MONASH University

WP1.2 Technical modelling of electrification of transport profiles - Milestone Report: EV charging profile aggregation methodology and results (DRAFT v2)

Course Title

Self-Review team members

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CONTENTS

DISCLAIMER AND ACKNOWLEDGEMENT

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Executive Summary

This milestone report builds upon the previous report on EV charging profile extraction and focuses on the aggregation and modelling of EV charging profiles to provide insights into EV charging behaviours under different diversity scenarios, e.g., different mixes of chargers installed. As the adoption of EVs continues to rise, understanding their charging behaviours is crucial for network management and planning.

Our study employs an aggregated probability distribution approach to model EV charging demand considering many factors such as types of chargers, segmentation scenarios, and temporal distributions of charging events. This method captures the variability in EV charging behaviours across different customer groups and time periods, providing an effective representation. Notably, in our obtained EV charging profiles from the previous deliverable, the majority of customers charge their EVs at home using a 2.3kW charger, while only a relatively small number use 3.7kW or 7.4kW chargers. As a result, we recognize that the EV charging profiles for these two charger types may not provide sufficiently accurate representative charging patterns due to the limited sample size. Obtaining more data from customers with 3.7kW and 7.4kW chargers would help strengthen the robustness of the results.

In this report, our analysis focuses on non-photovoltaic (PV) customers to avoid the complexities introduced by distributed solar PV generation and distributed batteries on charging profiles, further on overall demand. It is important to note that this report does not account for the presence of batteries, changes in EV ownership, or shifts in charging behaviour due to limited available data. Based on our designed charging segmentation, including morning-only, daytime-only, evening-only, and morning-evening charging, our comparative analysis on the aggregated EV charging demand per customer reveals noticeable differences among three kinds of chargers, in terms of peak charging intensity and duration, EV charging distribution spread, and etc. For instance, the 7.4kW charger exhibits the sharpest and highest peaks, indicating that users are able to complete their charging sessions the fastest compared to the 3.7kW and 2.3kW chargers. This is evident in all the segments (morning, daytime, night, and morning-night) where the distributions have much narrower and steeper peaks, based on our available data. In addition, we investigate some synthetic scenarios of aggregated EV charging demand where customers may choose to upgrade their chargers. The results seem to suggest that, if increasing customers upgrade from 2.3kW chargers to 3.7kW or 7.4kW chargers, it will, to a great extent, raise the charging demand at peak hours.

The developed EV charging aggregation framework/tool, along with the insights, in this report could be useful to the development of EV charging management strategies and grid management.

GLOSSARY OF TERMS/ABBREVIATIONS

PV	Photovoltaic
EV	Electric vehicle
DNSP	Distributed network service provider
PDF	Probability distribution function

1. Introduction

The electrification of transportation is a critical component of global efforts to reduce greenhouse gas emissions and combat climate change. As EVs become more prevalent, understanding their charging behaviours and impacts is essential for charging management, grid operation and planning. Effective modelling of EV charging profiles can provide insights to ensure that charging infrastructure can meet the growing (peak) demand while minimising impacts on the electrical grid. In this report, our analysis focuses on non-photovoltaic (PV) customers to avoid the extra complexities that solar PV may introduce to both EV charging profiles and overall demand.

Our previous studies on EV charging profile extraction (as provided in the previous deliverable) have primarily focused on the disaggregation of EV charging data, analysing individual charging events to understand usage patterns and energy consumption. While disaggregation provides valuable insights into various charging behaviours for customers, it falls short in capturing the broader trends and overall impact of EV charging on demand increase on the grid. This part of research transitions to an aggregated modelling approach, which offers a view of EV charging profiles and their potential impacts.

The following sections of this report provide a detailed overview of our EV charging aggregation approach. We begin with an analysis of EV profiles and charging frequencies, followed by a segmentation of charging patterns based on morning-only, daytime-only, evening-only, and morning-evening scenarios. The core of our methodology involves the development of a probability distribution model for diverse EV charging behaviours, followed by case studies. The case studies examine the aggregation results for different types of chargers and generate the likely aggregated charging demands. Several diversity scenarios as synthetic analysis are presented to show the changes in aggregated charging demand with potentially more customers upgrading their chargers from 2.3kW to 3.7kW and 7.4kW ones. This aggregation modelling tool, together with the generated insights, could be useful to stakeholders managing EV charging and the distribution network.

In the following, this report will present the overview of previously extracted EV charging profiles in Section 2. Then the charging pattern segmentation analysis is presented in Section 3 as a key step to model charging behaviours and distributions. Then the segmented behaviours and distributions are used to construct the EV EV charging profile aggregation model in Section 4. Section 5 presents case studies with synthetic diversity scenarios with different mixes of chargers, showing the aggregated EV charging profiles and impacts on the peak load.

82.12. Overview of EV charging profiles

Based on the correlated EV charging data extracted from our toolbox, we conducted some descriptive analysis. Specifically, we analysed the distribution of different charger types, the number of customers with different charger types, the average weekly charging frequency, and the average weekly EV correlated demands.

Based on our toolbox, we have identified three types of chargers, i.e., 2.3kW, 3.7kW, and 7.4kW EV chargers. Fig. 1 illustrates the distribution of non-PV customers by their type of charger. The pie chart shows that 87.5% of the customers use 2.3 kW chargers, 5.3% use 3.7 kW chargers, and 7.2% use 7.4 kW chargers, with the number of customers being 232, 14, and 19, respectively. The average EV charging consumption per day is 10.45 kWh across all non-PV customers. Note that, the current charger mix, after the original dataset goes through our disaggregation filter, may not reflect the actual charger mix, since the disaggregation toolbox filters out some of the customers in the original dataset to ensure the consistency and data integrity between 2022 and 2020.

As highlighted in the EV charging disaggregation report, after categorising each customer by charger type, the majority are found to use 2.3kW chargers for home EV charging, while only a small portion use 3.7kW or 7.4kW chargers. Consequently, we acknowledge that the disaggregated charging profiles for the 3.7kW and 7.4kW chargers may not fully represent typical charging patterns due to the limited number of customers using these chargers. Collecting more data from customers with 3.7kW and 7.4kW chargers would enhance the robustness of the results.

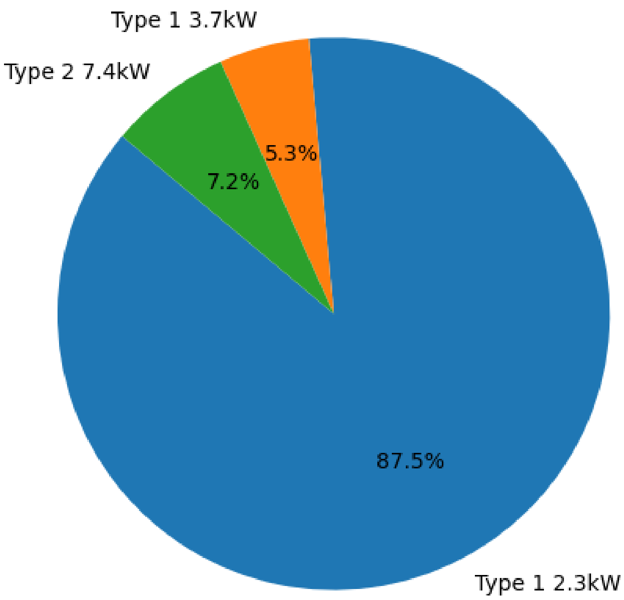

Figure 1 Distribution of EV customers by their using types of chargers in the process dataset (Note that this mix does not necessarily reflect the actual mix in the real world as the processed data can be biased due to limited sample size.)

We further examine the average weekly EV charging frequency and the average EV charging weekly demand (kWh), as presented in Table 1. The average weekly charging frequency across three charging rates is 3.19, with corresponding average EV weekly demand being 53.78kWh.

Table 1 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 demand (kWh)
Type 1 – 2.3	232	3.22	45.74kWh
Type 1 – 3.7	14	2.32	41.13kWh
Type 2 – 7.4	19	1.72	66.28kWh

From Table 1, we observe that customers using Type 1 – 2.3 kW chargers have the highest average weekly charging frequency at 3.22 times per week. This suggests that lower-powered chargers may require more frequent use to meet energy needs. Customers of the Type 1 – 3.7 kW chargers charge less frequently, averaging 2.32 times per week. This reflects a reduction in charging frequency as the charger's power capacity increases. The lowest charging frequency is observed among Type 2 – 7.4 kW customers, who average 1.72 times per week. This indicates that higher-powered chargers allow for fewer charging sessions while still satisfying energy requirements.

Despite the highest charging frequency, Type 1 – 2.3 kW chargers result in an average weekly energy demand of 45.74 kWh, which is moderate compared to other charger types. The Type 1 – 3.7 kW charger, with a lower charging frequency, results in a smaller average weekly energy demand of 41.13 kWh. This lower demand aligns with the lower frequency and indicates that these customers require less energy overall. Type 2 – 7.4 kW chargers, despite having the lowest charging frequency, have the highest average weekly energy demand at 66.28 kWh. This illustrates that customers of higher-capacity chargers draw more energy per charging session, resulting in a larger overall weekly demand. As charger capacity increases (from 2.3 kW to 7.4 kW), the average weekly charging frequency decreases, suggesting that more powerful chargers provide sufficient energy in fewer charging sessions.

To better understand the daily charging patterns of customers with different charger types, we analysed and created distribution charts showing the number of charging days per week, as depicted in Fig. 2 below. The results reveal that the highest proportion of customers charge their vehicles on 2-3 days per week, with a value of approximately 0.55. This suggests that a significant portion of customers prefer charging their EVs a few times a week. Following this, the second highest group consists of customers who charge their vehicles 4 to 7 days per week, representing around 0.35 of the customer base. Finally, a small proportion of customers, approximately 0.10, charge their vehicles only 1 day per week. This indicates that while a majority of customers charge their vehicles a few days a week, both minimal and frequent charging behaviours are less common.

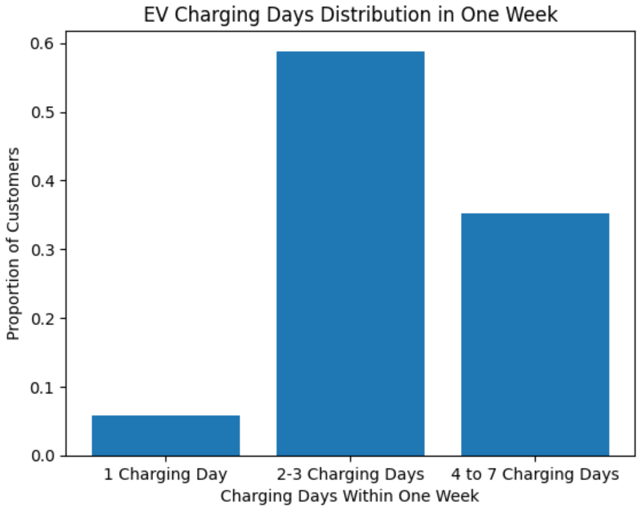

Figure 2 Charging frequency (approximate days) in one week for all non-PV customers

3. Charging pattern segmentation analysis

3.1. 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.

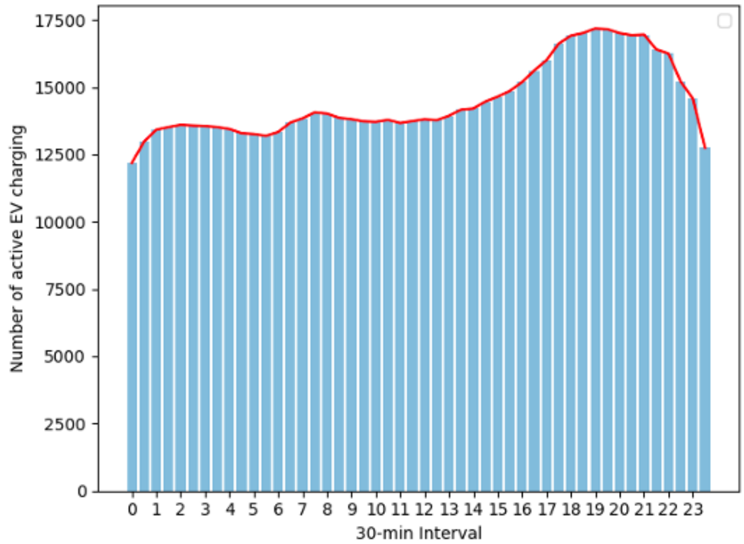

Figure 3 The number of active charging across a day

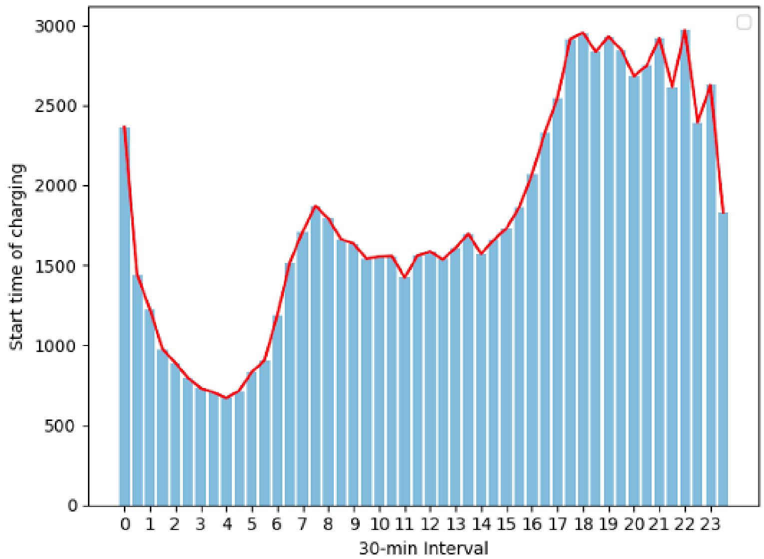

Figure 4 The start time distribution of charging events

We conducted a statistical analysis of the charging periods for all DNSPs. Fig. 3 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.4 further illustrates the distribution of the start time of charging. Based on the above two figures, we can observe that non-PV customers prefer night charging with a higher number of active charging and more charging sessions starting from the night times.

3.2. Charging patterns in different segmentations

By analysing the charging events, we understand that for non-PV customers, the main charging events occur during two time periods: late night and evening. Based on this result, we can segment all charging events to estimate the probability distribution for each segmentation [2] using our sample data.

Consider one day as a session and one complete charging cycle as a charging event. A session may have multiple charging events. Charging events can occur in the morning, evening, or both. For non-PV customers, they may also choose to charge their EVs at daytime. 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.
- **Morning-Evening Charging Segmentation**: If charging events in a session occur between 12 am and 8 am and between 4 pm and 12 am, this session is categorised under the morning-evening charging segmentation.

It should be noted that this classification is a hard classification. For example, if a charging event starts at 6 am and ends at 10 am, the segment between 8 am and 10 am will be ignored. This hard classification can lead to some charging data loss[2]. To address this issue and ensure the accuracy of our modelling, we adopted another method called soft classification. Specifically, for charging events like the one starting at 6 am and ending at 10 am, we categorise it under the morning charging segmentation. This method ensures that all relevant data points are considered, thereby reducing the potential for data omission. By doing so, we can better understand the charging behaviour of EV customers throughout different times of the day, enabling us to obtain a more accurate EV profile.

After categorising all sessions into different segmentations, we estimate the probability density function for each segmentation separately. Each segmentation includes three types of chargers: 2.3 kW, 3.7 kW, and 7.4 kW. For each type, we also estimate their probability density function individually.

For example, in the morning charging segmentation, to estimate the probability density function for 2.3 kW chargers, we count the number of charging events at each hour. This way, we create a dictionary that stores the count of charging events for each of the 24 hours. We also calculate the total number of charging events in a day. By dividing the count of charging events at each hour by the total number of charging events in a

[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.

[2] Hard classification often leads to truncation of charging events that span multiple time segments, resulting in incomplete data representation.

day, we obtain the probability density function for customers using 2.3 kW chargers in the morning charging segmentation. The same method is applied to other segmentations and charger types.
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, daytime, evening, and morning-evening charging segmentations, as given from Fig 5 to 8.

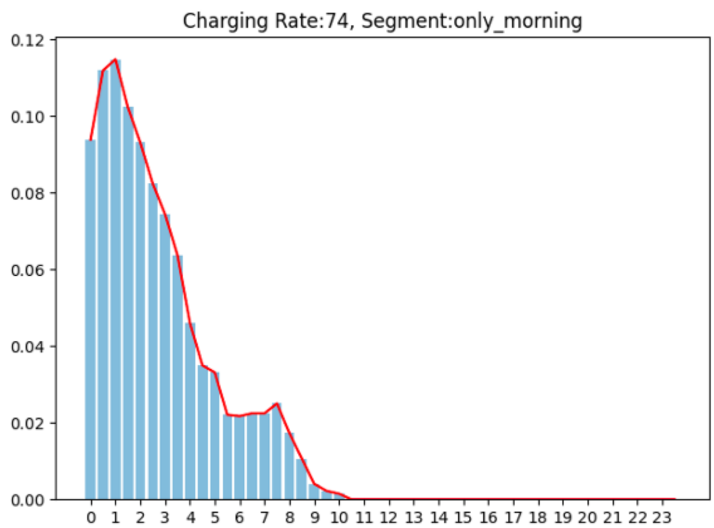

Figure 5 PDF for morning charging segmentation

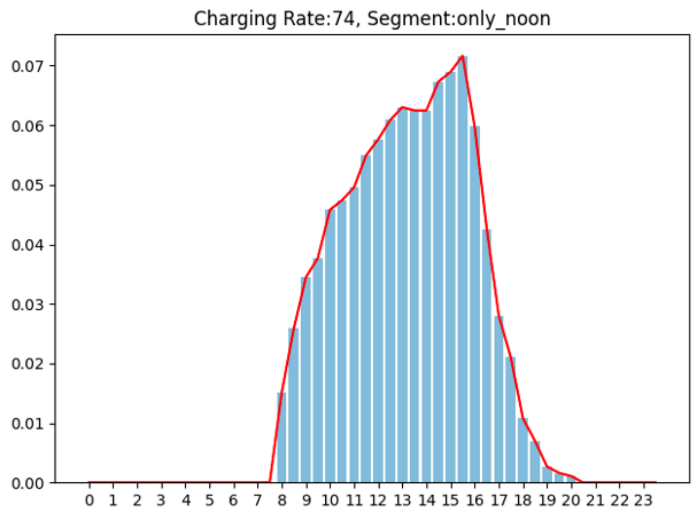

Figure 6 PDF for daytime charging segmentation

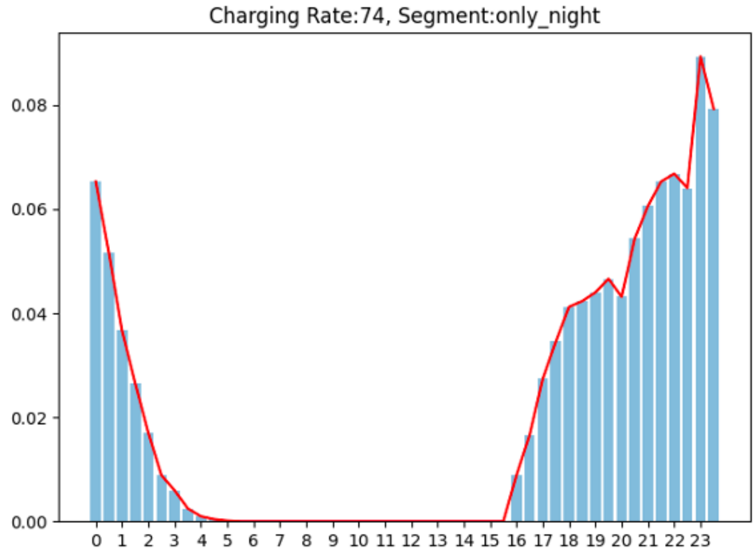

Figure 7 PDF for evening charging segmentation

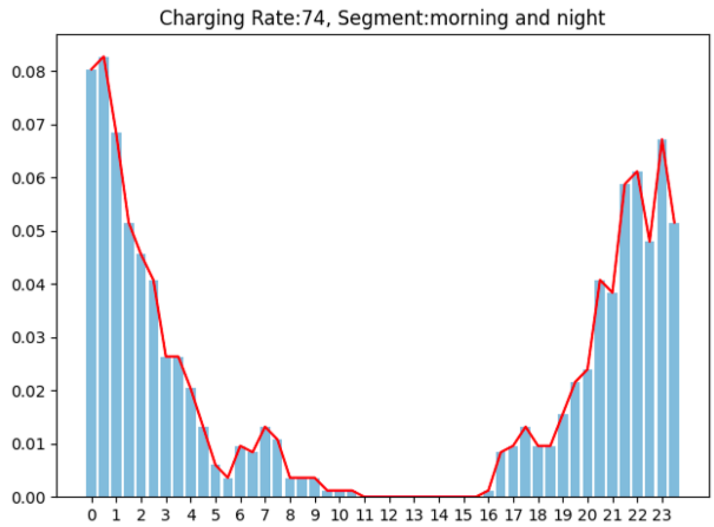

Figure 8 PDF for morning-evening charging segmentation

4. EV charging profile aggregation model

To model the charging demand profile, we use an aggregated probability distribution approach. This method integrates various factors influencing charging demand, including the number of customers, different types of chargers, scenarios of segmentation[3], and relevant temporal distribution of charging events. In this approach, the aggregated probability distribution is the foundation for modelling EV charging demand. This distribution is derived by considering multiple segments of EV customers and the corresponding events of charging events [3]. It enables us to capture the variability in charging behaviours across different customer groups and time periods, providing a detailed and accurate representation of the overall demand. In addition, the PDF for charging events is a core element in the probability distribution [4]. It captures the likelihood of charging events occurring at different times within each scenario. This probabilistic representation allows us to model the temporal distribution of charging demand in a detailed and accurate manner. Moreover, the PDF helps in representing the temporal distribution of charging events, capturing peaks and troughs in demand. For instance, PDFs of customers may show peaks in the evening when customers return home, while others charging PDFs peak during the day. The aggregation process combines the contributions of all scenarios for each charger type over the defined time steps. This method allows for a nuanced understanding of how different variables interact to influence the total demand on the charging at home, ensuring that our models reflect real-world usage patterns and variability.

When it comes to aggregation considering with the cluster based on different types of chargers, the model can be formulated by

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

where

- X: Aggregated probability distribution of charging demand
- 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.

The explicit aggregation process can be summarised as follows:

[3] In our case, the segmentation covers morning, daytime, evening, and morning-evening combinations as introduced before.

- **Temporal Aggregation**: The temporal distribution of charging events is a critical aspect of our model. By integrating the probability densities $P_{n,k,t}$ across all scenarios and charger types, we capture the fluctuations in demand throughout different times of the day. This integration allows us to identify peak and off-peak periods, providing insights into the times when the charging demand is highest and lowest.
- **Charging Rate Impact**: The charging rate for each type of charger is another crucial factor in our model. Different types of chargers have varying power levels, which directly impact the rate at which energy is consumed during charging sessions. By incorporating these rates into our model, we can accurately obtain the energy consumption and demand profiles for each charger type.
- **Weighted Contributions**: We consider the contribution of each scenario k within each charger type n , as well as relevant customer populations m_n . Each scenario has an associated probability $p_{n,k}$, which indicates the likelihood of that scenario occurring for customers using a specific type of charger. The probability density function for each scenario further refines this by capturing the likelihood of charging events occurring at different times.
- **Scenario Integration**: For each charger type and time step, the demand is calculated by summing the weighted contributions from all relevant scenarios. This step ensures that the demand profile reflects the combined effect of different usage patterns and probabilities.

When it comes to consider the aggregation from the perspective of an EV individual customer, we focus on how each customer's usage patterns and behaviours contribute to the overall demand, the model can be further formulated by:

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

Here, we account for the proportional contribution of each type of charger and scenario to the overall demand. By dividing the number of customers using a specific type of charger m_n by the total number of customers N. The ratio represents the proportion of the total customer base that uses each charger type. This allows us to understand the charging behaviour at a more granular level, considering how individual contributions aggregate to form the overall demand profile. It is particularly useful for scenarios where detailed insights into individual customer behaviours are necessary, such as in personalised energy management systems or targeted demand response programs.

In addition, it is not hard to observe that the majority of parameters in our model are highly interdependent, meaning that changes in one input can impact the overall results. As previously highlighted in the report, the charging patterns of EV might be influenced by seasonal variations. For instance, during winter months, EVs may require more frequent or longer charging sessions due to increased energy consumption for heating. This seasonal dependency necessitates careful consideration of temperature and climate data in our model to ensure accurate representation of charging demand. Furthermore, common sense suggests that EV usage is heavily tied to commuting patterns, implying that the day of the week is also a critical factor. Regarding this, we have incorporated scenario analysis in the subsequent sections of our study. This analysis will allow us to explore how different variables, such as seasonal conditions and weekly commuting patterns, influence the overall charging demand.

5. Case Study

In this section, we will use data from all DNSPs for aggregation. Specifically, 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 2, where non-PV customers tend to prefer charging their EVs at night times. A detailed discussion of the results will be presented in this section.

Table 2 Proportions of each charging segment

	2.3kW charger	3.7kW charger	7.4kW charger
Morning Only	14.73%	22.46%	20.05%
Daytime Only	22.95%	12.54%	17.68%
Evening Only	52.00%	57.25%	58.64%
Morning-Night	10.32%	7.76%	3.64%

5.1. Customers using 2.3kW charger

The PDFs of four kinds of charging segments for customers using 2.3kW chargers are depicted from Fig. 8 to Fig. 11. We first briefly describe each segment's distribution and then make a comparative analysis among these segments. For the morning charging segment in Fig. 9, The distribution peaks between 1 am to 3 am, with a steep rise initially, indicating that most charging events start around midnight. As the hours progress, the charging events gradually decrease but still show some residual probability around daytime. This tailing effect is likely due to longer charging sessions that start early in the morning and extend into the late morning, though the charging density significantly drops after 8 am.

For the daytime charging segment in Fig. 10, the distribution builds up slowly from 8 am, hitting its peak between 2 pm and 4 pm, implying that most customers initiate their charging sessions during late morning and early afternoon. A residual effect extends the distribution into the evening, similar to the morning-only segment but with a more pronounced skew towards the late afternoon. This suggests that daytime charging sessions can last into the night, although the probability decreases sharply after 4 pm.

For the evening charging segment in Fig. 11, this figure shows charging events occurring predominantly between 4 pm to 12 am. The distribution follows a bimodal pattern with a peak at the beginning of the night (5 pm to 7 pm) and another rise towards the end of the night (11 pm to 12 am). There is a substantial dip in charging events during the late night (between 10 pm to 11 pm), but the charging activity resumes toward the final hours before midnight. This suggests that some customers may start charging immediately after work and another group initiates charging before bed.

For the morning-evening charging segment in Fig. 12, the distribution has two significant peaks, one between 1 am to 4 am and the other between 8 pm to 12 am. The low probability of charging between 8 am and 4 pm reflects the absence of daytime charging. This pattern highlights a distinct dual peak in behaviour, where customers are more likely to charge their vehicles either in the early morning hours or late in the evening after work.

Comparing the four different charging segments, we find that the morning-only segment peaks much earlier than the daytime or night segments. Daytime-only charging peaks around 2 pm to 4 pm, while night-only peaks in the early evening and just before midnight. In addition, the morning-only and daytime-only segments have a broader distribution of charging probabilities extending beyond their defined time windows, indicating some overlap with other periods. However, the night segment is more concentrated with two clear peaks, showing distinct customer behaviour during those hours. Moreover, the night-only and morning-and-night segments have bimodal distributions, reflecting the fact that customers often charge either early or late, with gaps in between, especially in the evening hours. Also, the morning-only and daytime-only segments show overlap, with charging events trailing into the next segment, indicating that some sessions initiated earlier may last longer than their expected segment.

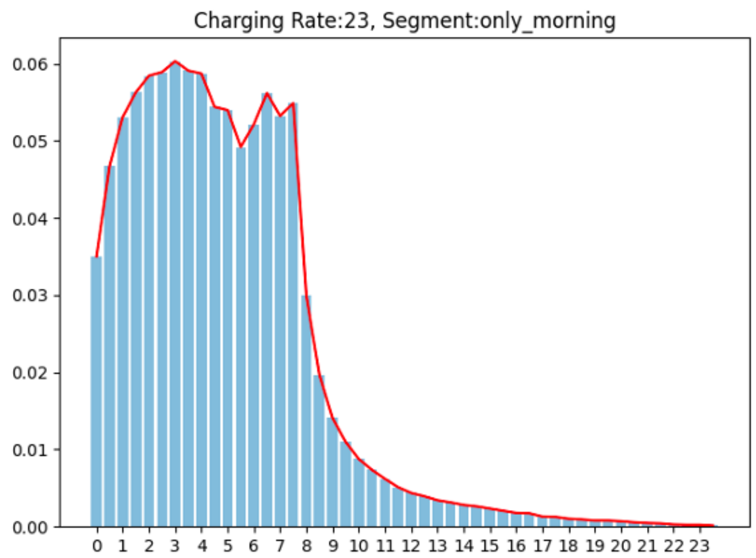

Figure 9 PDF for morning charging segmentation for 2.3kW charger

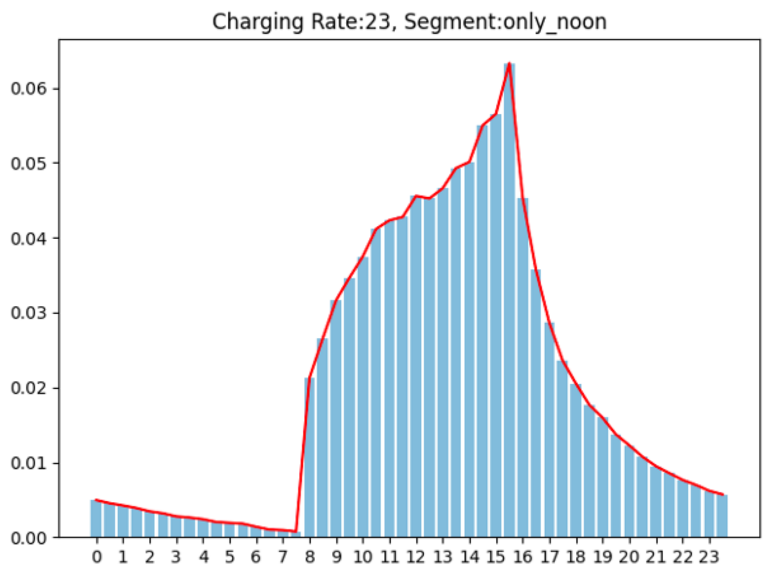

Figure 10 PDF for daytime charging segmentation for 2.3kW charger

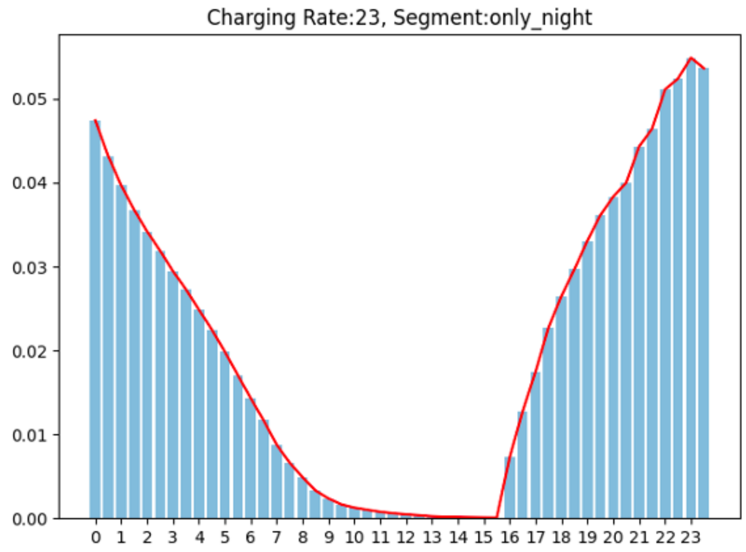

Figure 11 PDF for evening charging segmentation for 2.3kW charger

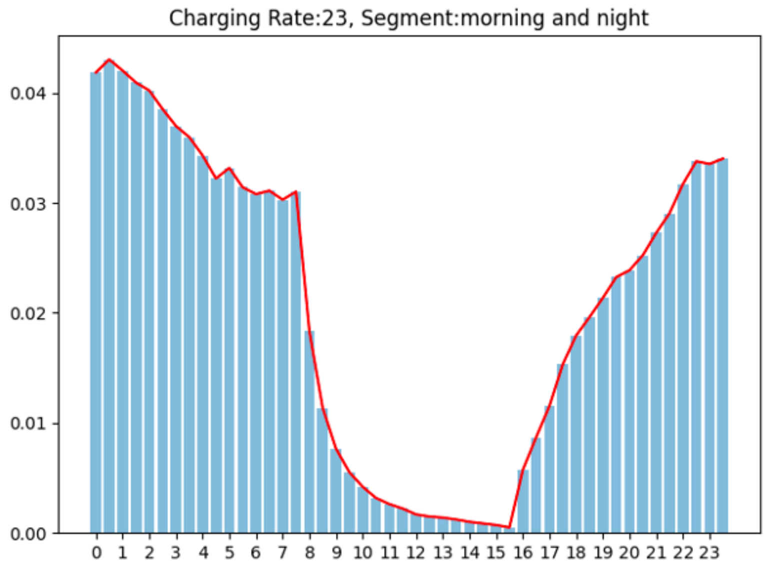

Figure 12 PDF for morning-evening charging segmentation for 2.3kW charger

5.2. Customers using 3.7kW charger

The probability distribution functions (PDFs) of EV charging using 3.7kW charger under different charging segments are presented from Fig. 12 to 15. For the morning charging segment in Fig. 13, The peak is sharper and higher compared to the 2.3kW charger, with the highest density occurring between 12 am and 2 am. The steep decline after 2 AM indicates that most charging sessions are shorter in duration, finishing earlier in the morning. However, a notable tail extends up to 8 am, with diminishing probability densities extending towards noon. The higher peak and sharper drop-off suggest that customers using 3.7kW chargers finish charging faster due to the higher power delivery, compared to the slower 2.3kW chargers. For the daytime charging segment in Fig. 14, the peak density occurs between 2 pm and 4 pm, and there is a sharper rise and fall compared to the 2.3kW charger. The shape indicates a much quicker start and end to charging sessions during these hours, with less overlap into the evening compared to the 2.3kW charger. The distribution is more concentrated, suggesting that the higher power charger completes sessions faster, which results in fewer residual charging events lasting into the late afternoon.

For the evening charging segment in Fig. 15, similar to the 2.3kW charger, there is a bimodal distribution, but the peaks are more pronounced. The first peak occurs between 5 pm and 7 pm, and the second peak happens between 10 pm and 12 am. The sharper nature of these peaks suggests a faster charging rate with less lingering charging activity. The concentration of these events in the early and late evening points to an efficient use of the 3.7kW charger, allowing users to complete their charging sessions in shorter bursts.

For the morning-evening charging segment in Fig. 16, like the 2.3kW charger, the distribution has two prominent peaks: one in the early morning (12 am to 4 am) and the other in the evening (8 pm to 12 am). However, the peak in the morning is significantly sharper and higher for the 3.7kW charger, and the evening peak, though less pronounced than the morning peak, is more distinct. The higher charger rate likely causes users to finish charging quicker, which explains the sharp drops in the distribution, particularly after the peak periods.

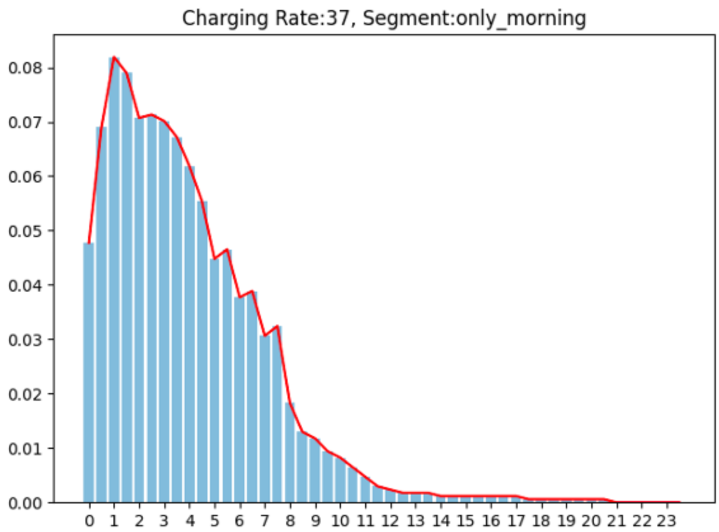

Figure 13 PDF for morning charging segmentation for 3.7kW charger

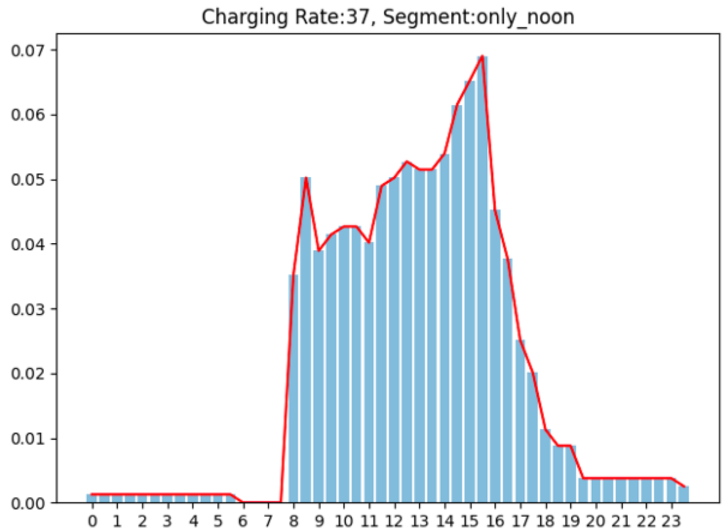

Figure 14 PDF for daytime charging segmentation for 3.7kW charger

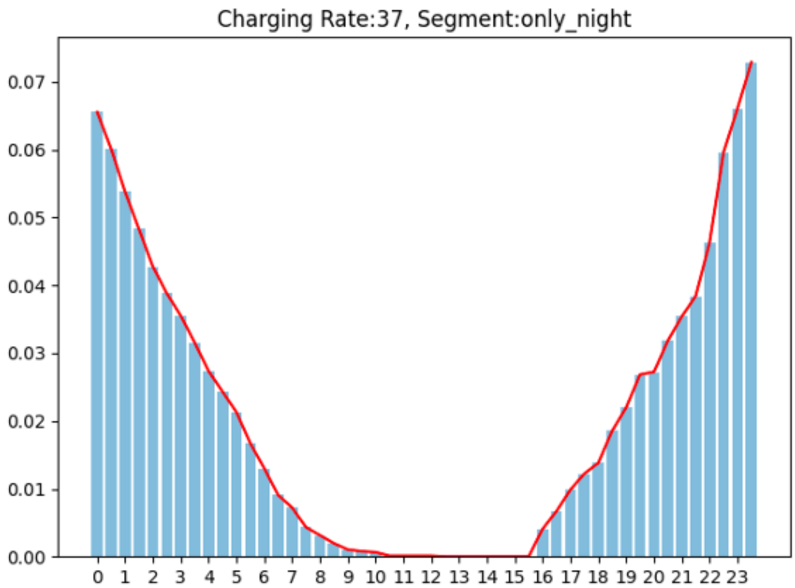

Figure 15 PDF for evening charging segmentation for 3.7kW charger

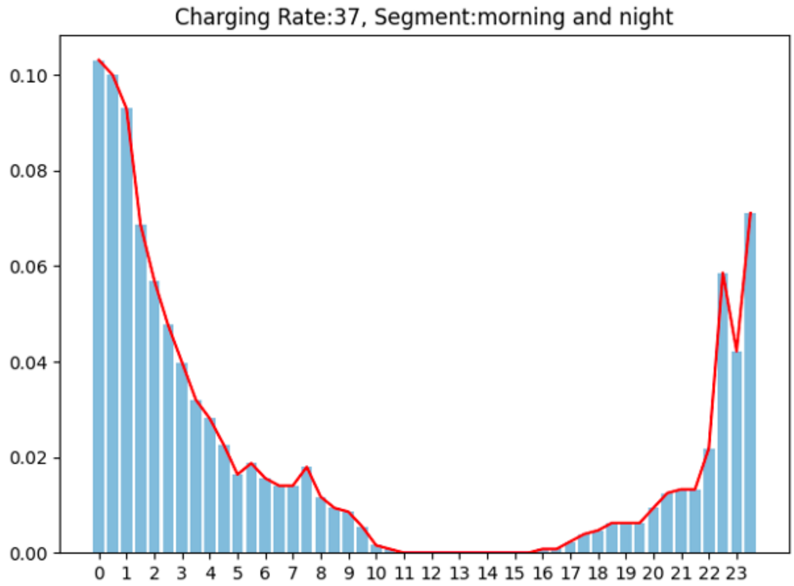

Figure 16 PDF for morning-evening charging segmentation for 3.7kW charger

5.3. Customers using 7.4kW charger

The PDFs of EV charging using 7.4kW charger under different charging segments are presented from Fig. 17 to 20. For the morning charging segment in Fig. 17, the distribution has a very sharp peak between 12 am and 2 am, and the probability density drops off steeply thereafter. The tail of the distribution extends up to 8 am but diminishes rapidly after 5 am. This pattern indicates that customers using the 7.4kW charger can complete their charging sessions much faster than users of lower-rated chargers, due to the higher power delivered per unit time.

For the daytime charging segment in Fig. 18, the probability distribution for daytime-only charging (8 am to 4 pm) shows a steady rise from around 8 am, reaching a peak between 12 pm and 3 pm. The distribution drops rapidly after the peak, with most charging sessions finishing by 4 pm. The sharp rise and fall suggest a quick charging process due to the high power delivery of the 7.4kW charger. There is minimal residual probability density beyond 4 pm, indicating that most charging events end within their intended window.

For the evening charging segment in Fig. 19, this figure depicts the charging events occurring predominantly between 4 pm and 12 am. Similar to lower power chargers, a bimodal distribution is observed, but with sharper and higher peaks. The first peak occurs between 5 pm and 7 pm, and the second peak occurs between 10 pm and 12 am. The rapid rise and fall between these peaks suggest efficient and quicker charging sessions, with less lingering activity. Users seem to complete their sessions in shorter bursts, reducing overlap into other periods.

For the morning-evening charging segment in Fig. 20, this plot shows the distribution for charging events occurring both during the morning and night. The morning peak is very sharp, between 12 am and 3 am, with a quick drop-off, while the night peak occurs between 9 pm and 12 am. The sharpness of these peaks reflects the faster charging rate provided by the 7.4kW charger. The concentration of the distribution around these periods suggests that users can efficiently finish their charging sessions within shorter time spans, compared to the lower-rated chargers.

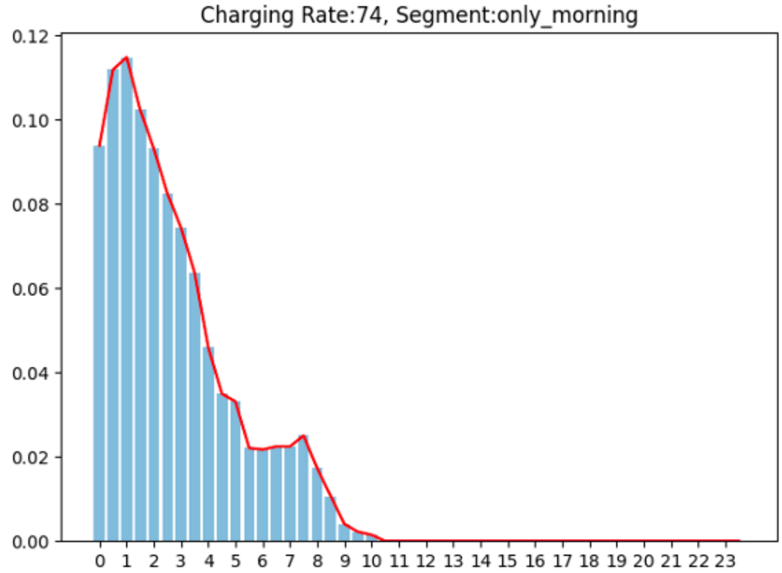

Figure 17 PDF for morning charging segmentation for 7.4kW charger

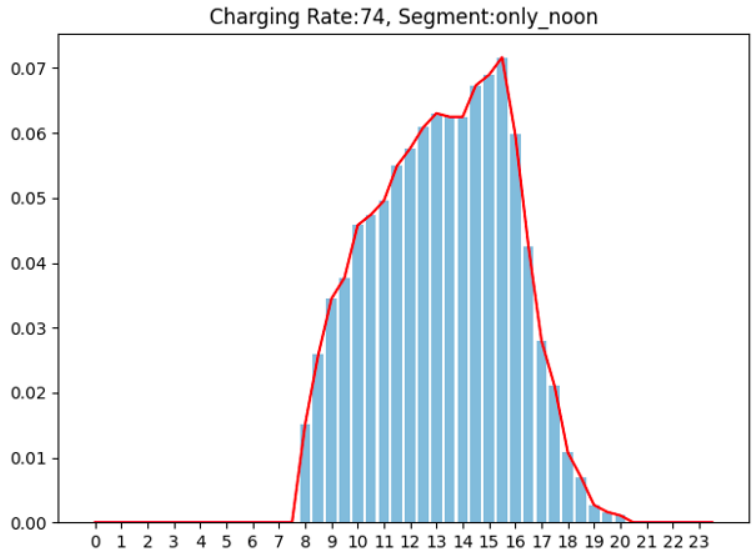

Figure 18 PDF for daytime charging segmentation for 7.4kW charger

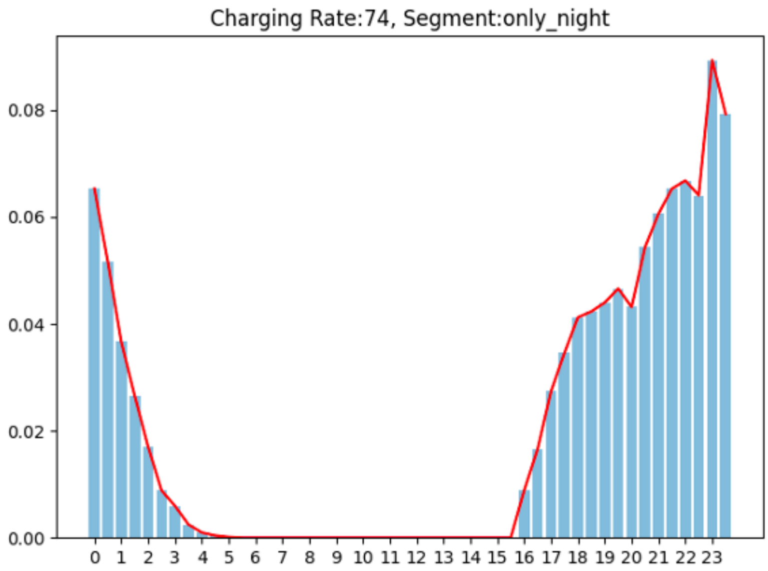

Figure 19 PDF for evening charging segmentation for 7.4kW charger

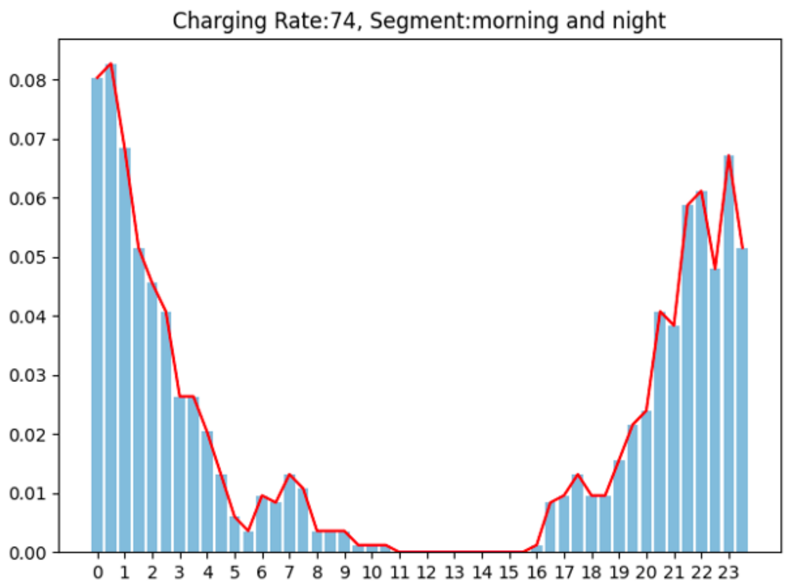

Figure 20 PDF for morning-evening charging segmentation for 7.4kW charger

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 exhibits the sharpest and highest peaks, indicating that users are able to complete their charging sessions the fastest compared to the 3.7kW and 2.3kW chargers. This is evident in all the segments (morning, daytime, night, and morning-night) where the distributions have much narrower and steeper peaks. The 3.7kW charger has intermediate peak sharpness, while the 2.3kW charger has the broadest and most gradual peaks, reflecting slower charging sessions.
- **Distribution Spread**: The 7.4kW charger's distributions are the most concentrated around the peak hours, with minimal overlap into adjacent periods. The 3.7kW charger exhibits a slightly broader

distribution, while the 2.3kW charger shows the widest spread, with tails extending well into the next segments. This suggests that the 7.4kW charger allows for more efficient charging, with users able to finish charging within their allocated segments, whereas the lower-rated chargers result in longer sessions.

- **Bimodal Patterns**: Both the night-only and morning-night segments display bimodal patterns across all charger types. However, the bimodal peaks for the 7.4kW charger are much sharper and occur closer to the segment boundaries (early morning and late night), reflecting the ability of users to finish charging faster. The bimodal distribution is less pronounced in the 2.3kW charger due to the slower charging rate, leading to more overlap between the peaks and more gradual transitions between periods.
- **Residual Charging**: Residual charging outside of the designated segment time windows is minimal for the 7.4kW charger, due to the faster completion times. The 3.7kW charger shows some residual charging activity, but it is significantly reduced compared to the 2.3kW charger. The 2.3kW charger shows the most overlap and residual charging beyond the defined time segments, indicating that users with this lower power charger experience longer charging sessions.
- **Efficiency**: The 7.4kW charger is the most efficient among the three charger types, completing charging sessions in much shorter periods. The quick rise and fall of the probability distributions reflect the ability of users to charge their vehicles more quickly and move on. The 3.7kW charger exhibits intermediate efficiency, while the 2.3kW charger is the least efficient, with users needing longer charging times to complete their sessions.

5.4. Scenario analysis on aggregated EV charging demand per customer

Following Equation (2) defined in Section 4, we can derive the aggregated EV charging demand based on our current charger mix: 232 customers with 2.3kW charger; 14 customers with 3.7kW charger; and 19 customers with 7.4kW charger. The corresponding proportion for three types of chargers are 87.5% for 2.3kW charger, 5.3% for 3.7kW charger, and 7.2% for 7.4kW charger. We then average such aggregated EV charging demand based on the total number of customers (i.e., 265 for non-PV customers), with results illustrated in Fig. 21. The pattern of this aggregated EV charging demand per user aligns with the study by the Central University of Queensland [5], where customers are more likely to charge their EVs at night and early morning times.

To examine how the aggregated EV charging demand may vary 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 mixes: 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 demand per customer for all these eight scenarios, as well as our current scenario are shown from Fig. 21 to Fig. 28, respectively.

Comparing all these eight scenarios, together with the original charger mix, we find that as the percentage of higher-powered chargers increases, the aggregated demand during the peak times (especially during late-night hours) also increases noticeably. Also, the current charger mix is heavily dominated by low-power 2.3 kW chargers, resulting in a lower overall aggregated demand. In contrast, the future scenarios predict more customers upgrading to 3.7 kW and 7.4 kW chargers, which drastically raises the demand during peak hours. The change is gradual across the figures, with the highest jump seen between the 5th and 6th figures, where the demand jumps from around 0.4 kW to over 0.6 kW at peak times.

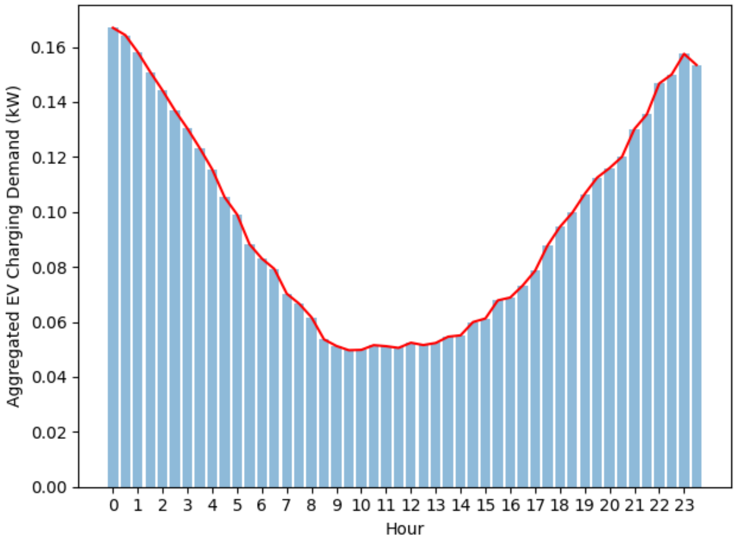

Figure 21 Aggregated EV charging demand per customer based on current charger mix (2.3kW – 87.5%, 3.7kW – 5.3%, 7.4kW – 7.2%)

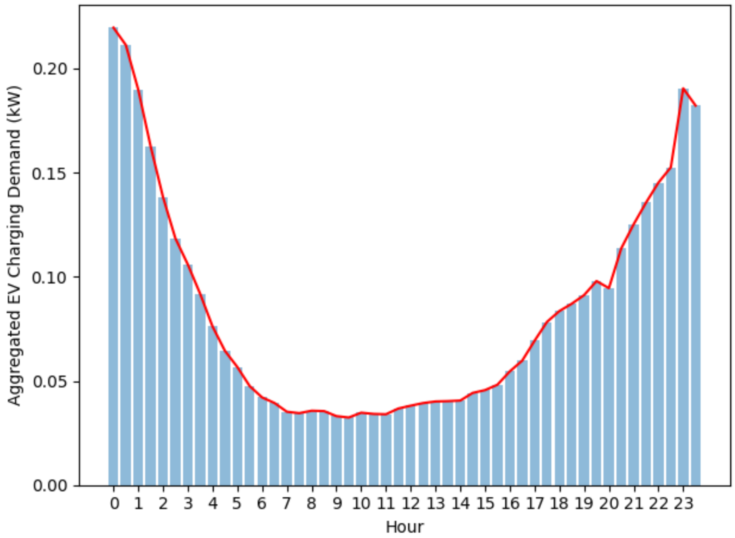

Figure 22 Aggregated EV charging demand per customer in Scenario 1 (2.3kW – 33.3%, 3.7kW – 33.3%, 7.4kW – 33.3%)

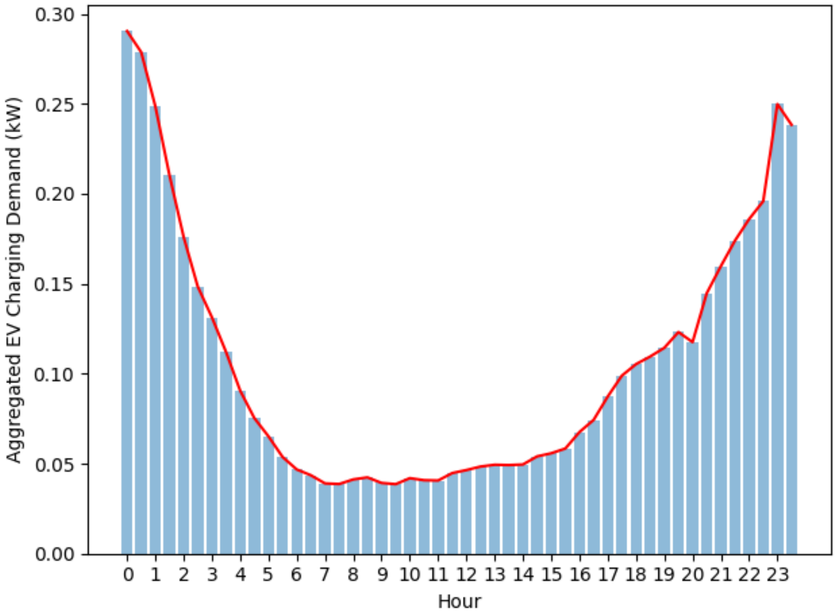

Figure 23 Aggregated EV charging demand per customer in Scenario 2 (2.3kW – 20%, 3.7kW – 40%, 7.4kW – 40%)

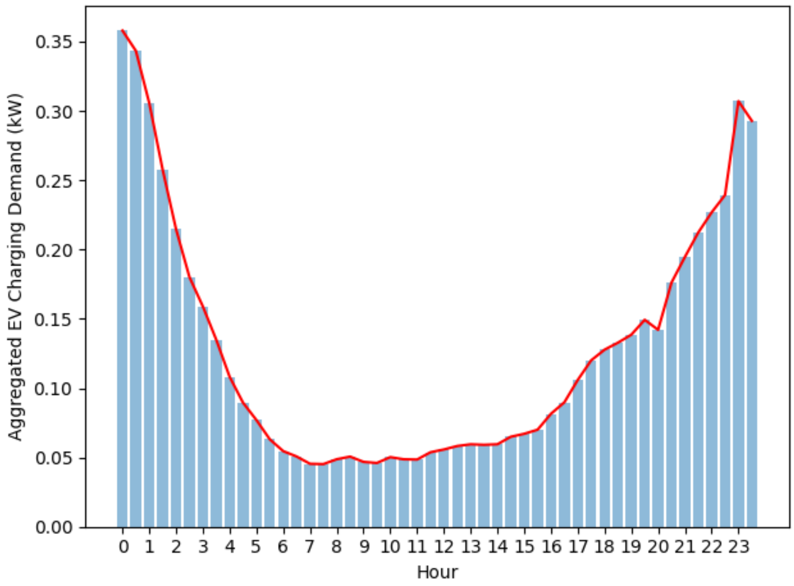

Figure 24 Aggregated EV charging demand per customer in Scenario 3 (2.3kW – 10%, 3.7kW – 45%, 7.4kW – 45%)

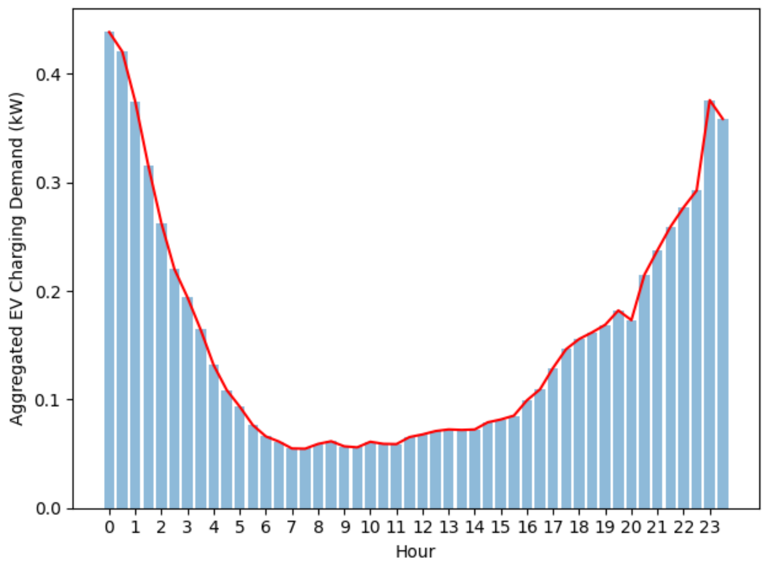

Figure 25 Aggregated EV charging demand per customer in Scenario 4 (2.3kW – 0%, 3.7kW – 50%, 7.4kW – 50%)

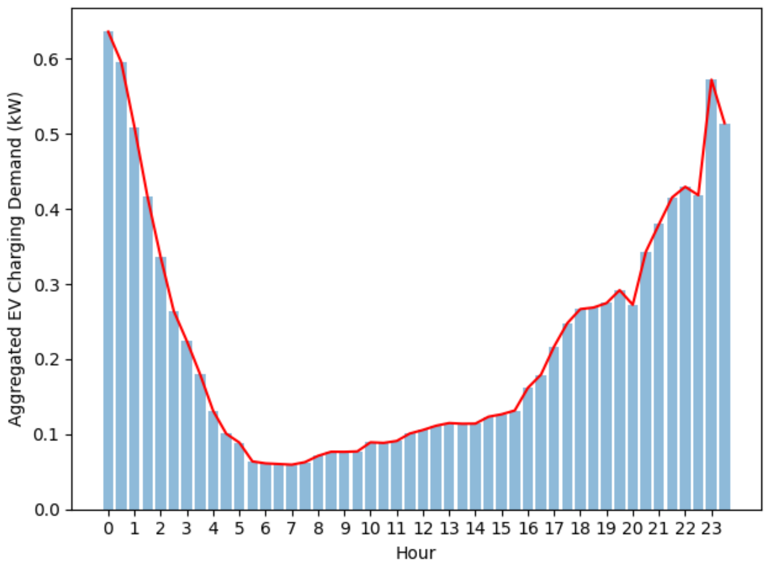

Figure 26 Aggregated EV charging demand per customer in Scenario 5 (2.3kW – 0%, 3.7kW – 30%, 7.4kW – 70%)

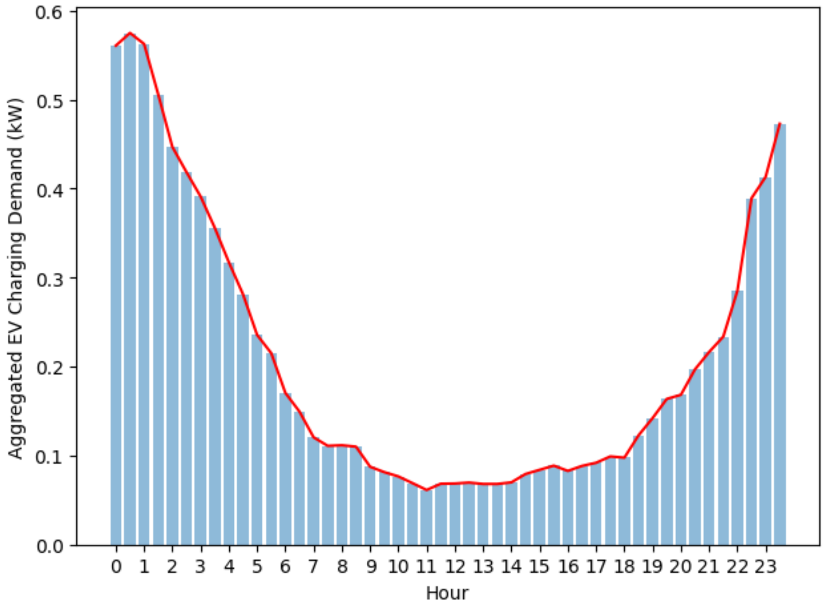

Figure 27 Aggregated EV charging demand per customer in Scenario 5 (2.3kW – 0%, 3.7kW – 100%, 7.4kW – 0%)

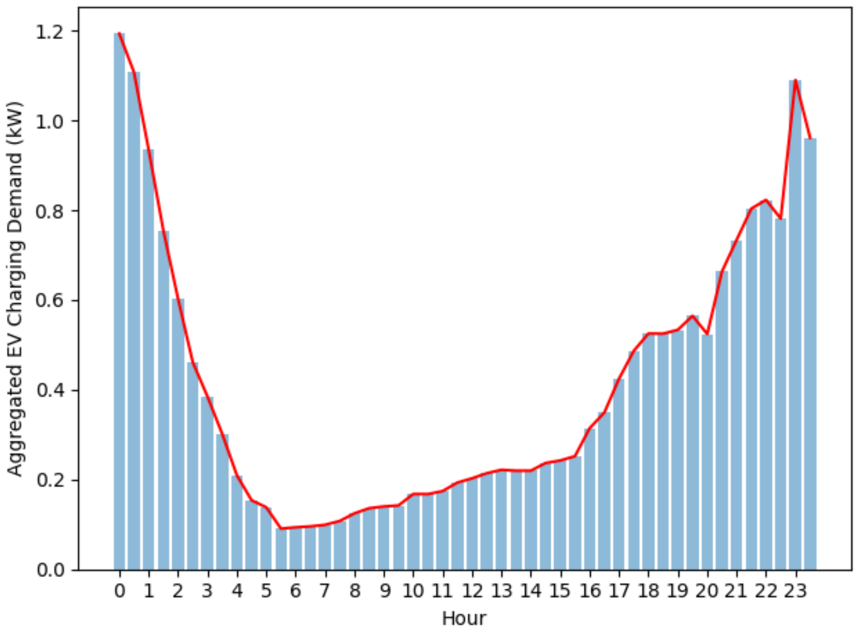

Figure 28 Aggregated EV charging demand per customer in Scenario 5 (2.3kW – 0%, 3.7kW – 0%, 7.4kW – 100%)

Conclusion

This report has investigated the electrification of transport profiles through an in-depth analysis of EV charging patterns and aggregated charging profiles. By employing an aggregated probability distribution approach, we have been able to capture interactions between various factors affecting EV charging demand, such as different types of chargers and daily usage patterns. Our focus on non-PV customers provided an improved understanding of the charging behaviours with three types of chargers, i.e., 2.3kW, 3.7kW, and 7.4kW, and their aggregated charging profiles with diverse mixes.

The analysis of EV profile modelling results from the previous project deliverable (i.e., EV charging profile extraction) reveals insights into charging demand patterns across different types of chargers at various periods of the day, including morning-only, daytime-only, evening-only, and morning-evening charging segments. Our comparative analysis among 2.3kW, 3.7kW, and 7.4kW chargers provided the following insights.

1) Peak Charging Intensity and Duration: The 7.4kW charger exhibits the sharpest and highest peaks, indicating that users can complete their charging sessions faster compared to the 3.7kW and 2.3kW chargers. This is evident in all the segments (morning, daytime, night, and morning-night) where the distributions have much narrower and steeper peaks. The 3.7kW charger has intermediate peak sharpness, while the 2.3kW charger has the broadest and most gradual peaks, reflecting slower charging sessions;

2) Distribution Spread: the 7.4kW charger's distributions are the most concentrated around the peak hours, with minimal overlap into adjacent periods. The 3.7kW charger exhibits a slightly broader distribution, while the 2.3kW charger shows the widest spread, with tails extending well into the next segments. This suggests that the 7.4kW charger allows for more efficient charging, with users able to finish charging within their allocated segments, whereas the lower-rated chargers result in longer sessions;

3) Bimodal Patterns: Both the night-only and morning-night segments display bimodal patterns across all charger types. However, the bimodal peaks for the 7.4kW charger are much sharper and occur closer to the segment boundaries (early morning and late night), reflecting the ability of users to finish charging faster. The bimodal distribution is less pronounced in the 2.3kW charger due to the slower charging rate, leading to more overlap between the peaks and more gradual transitions between periods.

Besides analysis on the aggregated EV charging demand based on the current mix of three kinds of chargers (in our obtained dataset), we investigate the possible future scenarios of aggregated EV charging demand following diverse scenarios, where customers may choose to upgrade their chargers. The results seem to suggest that, if more customers upgrade from 2.3kW chargers to 3.7kW or 7.4kW chargers, it will, to a great extent, raise the charging demand at peak hours.

Overall, this report presents a detailed and scenario-based analysis in understanding aggregated residential EV charging profiles with different mixes of EV chargers possibly evolving over time. Our methodology provides a useful framework for modelling, aggregating, and projecting aggregated EV charging demand, potentially enabling better network management and infrastructure updates, as we transition to more sustainable transportation systems. Continued refinement of this approach, along with the incorporation of large-scale diverse real-world data, may further enhance the accuracy and reliability of our models.

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