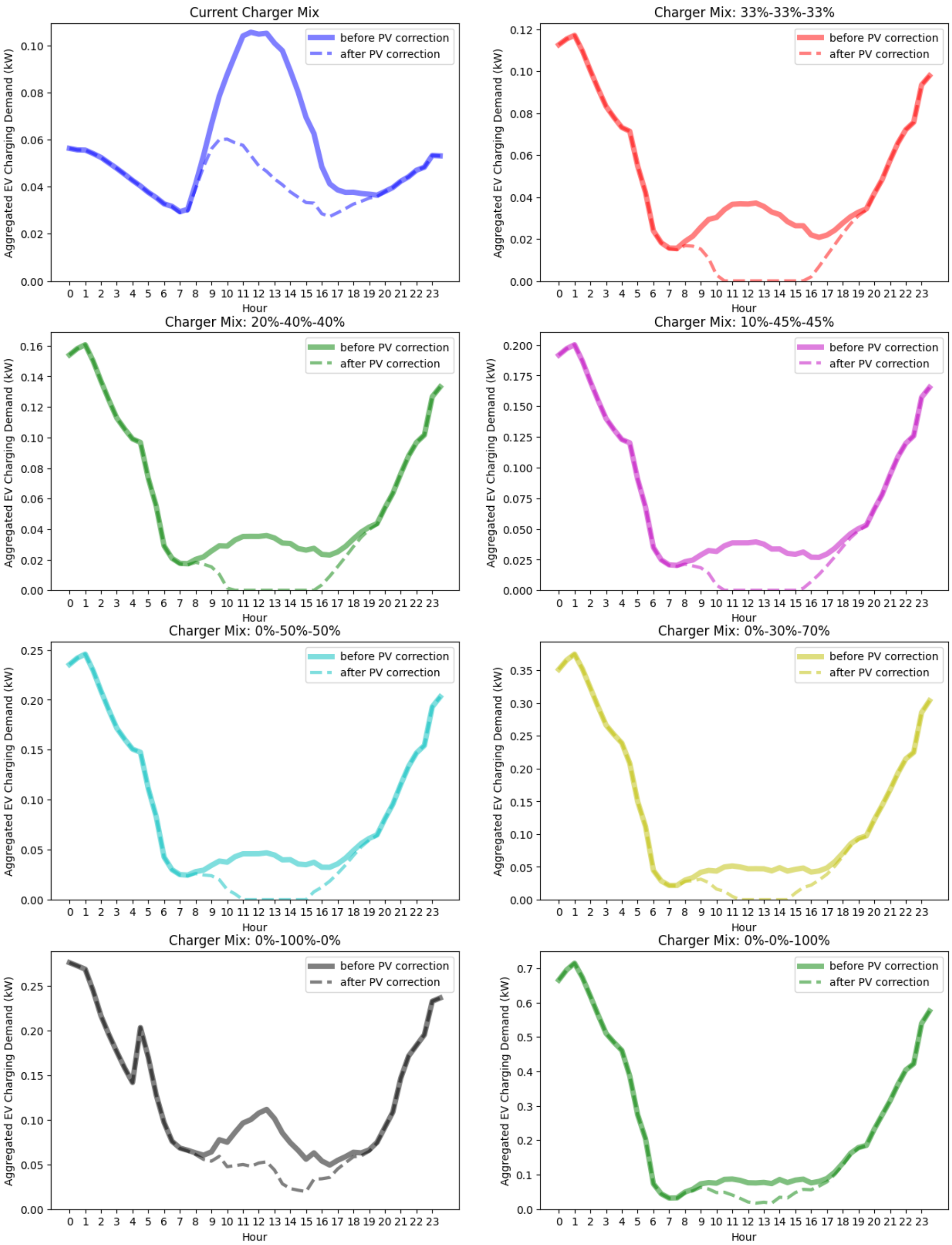

Figure 36 Aggregated EV charging consumption per customer considering PV impacts in different charger mixes

To align with the common EV charging consumption per PV customer (whose maximum value is often between 0.3 and 0.5kW reported by the Ausgrid [15]), we use the charger mix of (0% of 2.3kW charger, 30% of 3.7kW charger, and 70% kW charger) and then tune the probability distributions of the four charging segments defined in Section 3.2, including morning-only, daytime-only, evening-only, and multi-charging with daytime-charging segments. This analysis aims to monitor possible variations in PV customers' charging behaviours. Table 6 below presents the modified probability distribution of charging segments by moving a certain proportion of charging at the evening-only segment into the daytime-only segment. Such modifications may also reflect the real-world charging behaviours of PV customers for two reasons: 1) as discussed above, the proportion of daytime-only and multi-charging with daytime charging segments seems to be underestimated due to the lack of solar PV generation data; and 2) PV customers tend to utilise the solar PV generation to charge their EVs.

Table 6 Aggregated EV charging consumption per customer in all eight scenarios

		3.7kW charger	7.4kW charger
Current PDF	Morning Only	23.24%	35.30%
	Daytime Only	***18.35%***	***10.03%***
	Evening Only	***44.17%***	***50.61%***
	Multi-Charging with Daytime Charging	14.24%	4.05%
Modified Scenario 1 (10% from evening-only to daytime-only)	Morning Only	23.24%	35.30%
	Daytime Only	***28.35%***	***20.03%***
	Evening Only	***34.17%***	***40.61%***
	Multi-Charging with Daytime Charging	14.24%	4.05%
Modified Scenario 2 (20% from evening-only to daytime-only)	Morning Only	23.24%	35.30%
	Daytime Only	***18.35%***	***30.03%***
	Evening Only	***44.17%***	***30.61%***
	Multi-Charging with Daytime Charging	14.24%	4.05%
Modified Scenario 3 (all evening-only moving to daytime-only)	Morning Only	23.24%	35.30%
	Daytime Only	***62.52%***	***60.64%***

	Evening Only	***0%***	***0%***
	Multi-Charging with Daytime Charging	14.24%	4.05%

The aggregated EV charging consumption profiles per customer using the modified PDFs are shown in Fig. 37, with the corresponding meter load profile per customer shown in Fig. 38 for cross comparison.

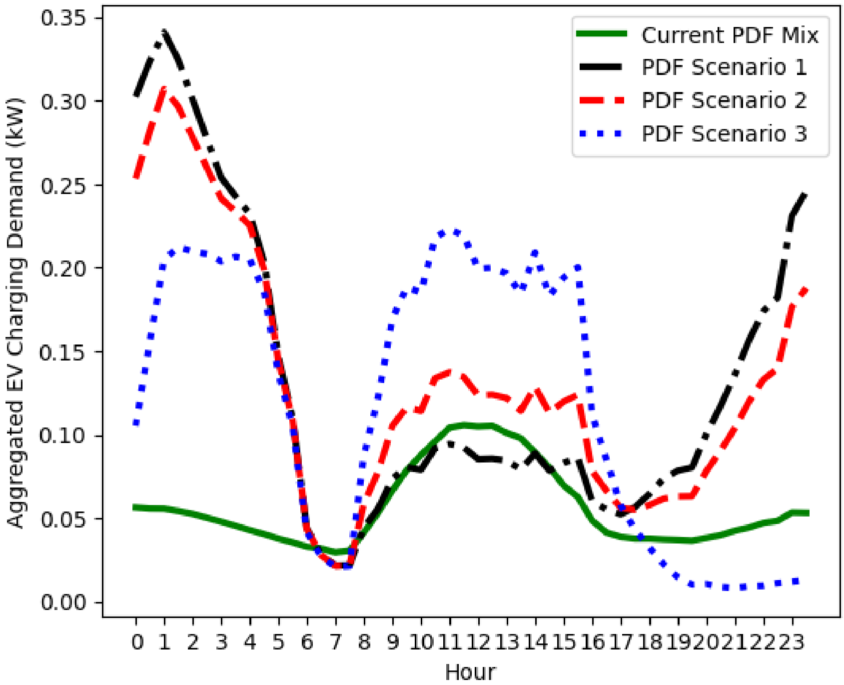

Figure 37 Aggregated EV charging consumption per customer with various PDF mixes

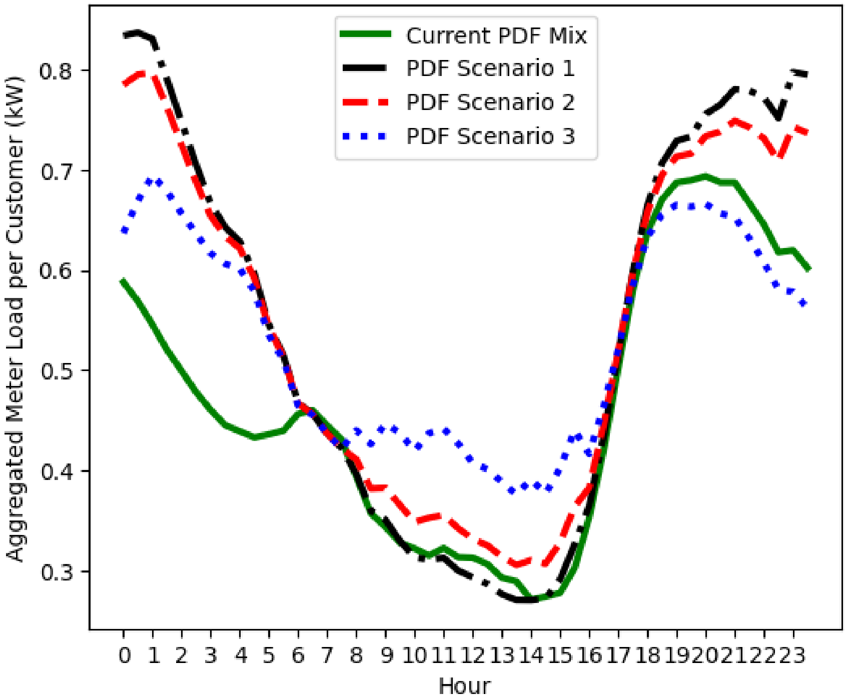

Figure 38 Aggregated meter load per customer with various PDF mixes

Specifically, in Fig. 37, shifting 10% of the evening-only charging to daytime causes a slight decrease in the evening peak and a noticeable increase in the daytime period. This shift begins to distribute the charging consumption more evenly across the day. With a 20% shift, the evening peak decreases further, and the daytime charging consumption rises more significantly. This scenario results in a flatter consumption profile, indicating a move towards more efficient utilisation of solar PV energy. In this extreme case, where all evening-only charging is moved to daytime, the evening peak is almost completely eliminated, and the daytime period experiences a substantial increase in consumption. This scenario reflects a significant behavioural change, where customers prioritise charging their EVs during solar PV generation hours.

Correspondingly, in Fig. 38, as 10% of the evening charging shifts to daytime, the evening peak reduces slightly, and the load during daytime increases modestly. This shift begins to alleviate the stress on the grid during the evening. A more pronounced reduction in the evening peak is observed with the 20% shift. The daytime load increases more significantly, which flattens the overall load curve, indicating a better distribution of energy consumption throughout the day. The most extreme scenario shows a substantial reduction in the evening peak, with a corresponding increase in the daytime load. This results in a much smoother load profile, with less variation between the peak and off-peak periods. This smoother profile is beneficial for grid stability, as it reduces the need for peaking power plants and can lead to more efficient use of renewable energy sources like solar.

Based on the above observations, the insights regarding the impact of shifting evening charging to daytime charging for EV customers with PV installation are summarised as follows.

- Reduction in Peak Load: The key impact of shifting evening charging to daytime is the reduction in the evening peak load. As the evening period is typically associated with high residential consumption, reducing the additional load from EV charging can significantly alleviate grid stress during this time.
- Better Utilisation of Solar PV Energy: By shifting the charging to daytime, when solar PV generation is at its peak, customers can make better use of their PV systems, effectively charging their EVs with clean energy. This not only supports the use of renewable energy but also reduces reliance on grid electricity, which may be more expensive and less environmentally friendly during peak times.
- Shaping the EV Charging Profile: The modifications in the charging profile’s distribution, as seen in Fig. 48, lead to a more even distribution of load throughout the day. This balanced load profile helps in optimising the operation of the electrical grid, potentially reducing the need for infrastructure upgrades and lowering overall electricity costs.

Conclusion

This report provides an analysis of EV charging profiles for customers with solar PV systems, contributing useful insights to the ongoing efforts to optimise EV charging and enhance grid stability. By employing both disaggregation and aggregation methodologies, this study highlights the interaction between EV charging behaviour and PV self-consumption, revealing EV charging patterns of customers with PV.

In the disaggregation task, we identify and extract EV charging loads from overall household energy usage by analysing smart meter data and applying advanced statistical filtering techniques. This process, though effective, was constrained by the absence of behind-the-meter solar PV generation data, which limited the ability to fully capture the extent of EV charging directly supported by solar PV power. Despite these limitations, the study successfully extracted distinct EV charging profiles from household meter data, offering a clearer picture of individual charging behaviours of customers with PV. Notably, the disaggregation approach accounted for various external factors, including customer behaviour variability, extreme weather conditions, and temporal fluctuations in energy use, leading to the characterisation of EV charging patterns. The results underscore the need for the inclusion of solar PV generation data to further enhance the accuracy of disaggregated EV charging profiles.

The aggregation task of the report extended the analysis to a broader level by modelling the collective EV charging consumption of PV customers. This was achieved by developing a probability distribution model that categorised charging events into four distinct segments: morning-only, daytime-only, evening-only, and multi-charging (which includes at least one daytime charging session). By integrating these segments across different charger types, the aggregated charging profiles reflected the diversity of customer behaviour and the varying consumption characteristics based on charging equipment. The findings revealed that higher-powered chargers, such as the 7.4kW model, are associated with faster and more intense charging events, producing sharper peaks in energy consumption. In contrast, lower-powered chargers, such as the 2.3kW unit, result in more gradual and prolonged charging sessions, which have a different impact on grid consumption.

Importantly, the aggregation analysis demonstrated that solar PV systems could significantly mitigate daytime EV charging consumption by aligning charging times with peak solar PV generation periods. When comparing the meter load to those derived from non-PV customers' data, we observed that the installation of solar PV systems can somewhat alter residential energy consumption patterns. This change is likely because EV owners with solar PV systems may prefer to charge their vehicles during the day, taking advantage of solar PV power. Consequently, their consumption for EV charging at night, particularly during peak hours, shifts partially to daytime. Therefore, integrating solar PV systems for EV owners not only allows them to utilise solar PV energy instead of purchasing electricity from the grid but also contributes to peak load reduction for the grid. In addition to comparing non-PV customers with PV customers, we also carried out a synthetic analysis to assess the impact of increased daytime charging on both aggregated EV charging profiles and overall meter load. The findings offer insights into three key areas: 1) Reduction in peak load:

The main effect of shifting EV charging from evening to daytime is the reduction of the evening peak load. Since the evening generally experiences high residential electricity consumption, lessening the additional burden from EV charging can significantly reduce strain on the grid during this period. 2) Better utilisation of solar PV energy: By moving charging to daytime, when solar PV generation is at its highest, customers can make the most of their PV systems, effectively charging their EVs with clean energy. This approach not only enhances the use of renewable energy but also decreases reliance on grid electricity, which may be more expensive and less environmentally friendly during peak times. 3) Shaping the EV charging profile: A charging profile with increased daytime charging results in a more even distribution of load throughout the day. This balanced profile supports the optimisation of grid operations, potentially reducing the need for infrastructure upgrades and lowering overall electricity costs.

However, the analysis also pointed out the limitations in our current understanding due to the absence of real-time solar PV generation data behind the meter. This gap highlights the potential for future enhancements in energy management systems that integrate real-time PV generation data with EV charging models, allowing for more precise predictions of energy flows and improved grid stability.

Moreover, the report uncovered useful insights into the potential future evolution of charging behaviours as more customers adopt higher-powered chargers and modify their routines to align with solar PV generation. These behavioural shifts, driven by both technological advancements and the increasing affordability of renewable energy sources, present both opportunities and challenges for energy infrastructure planning. As EV adoption and solar PV installation rates continue to rise, the importance of predictive models that account for these factors will grow, guiding investments in grid upgrades, charging infrastructure, and renewable energy storage solutions.

In conclusion, the findings of this report try to provide critical foundations for future research and policy development in the realm of EV charging and renewable energy integration. The analysis highlights the need for enhanced data collection, particularly regarding behind-the-meter solar PV generation, and suggests continued efforts to refine disaggregation and aggregation methods.

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